Hindawi
Mobile Information Systems
Volume 2022, Article ID 9587049, 12 pages
https://doi.org/10.1155/2022/9587049

Research Article

Analyzing the Influence of College Aesthetic Education Teaching on College Students' Innovation Ability and Artistic Literacy Based on Decision Tree Classification Model

Minghui Wang

Institutes of Chifeng, Chifeng 024000, China

Correspondence should be addressed to Minghui Wang; 2018010500089@jlxy.nju.edu.cn

Received 6 June 2022; Revised 9 July 2022; Accepted 11 July 2022; Published 16 August 2022

Academic Editor: Liping Zhang

University-level aesthetic education can help students develop their aesthetic sensibilities, enhance their artistic and creative skills, maximise their artistic and creative potential, and produce more and higher-quality works of art. Aesthetic ability is crucial for students' quality because it helps them better appreciate the appeal of artistic creations, enhance their art education, and advance in their future growth and development. Therefore, it should place a high value on aesthetic education at the university and work at various levels to gradually cultivate students' sentiments and enhance their aesthetic skills. A new "Big Data era" has emerged as a result of the expanding and widespread use of IT and the massive amount of data that needs to be stored and used. There are several widely used methods for classifying data, including decision trees, Bayesian classification, Bayesian networks, and neural networks. In order to more effectively develop students' aesthetic ability in college aesthetic education teaching activities, the impact of college aesthetic education on college students' creative ability and artistic literacy was examined. This was done on the basis of a decision tree classification model. According to the experimental results, the decision tree model significantly increased the accuracy of preference classes while maintaining the same level of overall accuracy. The F-value of the decision tree model on various data sets was improved by 0.318 and 0.221, respectively, in comparison to the SVM algorithm. The development of innovation ability in university aesthetic education is crucial for developing students' personalities, bettering study habits, enhancing aesthetic literacy, and developing comprehensive ability. As a result, we analyze the impact of university aesthetic education on college students' innovation ability and artistic literacy using the decision tree classification model.

1. Introduction

The teaching of aesthetic education is an essential component of the university curriculum in China and a crucial curricular strategy for achieving the objective of comprehensive development of high-quality education in moral, intellectual, aesthetic, physical, and labour skills [1]. Innovation is built on the knowledge and experiences of students. The new curriculum describes the nature of the art course as "humanistic," and the course objectives consistently incorporate the fundamental educational ideas of "people-oriented" and "student development-oriented" instruction [2]. As a result, many people now consider choosing a life of greater quality and taste to be a necessity, which calls for us to concentrate on developing and enhancing people's aesthetic aptitude [3]. This is due to aesthetic education teaching, which is recognized as one of the most productive fields for encouraging creativity and a good way to foster students' creative consciousness and capacities [4].

Teaching aesthetic education to students is the most efficient and reliable way to foster their artistic creativity [5]. The term "creative thinking" actually refers to "the process of conceiving new and original solutions to problems." With this way of thinking, we can think outside the lines of conventional thinking, approach problems from unusual or even unusual perspectives, and propose unusual solutions, leading to novel, unusual, and socially significant thinking outcomes [6]. Aesthetic education is regarded as a crucial component of education in the university art curriculum because it "has the important ability to enhance students' aesthetic interests and, as a result, to develop a more positive understanding of life and good habits of learning and living" [7]. The teaching of important subjects like physical beauty and audiovisual beauty needs to be strengthened, according to new university curriculum standards, in order to support Chinese university graduates' overall development and lay the groundwork for their future studies at the university [8]. Social standards for the calibre of a university education have changed as the information age has progressed [9]. Additionally, the budget is more sufficient for university amenities, art instructors, and instructional supplies [10]. Therefore, it is important to consider whether the original aesthetic education teaching method needs to be revised [11]. In order to find the connections and secrets hidden within the data when faced with such a large amount of data, data mining techniques are developed.

The phenomenon of "data explosion and knowledge poverty" is the result of the inability to access the knowledge concealed within the data. The budget for university facilities, art teachers, and instructional materials has increased, as have societal expectations for the calibre of higher education. Therefore, it is important to consider whether the original aesthetic education teaching model needs to be revised. The field of data mining, which integrates theories and methods from databases, artificial intelligence, machine learning, statistics, and other fields, is a crucial one in the information processing industry [12]. The creation of a classification function or classification model [13–15] through a method and research is the ultimate goal of classification. It is challenging for decision-makers to guarantee the accuracy of judgments and decisions based on personal experience and intuition without the support of adequate statistical data. This gap is precisely filled by the use of data mining techniques represented by decision tree models in performance evaluation.

The innovative points of this paper are as follows:

(1) This study timely grasps the development trend of aesthetic education and college students' innovation ability and innovatively studies the influence of aesthetic education on college students' innovation ability and artistic literacy from the perspective of decision tree classification model.

(2) In the context of aesthetic education teaching innovation, this study proposes a decision tree generation process for the innovative ability and artistic literacy of aesthetic education teaching. In this process, UCB is used as a criterion for category labeling, and the establishment of decision tree evaluation indexes is considered.

(3) This study innovatively introduces the ID3 algorithm into the process of exploring the influence of aesthetic education on innovation ability, effectively realizes the fuzzy analysis of aesthetic education data through the decision tree classification model, and further promotes the personalized development of aesthetic education on innovation ability.

The research framework of this paper contains five major parts, which are organized as follows. The first part of this paper introduces the background and significance of the study and then introduces the main work of this paper. The second part introduces the work related to the decision tree classification model of the influence of university aesthetic education teaching on the innovation ability and artistic literacy of college students. In the third part, the process of decision tree generation of innovation ability and artistic literacy in aesthetic education and the establishment of decision tree evaluation indexes in aesthetic education are sorted out, so that readers of this thesis can have a more comprehensive understanding of the idea of analyzing the influence of aesthetic education based on decision tree classification model. The fourth part is the core of the dissertation, which describes the application of the decision tree classification model in investigating the impact of aesthetic education on innovation ability and artistic literacy from two aspects: the analysis of the impact of aesthetic education on innovation ability using ID3 algorithm and the fuzzy analysis of aesthetic education data using decision tree classification model. The last part of the paper is a summary of the full work.

2. Related Work

2.1. The Influence of Aesthetic Education on College Students' Innovative Ability and Artistic Accomplishment. In the current social environment, high demands are placed on students, one of which is creative thinking. The traditional university model of teaching aesthetic education focuses on the standardization of curriculum, teaching materials, and classroom organization and usually uses a uniform assessment to evaluate the effectiveness of student learning and teacher teaching. The content of art courses should be closely related to students' life experiences, emphasizing the role of knowledge and skills in helping students beautify their lives and allowing them to experience the unique value of art in real life situations.

Rizvi et al. suggested that teaching aesthetic education should play such a fundamental role: guiding students to experience pictures and helping them to feel beauty, creativity, and freedom through pictures [16]. DU stated that Chinese ordinary should reject the copy-centered program and focus on developing students' modeling skills, creativity, and appreciation [17]. Liu pointed out that the current mainstream model of university aesthetic education continues the experience and skills orientation of the industrial era. For the information and networked era, students' self-employment should be fully equipped with their own thinking personality and ability personality [18]. The research results of Ma and Zhou about the teaching objectives and curriculum objectives of aesthetic education both put the development of students' innovation ability as the purpose of teaching aesthetic education [19]. Devasenapathy and Duraisamy discussed how specific strategies can be adopted to increase the richness and innovation of university aesthetic education. Integrating art into university aesthetic education can significantly increase the diversity and flexibility of the content, while fully incorporating students' hands-on and imaginative skills, thus improving their hands-on creativity [20].

How to tap the advantages of the subject, cultivate students' innovative spirit, and train high-quality talents is a question that all educators should consider. In terms of school instruction, aesthetic education teaching activities bear the special mission of cultivating and improving the aesthetic ability of individuals and require our special attention. Therefore, in college art teaching, teachers ought to emphasize the cultivation of innovative thought so as to effectively promote the development of students.

2.2. Decision Tree Classification Model. The purpose of higher education in China is to develop builders and successors who grow morally, intellectually, physically, aesthetically, and laboriously in all spheres. This places the goal of aesthetic education on par with learning scientific and cultural knowledge, enhancing personality development, and cultivating the spirit of labour. Secondary schools and universities, which are primary educational institutions, are relatively behind in the compulsory education stage. Although there is still a significant amount of money spent annually on updating hardware, very little data analysis, let alone data mining, is carried out. The development of database technology has advanced to a new level. It has the ability to not only search through historical data but also discover possible connections between historical data.

In order to obtain the ideal decision tree model, Hou conducted an in-depth study on attribute selection and pruning optimization. During the construction process, the impact of the cost of the decision tree model in the actual decision-making process was analyzed [21]. Guo argued that Quinlan's entropy function has the defect of biasing the attributes that take more values and suggested restricting the decision tree to a binary tree so that the attributes that take more values have the same chance as the attributes that take less values [22]. Lino et al. used the decision principle of classification learning and balancing cost, sensitive to the presence of cost, to establish an objective function with the goal of cost minimization [23]. Venkatesan et al. proposed an optimization algorithm MID3 to overcome the poor ability of ID3 to learn simple logical expressions [24]. Mclean et al. proposed a cost-sensitive decision tree model, which quickly became a hot research topic in the related field. Nearly nine different types of cost-sensitive decision models including misclassification cost, testing cost, instructor cost, computational cost, intervention cost, unnecessary achievement cost, human-computer interaction cost, case cost, and instability cost were developed [25].

Decision tree model effectively integrates the advantages of fuzzy theory and decision tree, which not only has strong decision analysis capability, but also can deal with vagueness and uncertainty well and is gaining more and more attention.

3. Thoughts on Analyzing the Influence of Aesthetic Education Teaching Based on Decision Tree Classification Model

3.1. Generation Process of Decision Tree of Innovation Ability and Artistic Accomplishment in Aesthetic Education Teaching. A core part of aesthetic education can be described as education that develops students' creative abilities and artistic skills [26]. The most central part is the development of creative abilities, including the ability to recognize beauty, develop it, and appreciate it, all of which must be developed for appreciation [27]. Decision tree generation is a process of recursively selecting the most distinguishing feature and using this feature to divide the given training data, resulting in the best classification for each subset of data [28]. The data transformation process is shown in Figure 1.

Firstly, the root node is constructed and all training sample sets are placed on the root node to select the best feature attributes. The mined data, especially from different data sources, may use inconsistent descriptions for the same object, and input errors may also lead to inconsistencies. The ID algorithm always chooses the property that has the greatest gain in information among all the properties for the current node to split. The formula to calculate the classification of a given sample is as follows:

$$I(s_1, s_2, \ldots, s_m) = -\sum_{i=1}^{m} p_i \log_2 (p_i), \tag{1}$$

where S is collection of sample data, m is number of different values, C_i is category, S_i is number of samples, and p_i is probability of belonging to any sample of C_i

Entropy is a concept to measure the amount of information. In information theory, it represents the uncertainty of random variables. It focuses on the quantification of information. The formula is as follows:

$$P(X = x_i) = p_i, \quad i = 1, 2, \ldots, n. \tag{2}$$

X is discrete random variables, and $P(X = x_i)$ is probability distribution of discrete random variables.

In order to fully motivate and stimulate students' motivation and initiative, as well as to help cultivate and protect their interest and confidence in learning, the teaching material should strive to be novel and interesting [29]. According to phenomenology, in the educational process, consideration should be given to the learner's experience as well as their subjective perception, experience, and the objectivity of the knowledge itself [30]. A specific situation or atmosphere corresponding to the teaching content is introduced or created in the contextual teaching process from the pedagogical needs, so that the students' emotions are resonant, in order to achieve the established pedagogical purposes. Students can quickly and accurately understand the material being taught, and their mental faculties are fully and harmoniously developed, allowing them to experience concrete emotions in the objective situation. Suppose a decision tree is constructed for a data set with two numbers of class attribute values, in which there are p positive

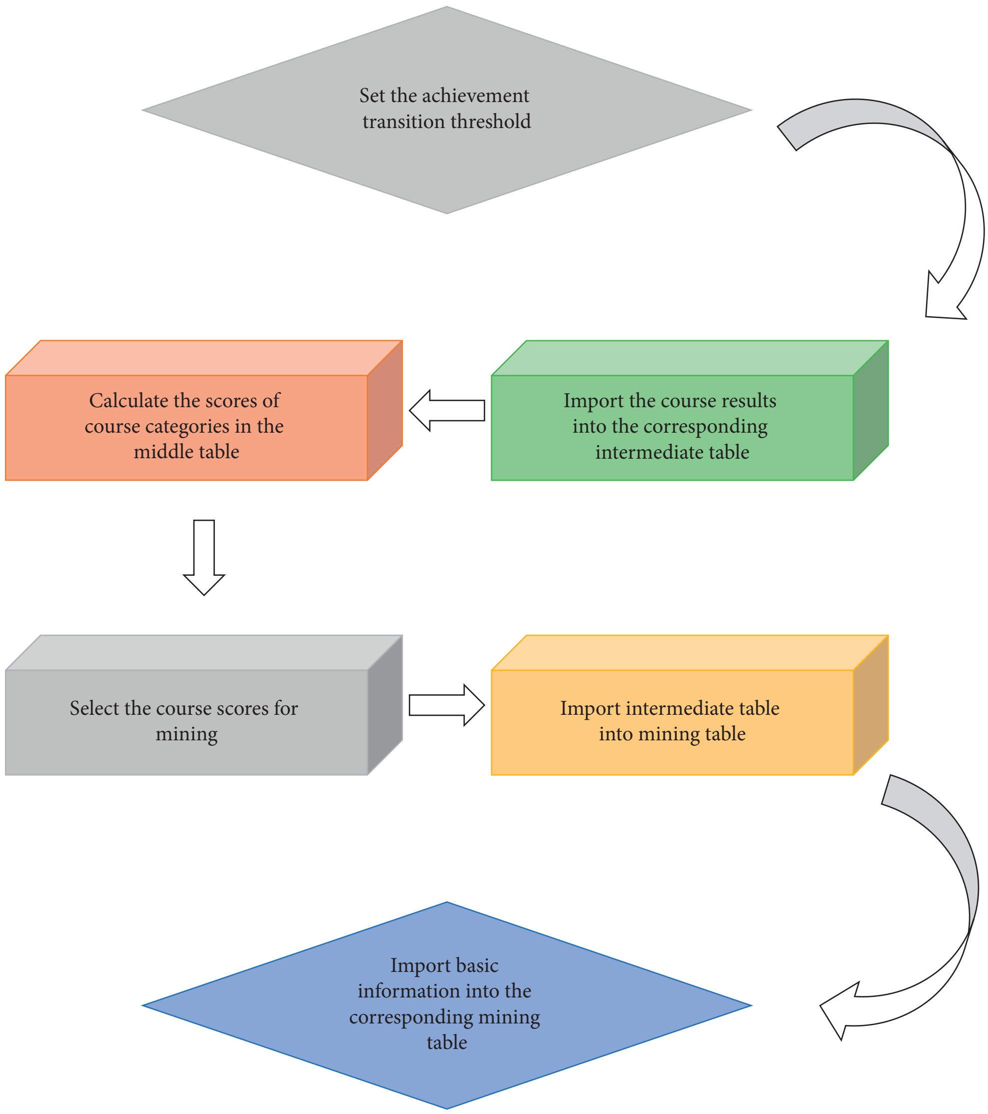

Figure 1: Flowchart of data conversion processing.

samples and n negative samples at a certain node; the class labeling method for that node is as follows:

$$\begin{cases} P, & \text{if } p \times FN > n \times FP, \\ N, & \text{if } p \times FN < n \times FP. \end{cases} \quad (3)$$

P: this node is judged as a positive node, N: this node is judged as a counterexample node, FN is the price to be paid when the positive node is wrongly judged as the negative example, and FP is the price to be paid when the counterexample node is wrongly judged as a positive example.

If the correct rate of the selected features after classification of the sample data is similar to the correct rate obtained by random classification, then the selected feature values are indistinguishable. Not using such features for classification has no effect on the accuracy of decision tree classification. In the decision tree model, we redefine the split attribute selection factor:

$$\text{ASF}\left(A_i\right) = \frac{\left(2^{\text{Average gain}\left(A_i\right)} - 1\right)}{TC\left(A_i\right)_{\text{normal}}} * \text{Incr} - \text{UCB}\left(A_i\right), \quad (4)$$

A_i is the i attribute in the set A, Average gain(A_i) is average information gain, $TC(A_i)_{\text{normal}}$ is standardized test cost, and Incr − UCB(A_i) is UCB dosage.

Until all subsets of the training sample data can be classified substantially correctly or the features are empty, each sample subset can be assigned to a leaf node. The process of generating a decision tree is shown in Figure 2 below.

Second, according to this feature property, the training sample set on the node is subset so that each training sample subset is the best classification under the current conditions. The scientific, rational, and interesting teaching methods are used to attract students, make them learn actively, and stimulate their creative impulse for beautiful things. Selection of data is done by choosing data appropriate in data

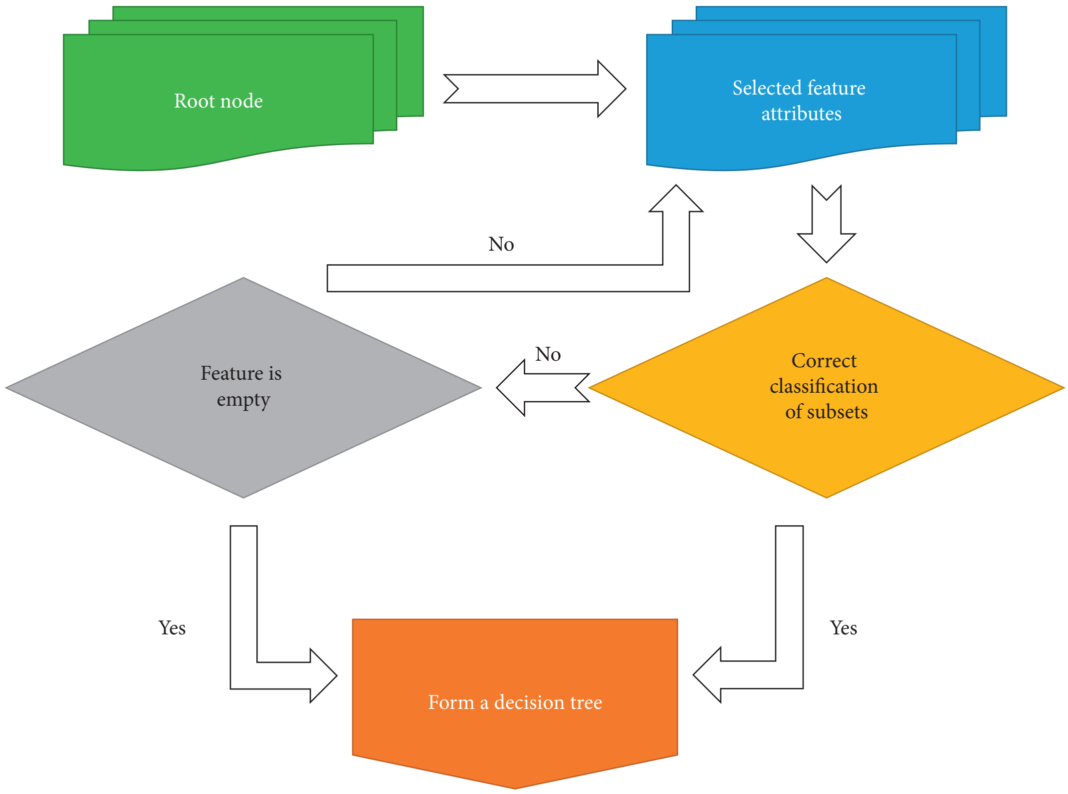

Figure 2: Building a decision tree.

mining operations out of all data associated with data for business purposes and dropping data irrelevant to data mining. In the process of learning the art, on the one hand, you will be exposed to novel knowledge and techniques, and on the other hand, you will encounter new problems and generate new ideas. This leads students to pay attention to the content and generate positive attitudinal tendencies, thus stimulating the need for reflection and inquiry and developing innovative thinking. The amount of information required for a decision tree to make a correct category judgment for an example is

$$I(p,n) = -\frac{p}{p+n}\log_2\frac{p}{p+n} - \frac{n}{p+n}\log_2\frac{p}{p+n}, \quad (5)$$

where p, n are the sizes of positive and negative examples in vector H

Finally, it is determined that if the segmented subset of samples can be broadly acknowledged as the correct classification, and if so, leaf nodes are created. In order to improve the inspiration and interest of learning content to meet the needs of the new era, teachers should carefully choose and write the content, reform traditional teaching content, teaching methods, and teaching mode of homogeneity, and use colourful and modern teaching facilities and technical conditions. Data integration is the blending of information from various data sources and storage in a single data store. The redundant attributes should be removed during this process. Students will look for potential solutions in order to more effectively solve problems. It is the responsibility of aesthetic educators to support student development. The teaching of aesthetic education must take into account its own survival and development in the context of modern education, which promotes "getting out of the books and out of school." It can be seen that the feature "quality improvement" has the greatest information gain, and when choosing the features of the decision tree, this feature can be chosen as the root node or inner node.

3.2. Establishment of Decision Tree Evaluation Index in Aesthetic Education Teaching. In the decision tree algorithm, the correctness of the classification and the complexity of the decision tree are the two most important factors to be considered. The following are the quantitative evaluation criteria for decision trees. The preference cost is used to penalize the overpreference behavior of the preference classes and reduce the incorrect classification, thus ensuring the overall accuracy of the decision tree. The effective preferences of nodes are calculated by the following formula:

$$\mathrm{EP} = \mathrm{EP}(i) = \frac{n_i \times \mathrm{pref}(l_i)}{\sum_{j \neq i} n_j c_{ij} + 1}, \quad (6)$$

n_i is the number of examples.

First, in the process of decision tree learning, one must choose one of a set of hypotheses to match the training case set. If it is known in advance that the function to be learned belongs to a small subset of the entire hypothesis space, then the training cases are incomplete. It is also possible to learn useful hypotheses from the training case set so that the unknown examples can be correctly classified. Before giving the formula for splitting the attribute selection factor, it is necessary to define the EP increment:

$$\text{Incr} - \text{EP}(A) = \sum_{i=1}^{n} \text{EP}(A_i) - \text{EP}, \tag{7}$$

where EP is the effective preference of nodes without attribute A as split attribute and $\sum_{i=0}^{n} \text{EP}(A_i)$ is the sum of effective preferences of all child nodes split by splitting attribute A

Before receiving the information, the receiver's uncertainty about the information symbol sent by the source becomes the self-information quantity, that is:

$$I(a_i) = -\log 2\ p(a_i), \tag{8}$$

where a_i is the information symbol sent by source and $P(a_i)$ is the probability of a_i

We need to reform the so-called experts' practice of arranging teaching contents wishfully without regard to students' individual characteristics and actual requirements and avoid "one-size-fits-all" teaching contents, teaching methods, and teaching forms. The order of data cleaning, data selection, and data integration is determined by the data source and the data mining environment. If possible, selecting data first can reduce the amount of data later. Determine whether the nodes meet the conditions to stop splitting; e.g., the number of node samples is less than a specified threshold. The basic flow of decision tree imputation is shown in Figure 3.

The cultivation of aesthetic ability requires respecting and giving full play to students' subjectivity, i.e., allowing them to realize the cognition and appreciation of artworks through independent and cooperative inquiry. This process cannot be achieved without the teacher's organizational management and necessary guidance. Without this ability, it is difficult to achieve overall control of the art class. Since self-information can only reflect the uncertainty of information symbols, the information entropy is needed to measure the uncertainty of the whole information source:

$$\begin{aligned} H(X) &= [-p(a_i)\log 2(a_i)] + \cdots + [-p(a_n)\log 2(a_n)] \\ &= -\sum_{i=1}^{n} p(a_i)\log 2(a_i), \end{aligned} \tag{9}$$

where a_i is the possible values, $p(a_i)$ is the probability and n is the number of all possible symbols of the source.

In the grade management of the academic affairs system, grades have multiple attributes. Before performing the decision tree algorithm, the characteristic attributes of grades are summarized, the attributes that are irrelevant or weakly related to the analytical mining of grades are eliminated, and the relevant attributes are selected as the nodes of the decision tree. The minimum conditional attributes of the fuzzy partition are selected as the extended attributes. Among them,

$$\text{FE}(D, A_i) = -\sum_{j=1}^{k_i} \frac{m_{ij}}{m_i} E\left(D \cap A_{ij}\right), \tag{10}$$

where D is the leaf node, A_i is the unused conditional attributes, and $FE(D, A_i)$ is the fuzzy partition entropy.

Secondly, the decision tree is actually tested on a test case set, which is equivalent to training the decision tree in the test set. Teaching students according to their abilities and strengths is the key to enhancing their sense of creativity. While perceiving the charm and charm of art works, we use professional language to aptly describe and comment on art works to enhance students' cultural taste. The decision tree induction algorithm calculates the gain amount of information from one property to another and selects the property with the greatest gain as the test property for the given set, thus generating the corresponding branch nodes. Students apply their art knowledge and aesthetics to the artwork, rethink the work, form a new artistic outline in their own thinking, and mobilize their art knowledge and creative experience in the process of enjoying the artwork. The generated nodes are labeled as corresponding attributes, and the corresponding branches of the decision tree are generated according to the different values of the attribute, each branch representing a subset of the divided samples.

The generated decision tree then compares the predicted class labels with the actual class labels after receiving each sample in the test set one at a time. This completes the process. The best splitting point is chosen if the chosen splitting attributes are continuous; if they are discrete, the best splitting subset is chosen. The stages and imbalances of each student's physical and mental development should be taken into consideration. For instance, understanding the creative endeavours of people in various eras and cultures and developing a deeper understanding of the harmonious but disparate artistic endeavours are both made possible by appreciating classical art works from ancient and modern times. The initial training data set is then divided into a number of independent split subsets based on the selected split points or split subsets. The training set's splitting property is used to choose these subsets, and the generated branch points are split in the same manner until the splitting produces child nodes that are leaf nodes labeled with classes.

4. Application and Analysis of Decision Tree Model in Exploring the Influence of Aesthetic Education on Innovation Ability and Artistic Accomplishment

4.1. Using ID3 Algorithm to Explore the Influence of Aesthetic Education on Innovation Ability. The ID3 algorithm calculates the gain of information which is used as the foundation for selecting the test attributes. The ID3 algorithm picks the property with the greatest gain of information as the internal node each time, so that when testing nodes other than the leaf nodes, the one with the lowest entropy of the attribute can be found to split the nodes. Information gain or information gain ratio is an important reference data for selecting feature values. The data classification of decision tree is to make a large amount of cluttered data into order. The running time of decision tree algorithm in this paper was compared with SLIQ algorithm and SPRINT algorithm on different data sets in a standalone environment. The results are shown in Figure 4 below.

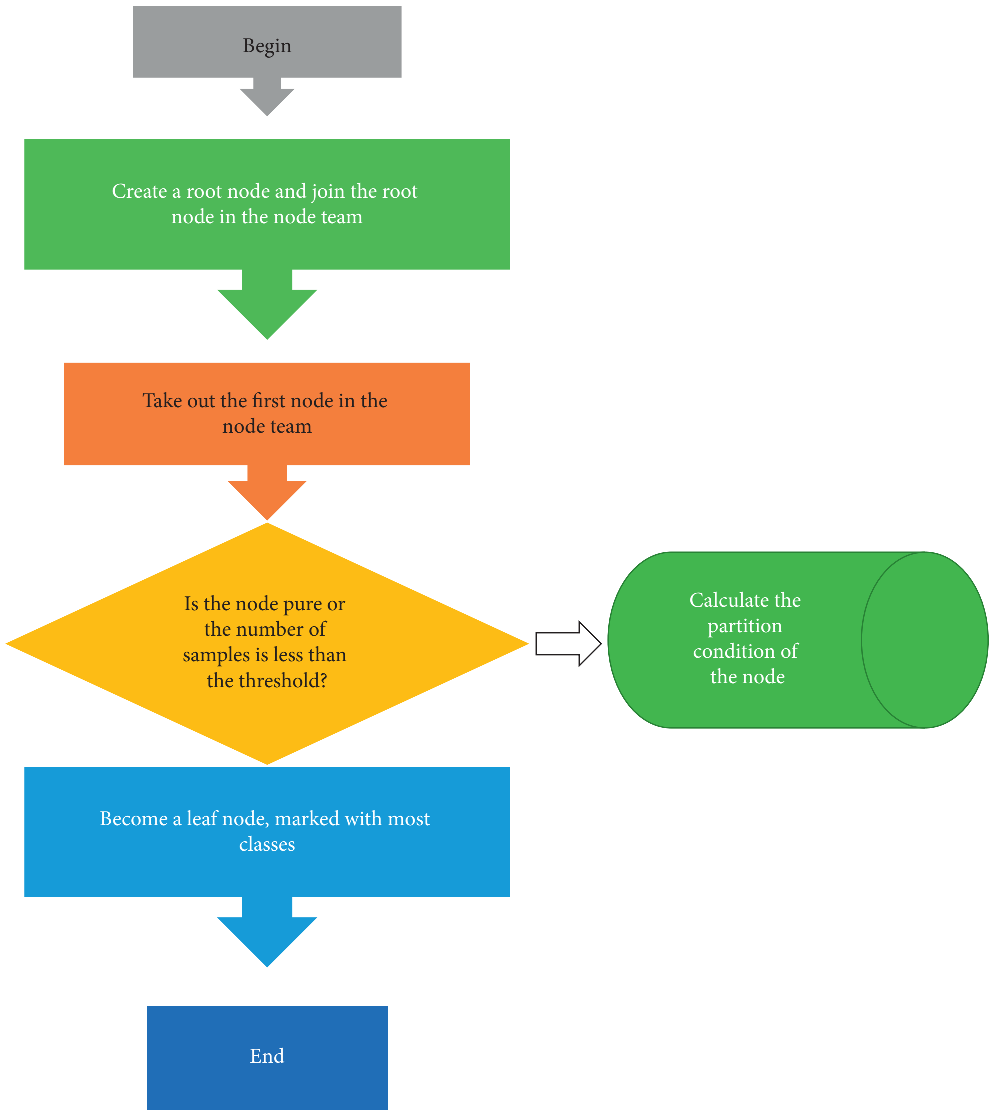

Figure 3: Basic flowchart of tree homing.

First, the information gain of all features is calculated for each node including the root node based on the top-down structure of the decision tree. The feature with the greatest information gain is found as the feature of the split node, and the child nodes are split according to the different attributes of the feature. The algorithm is simple to implement, has a clear theoretical foundation, strong learning, and classification capabilities, and is well suited to handle large-scale learning problems. Therefore, it has become an excellent tool for knowledge acquisition in the field of data mining. The acquisition of structured data is mainly done by the provided data import function, mainly students' performance data, which are mostly stored in the school database and can be imported directly. For the sake of validating the proposed model, four data sets were selected as experimental data, and the test results based on the information gain rate criteria are presented in Table 1.

The teaching of art classes cannot be separated from the reality of life. When creating works, students should combine their social environment and real life experience, create beauty from life, try their best to enhance the infectiousness of their works, and make the artistic effect reflected in the real life emotion. Although art is higher than real life, it still comes from real life after all. In order to test the performance of the design in a parallel environment, we compared the design with the SPRINT algorithm which has good parallel performance. The results are shown in Figure 5 below.

To analyze the subnodes, the previous steps are then repeated. That is, at a specific node, a specific feature is chosen to divide and create various branches in accordance with predetermined rules. Data that is semistructured is typically information about the fundamentals of the students. These semistructured data are structured based on their characteristics by choosing operations to extract the common parts and removing the ambiguous parts. The process of evaluating student artwork involves colliding the creator's emotional expression with the student's own emotional experience. It is comparable to students taking part in the recreation of the work and enables them to have an emotional connection with the artist that transcends time

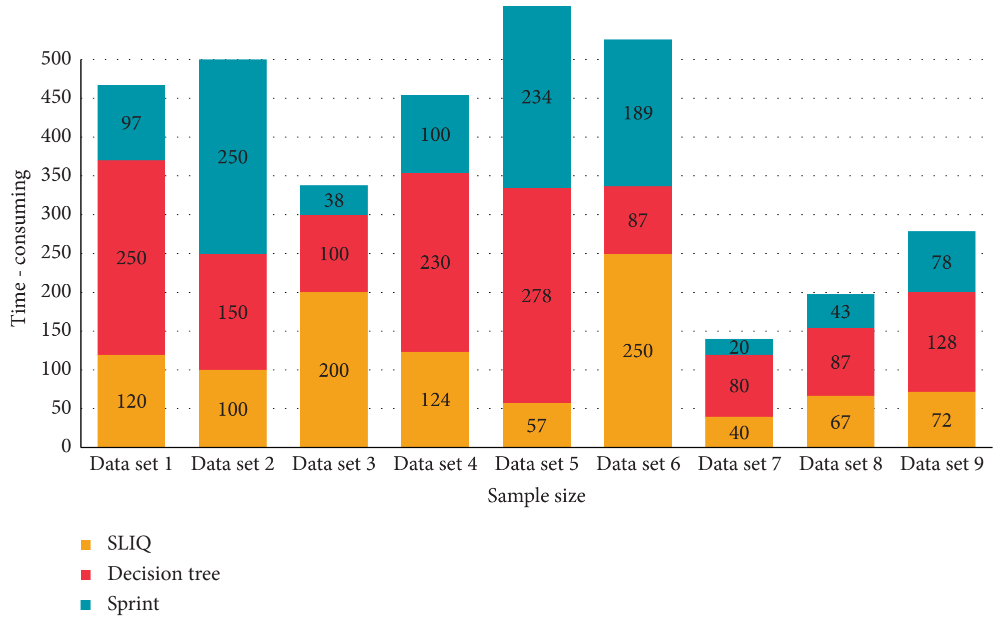

Figure 4: Comparison of running time of decision tree algorithm.

Table 1: Test results based on information gain rate standard.

Data set	Glass	Vehicle	Wine	Iris
Misclassification cost	652	734	781	834
Profit	17450	18734	28173	32615
Classification accuracy	78.4%	83.9&	90.5%	94.9%

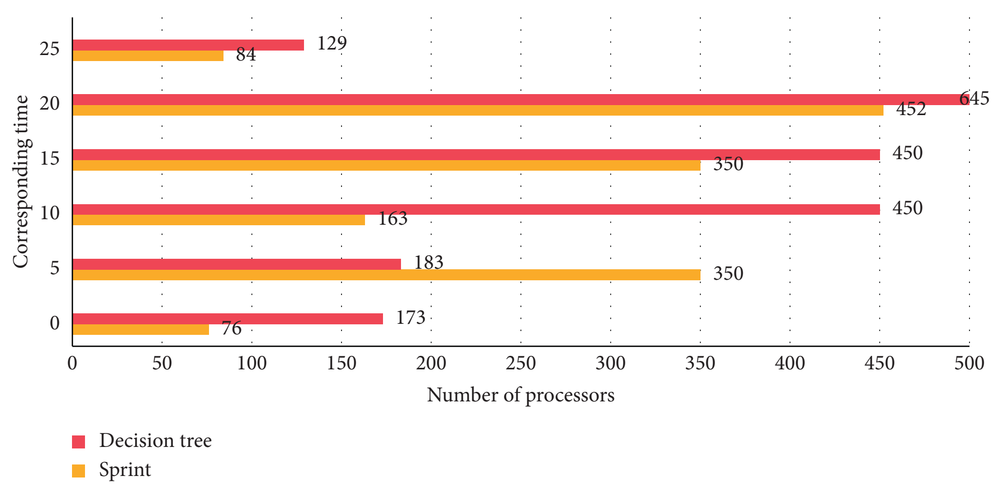

Figure 5: Comparison with SPRINT in parallel environment.

and space. The ideal outcome is for the algorithm's response time to increase linearly with the number of processors since the number of samples assigned to each machine is constant. The vertical scaling performance of 10 K, 20 K, and 30 K decision trees is compared in Figure 6.

After all features had been chosen or the calculated information gain values were minimal, the splitting was finally halted. Additionally, a student information questionnaire was created for the students to complete in order to include as much basic information about the students as possible. In order to facilitate further data mining, this information was manually entered into the educational information mining database. The integrated use of international educational resources is another significant way to support aesthetic education in an efficient manner for the development of artistic literacy. The incorporation of educational resources can be used to continually widen students' artistic horizons and assist them in exploring and understanding more in-depth artistic connotations and viewpoints. Decision trees are generated until they are unable to

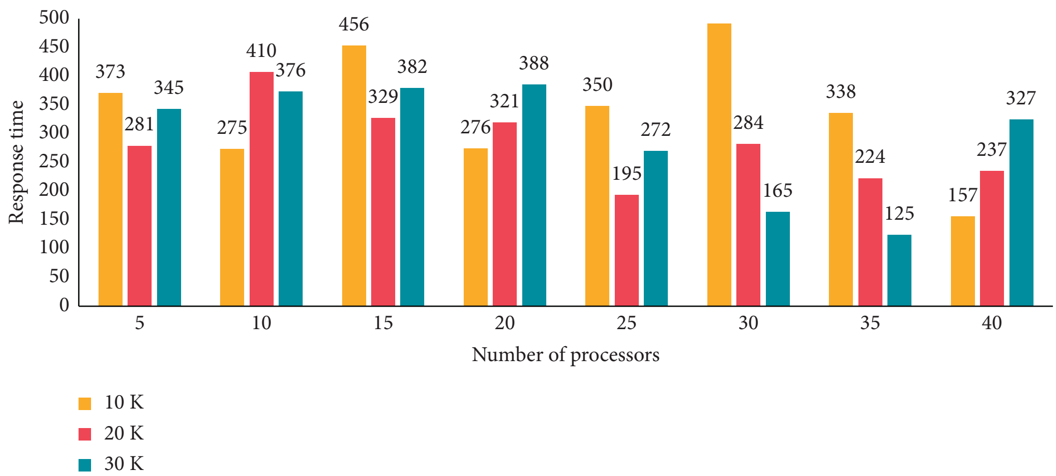

FIGURE 6: Scale up performance of decision tree.

be generated after each sample of data is scanned in turn. By removing branches of the tree that do not increase or decrease prediction accuracy, the classification error tree-pruning technique addresses the issue of decision trees overfitting data sets. In order for students to develop appropriate aesthetic values and advance their aesthetic abilities, teachers must simultaneously help students bring their ideas into the classroom. In order to create a decision tree with fewer nodes, shallow uniform depth, quick data classification, and efficient large-scale data processing, the information entropy technique is introduced.

4.2. Research on Classification Model of Decision Tree Fuzzy Analysis of Aesthetic Education Teaching Data. For the purpose of detecting regularities among the data, fuzzing of the figures becomes essential.

The original data are first fuzzified using the trapezoidal affiliation function to calculate the corresponding affiliation degree to achieve the unification of the data from quantitative to qualitative change. That is, the original training data set is always read without writing a subset of the delineated data for the subnodes. We make a compromise between finding the best division of continuous attributes and simplifying the data division. Instead of evaluating the partition points between each pair of adjacent attribute values one by one, a map normalization job is run on the dataset to compute an approximate isobath histogram for each continuous attribute before orienting it to the tree. The total amount of training data is held constant and the configuration of the number of processors is varied. The size of the training dataset is 500,000 and 1 million records, respectively. The results of the acceleration performance test for the decision tree are shown in Figure 7.

Art teachers need to innovate and improve diversified teaching modes, change the traditional single and boring teaching mode, and permeate the cultivation of art literacy into various teaching forms. For example, appreciate art works of different genres or create an excellent art teaching environment for students with the help of multimedia teaching equipment. It can not only let students understand our excellent national art and cultural traditions and foreign excellent art achievements, but also cultivate students' creative consciousness, creative inspiration, creative thinking, good emotion, and healthy psychology.

Second, the original sample data are fuzzified according to the trapezoidal affiliation function using the fuzzy logic toolbox in the software. In this way, all statistical attributes of the training set data can be used to make decisions, thus resisting noise. Thus, students can truly immerse themselves in the teaching classroom, fully exploit their artistic potential, and stimulate and cultivate their interest in art. In the process of appreciating all kinds of art works, we cultivate their aesthetic ability and creative thinking and ensure that their art knowledge structure is constantly improved and enriched and provide strong aesthetic experiences in the process of cultivating their artistic literacy, thus laying a solid foundation for the development of their artistic literacy. The correlation between unclassified and classified attributes is then calculated according to the set correlation closure values. Different correlation closure values affect the number of uncategorized attributes, which in turn affects the mining results. It allows students to gain emotional pleasure at the beginning, while enhancing character and enlightening thoughts and ultimately allowing art education to sublimate to the overall goal of comprehensive quality education. Keeping the number of processors in the distributed environment constant, the size of the training data set was varied, and the scaled-up performance of the algorithm was tested using 5, 30, and 55 processors. The results are shown in Figure 8.

Finally, decision trees and corresponding knowledge rule sets are generated based on the generalized decision tree model. In addition, the user does not need to know much background knowledge during the learning process. As long as the training samples can be expressed in an attribute-conclusion manner, they can be learned by the algorithm. Instead, a leaf node is created to store a subset and the class distribution of the subset samples. So as to check the stability of the suggested algorithm, the following dataset from the

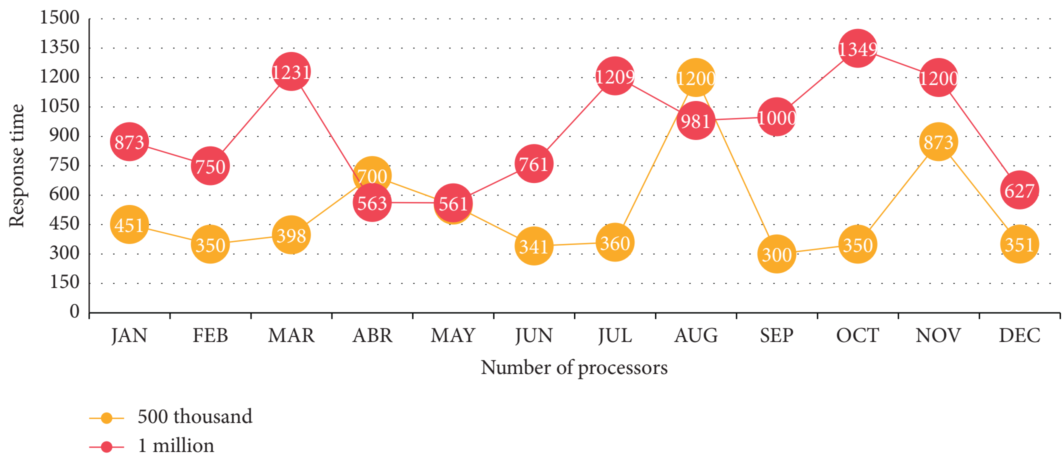

Figure 7: Acceleration performance of decision tree algorithm.

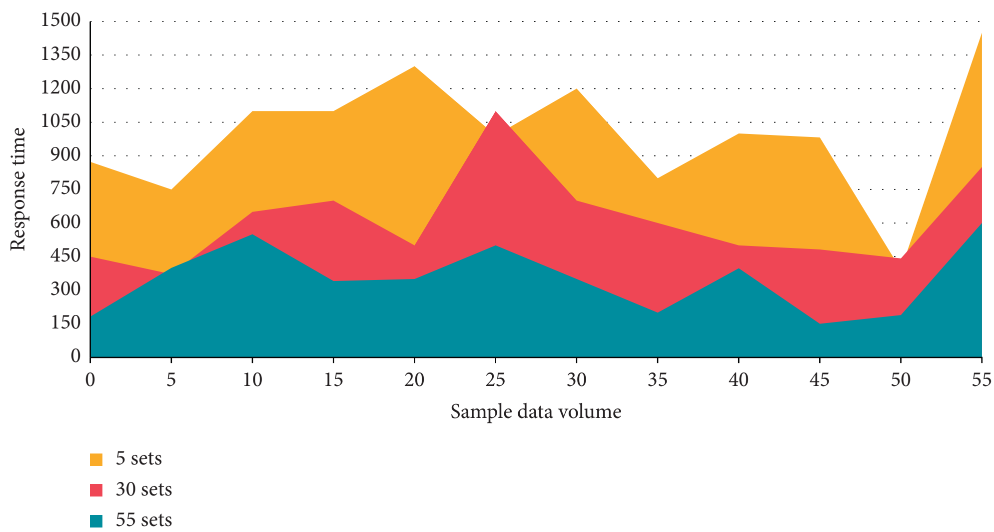

Figure 8: Size up performance of decision tree algorithm.

machine learning repository is selected as the test material in this article. The results of comparing various parameters of decision tree model and SVM algorithm are demonstrated in Table 2.

As can be seen from Table 2, the overall accuracy and F-value of the decision tree model on different data sets improved by 0.318 and 0.221, respectively, over the SVM algorithm, indicating that the decision tree model significantly improved the accuracy of the preference classes and ensured the same overall accuracy.

It is not enough to confine the development and improvement of students' artistic literacy to the aesthetic education classroom. To successfully innovate ways to cultivate students' art literacy, art teachers must overcome this situation and incorporate theoretical knowledge with art practice activities. The development of art practice activities can successfully produce a top-notch and authentic art environment for students, subtly bringing their artistic spirit into play. The category with the most samples in the subset of categorical attributes is then found as the value of the leaf node's categorical attribute during the tree-pruning process for the leaf nodes that were created as replacements. When compared to moral and intellectual education, aesthetic education in schools has some unique characteristics. Its vivid imagery aids students in understanding and helps them recognize, as well as allowing them to be fascinated and educated by aesthetics.

Table 2: Results of comparison.

Algorithm	Decision tree classification model	SVM
Virginica accuracy	0.93	0.81
F-value	0.782	0.561
Overall accuracy	0.985	0.667

5. Conclusions

University aesthetic education is a crucial stage in giving students fundamental art knowledge, abilities, and a sense of free creativity. It also plays a significant role in developing students' artistic literacy. In order to transition from passive acceptance of learning to active learning, students should be actively motivated in art classes, allowing their subjective initiative full play and broadening their imagination. Aesthetic training instruction is having difficulty keeping up with modern developments. We can only respond to the needs of the expansion of aesthetic education in colleges and improve student quality by prioritising the development of students' innovative ability. In education, the numbers conceal the laws. These rules can be mined using a variety of techniques, and they can be mined under a variety of circumstances. The potential correlation between the data cannot be uncovered by methods like the key indicator method or balanced scorecard, which can only obtain some of the data's surface information. To effectively close this gap, performance evaluation can apply data mining techniques as represented by decision tree models. We explore the influence of aesthetic education on innovation ability using ID3 algorithm and explore the fuzzy analysis of aesthetic education data using decision tree classification model, all of which are based on the decision tree classification model. We also analyze the impact of aesthetic education on the artistic literacy and innovation ability of college students. In order to achieve the educational goal of developing innovative personnel, we therefore analyze the impact of aesthetic education on innovation ability and artistic literacy using the decision tree classification model. We find that aesthetic education can create a welcoming environment for innovation education and make the most of the way that art classes are geared toward improving students' innovation ability.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares that there are no conflicts of interest.

Acknowledgments

This study was supported by Rural Basic Education Reform in Chifeng Helps Rural Revitalization.

References

[1] T. Liu, S. Li, and T. Guan, "A study of innovative education practice model to strengthen the training of educational and teaching ability for normal-school students," *Frontier of educational research: Chinese and English version*, vol. 9, no. 3, p. 5, 2019.

[2] Y. B. Liu, L. L. Xue, H. P. Xue, and P. Hou, "Effectiveness of education courses in enhancing clinical educators' teaching ability," *The Journal of Continuing Education in Nursing*, vol. 50, no. 8, pp. 367–373, 2019.

[3] L. Zhou, "Research on aesthetic education in instrumental music teaching," *Literature & Art Studies: English version*, vol. 10, no. 5, p. 5, 2020.

[4] A. B. Zhanys, A. O. Dautov, A. U. Aktayeva, and A. Z. Askarova, "Thinking development and aesthetic education of students in the process of teaching mathematics by example solutions for one problem," *IOP Conference Series: Materials Science and Engineering*, vol. 934, no. 1, Article ID 012045, 2020.

[5] Y. H. Shih, "Aesthetic education for young children in taiwan: importance and purpose," *International Education Studies*, vol. 11, no. 10, p. 91, 2018.

[6] A. Juliana, "Peirce and aesthetic education," *Journal of Philosophy of Education*, vol. 52, no. 2, pp. 246–261, 2018.

[7] J. Yao, Z. Ye, and Y. Gao, "Based on the art model of "3A" in experimental base, research and practice on the cultivation of innovation ability of landscape art curriculum," *Review of Educational Theory*, vol. 4, no. 2, pp. 42–46, 2021.

[8] P. Wei, "Art education and innovation ability training on college students," *Journal of educational theory and management*, vol. 1, no. 1, p. 3, 2017.

[9] M. Graham and S. Moore, "Elementary art education, innovation, and Darwin's paradox," *Childhood Education*, vol. 94, no. 4, pp. 4–12, 2018.

[10] J. Wang, X. Wang, Z. Weng, Y. Wei, D. Han, and C. Gong, "Implementation path exploration of innovation and entrepreneurship education reform under the background of "new engineering," *Advances in Applied Sociology*, vol. 12, no. 04, pp. 102–111, 2022.

[11] J. N. Kim, "The educability of artistic knowledge in the light of kant's "judgement" and hirst's 'art as a unique form of knowledge," *The journal of Educational Studies*, vol. 49, no. 1, pp. 83–104, 2018.

[12] J. Chen, Y. He, Y. Zhang, P. Han, and C. Du, "Energy-aware scheduling for dependent tasks in heterogeneous multiprocessor systems," *Journal of Systems Architecture*, vol. 129, Article ID 102598, 2022.

[13] M. Zhao, C. H. Chang, W. Xie, Z. Xie, and J. Hu, "Cloud shape classification system based on multi-channel cnn and improved fdm," *IEEE Access*, vol. 8, pp. 44111–44124, 2020.

[14] Y. Ding, Z. Zhang, X. Zhao et al., "Multi-feature fusion: graph neural network and cnn combining for hyperspectral image classification," *Neurocomputing*, vol. 501, pp. 246–257, 2022.

[15] M. Gao, R. Liu, and J. Mao, "Noise robustness low-rank learning algorithm for electroencephalogram signal classification," *Frontiers in Neuroscience*, vol. 15, Article ID 797378, 2021.

[16] S. Rizvi, B. Rienties, and S. A. Khoja, "The role of demographics in online learning; a decision tree based approach," *Computers & Education*, vol. 137, pp. 32–47, 2019.

[17] J. Du, "Evaluation method of English teaching quality based on fuzzy comprehensive evaluation," *International English education research: English version*, no. 1, p. 3, 2018.

[18] X. Liu, "The application of data mining technology in the teaching evaluation in colleges and universities," *Journal of Computational and Theoretical Nanoscience*, vol. 14, no. 1, pp. 7–12, 2017.

[19] X. Ma and Z. Zhou, "Student pass rates prediction using optimized support vector machine and decision tree," in *Proceedings of the 2018 IEEE 8th Annual Computing and Communication Workshop and Conference (CCWC)*, pp. 209–215, IEEE, Las Vegas, NV, USA, January 2018.

[20] K. Devasenapathy and S. Duraisamy, "Evaluating the performance of teaching assistant using decision tree ID3 algorithm," *International Journal of Computer Application*, vol. 164, no. 7, pp. 23–27, 2017.

[21] J. Hou, "Online teaching quality evaluation model based on support vector machine and decision tree," *Journal of Intelligent and Fuzzy Systems*, vol. 40, no. 2, pp. 2193–2203, 2021.

[22] B. Guo, “Analysis on influencing factors of dance teaching effect in colleges based on data analysis and decision tree model,” *International Journal of Emerging Technologies in Learning (iJET)*, vol. 15, no. 9, p. 245, 2020.

[23] A. Lino, A. Rocha, L. Macedo, and A. Sizo, “Application of clustering-based decision tree approach in SQL query error database,” *Future Generation Computer Systems*, vol. 93, pp. 392–406, 2019.

[24] E. Venkatesan, S. Anu, and H. Nair, “A study and analysis of education data using decision tree algorithms,” *REM - International Engineering Journal*, vol. 6, no. 2, pp. 1–6, 2021.

[25] S. Mclean, K. N. Meadows, A. Heffernan, and N. Campbell, “Using online decision trees to support students’ self-efficacy in the laboratory,” *Advances in Physiology Education*, vol. 44, no. 3, pp. 430–435, 2020.

[26] J. A. Clarin, “Academic analytics: predicting success in the licensure examination of graduates using CART decision tree algorithm,” *Journal of Advanced Research in Dynamical and Control Systems*, vol. 12, no. 1, pp. 143–151, 2020.

[27] A. Khalaf, A. S. Hashim, and W. Akeel, “Predicting student performance in higher education institutions using decision tree analysis,” *International Journal of Interactive Multimedia and Artificial Intelligence*, vol. 5, no. 2, pp. 26–31, 2018.

[28] Y. Mu, X. Liu, and L. Wang, “A Pearson’s correlation coefficient based decision tree and its parallel implementation,” *Information Sciences*, vol. 435, pp. 40–58, 2018.

[29] S. Li, S. Laima, and H. Li, “Data-driven modeling of vortex-induced vibration of a long-span suspension bridge using decision tree learning and support vector regression,” *Journal of Wind Engineering and Industrial Aerodynamics*, vol. 172, pp. 196–211, 2018.

[30] H. Sun and X. Hu, “Attribute selection for decision tree learning with class constraint,” *Chemometrics and Intelligent Laboratory Systems*, vol. 163, pp. 16–23, 2017.