As computer and multimedia technology advances and as the variety of knowledge display forms expands, there are more ways for people to obtain knowledge and information. The best course in musicology is voice performance. A crucial issue is how to select and categorize valuable curriculum materials of varying quality levels. This paper implements an automatic classification and integration algorithm for vocal performance learning materials using machine learning technology and tests it on the corresponding dataset, beginning with multidimensional association rule mining technology and the premise that multimedia data contain numerous useful characteristics. Experiments demonstrate the classification precision and data integration capacity of the proposed algorithm. Vocal performance is the most engaging course in musicology. To cultivate corresponding talents, we can rely on college and university offline courses and the rapidly developing multimedia technology to train talents online. An important topic is how to efficiently select and classify curriculum materials of varying quality in order to provide them to students with different learning needs. We can achieve the automatic classification of the course content by leveraging the superior learning capabilities of artificial intelligence and machine learning technology. Consequently, this paper implements an automatic classification and integration algorithm for vocal performance learning materials using machine learning-related technology and conducts an experimental test on the corresponding dataset, beginning with multidimensional association rule mining technology and the perspective that multimedia information itself contains a large number of useful characteristics. Experiments demonstrate that the proposed algorithm has a high level of classification accuracy and data integration capability.

1. Introduction

The vocal performance is a distinct type of musical performance art from instrumental music. Vocal music performance refers to singing and voice-based musical performances. In general, vocal music performance should not be exclusive, with the exception of bel canto, popular, national, opera, and other forms, including the whistle, oral skill, and other special vocal music performance forms [1–3].

Vocal performance art is a comprehensive art form that combines intellect, physical strength, creativity, and expression. As with other art forms, vocal performance art is governed by an aesthetic consciousness and emphasizes aesthetic principles. Then, we must establish a standard that permits us to measure and evaluate the work’s beauty or lack thereof. Determine the scientific and philosophical basis between vocal performance art and aesthetics, and use philosophical reasoning to logically demonstrate the aesthetic law in vocal performance art so as to elevate the aesthetic law in vocal performance art to a scientific level and achieve a true understanding, which not only aids in the comprehension of the aesthetic principle in vocal performance art, but also enhances the aesthetic connotation in vocal performance art.

Good singing is the result of two factors: first, an innately good voice and the sensitivity and coordination of physical functions related to singing; and second, daily practice and effort. It requires singers to be unafraid of adversity, long-term training, and even lifelong learning to improve their singing abilities; expand the psychological and cultural structure, including intellectual structure, ethics, and aesthetic ability; balance people’s logical thinking and image thinking; promote the development of the association and fantasy ability. It can be argued that the performer’s
comprehension, perception, imagination, and expression of musical works will continue to infuse new life and sublimate as the cultural legacy of the populace improves [4].

In the context of human artistic culture, vocal music performance occupies a prominent position. Therefore, we must vigorously develop vocal music performance and strive to cultivate high-quality and large-scale vocal music performance talents in order to promote the development of national humanities and social sciences, flourish national cultural endeavors, and enrich the spiritual lives of the populace. To meet China’s current demand for talent, however, training provided by various institutions of higher education alone is insufficient. Therefore, it is necessary to investigate new methods of talent development [5]. As network and multimedia technologies advance, more and more information and videos of high-quality vocal music performances are becoming available on the Internet. Likewise, a multitude of professionals have developed a multitude of professional vocal music courses and video knowledge resources. If we can utilize the aforementioned data and resources effectively, we will be able to play a significant role in promoting and cultivating voice talent in China.

Despite the abundance of vocal performance course materials available on the Internet, the quality of these materials varies. The use of inferior courses as learning materials for the general public will have a devastating effect on their education. Concurrently, there are numerous types of content on the network. Beginners are frequently unable to distinguish which video materials are more important for their current learning and which materials must be learned in the beginner’s desired direction [6–8]. Beginners would benefit greatly if there was a way to automatically categorize and integrate these vast learning resources. Due to the ongoing advancements in computer technology and artificial intelligence technology, we can rely on artificial intelligence technology to complete this task.

Changes in human activities continuously generate vast quantities of data. Humans utilize the power of information technology to store these data in order to provide more assistance for the present and future of society. Data mining was developed to extract valuable research content from massive datasets. Using data mining technology and objective statistics and analysis, we can discover hidden laws in massive datasets [9].

There are numerous examples of the benefits and conveniences that information technology provides. Major universities, as the backbone of fostering national talent, are among those who believe that technology alters life. The school has reaped incalculable benefits from the implementation of information management, which not only facilitates the majority of teachers and students but also retains a vast amount of meaningful data. Prior education was primarily dependent on years of experience, and the database lacked guiding significance. When data mining is applied to the field of education, it is possible to extract hidden, important, and practical information from vast amounts of educational data in order to use the mined knowledge to predict future dynamics and to more scientifically advise, direct, and improve education.

2. Related Works

2.1. The Development of the Online Educational Platform. The education platform of Internet networks is the online education platform. It is, in essence, a national resource-sharing system with zero distance [10]. It is a new way of communicating, a new platform for education and learning, and a new tool platform all rolled into one.

On the basis of increasing efficiency, the online education platform employs all tools to carry out instructional tasks. The essence of network education research is to use sophisticated network technology to modify the communication mode between teachers and students, enhance the efficiency of students’ mastering knowledge, and improve their ability.

In recent years, a new type of education centered on network expansion has swept the globe, and Internet behemoths and capital markets have promoted its rapid growth. Users are more accepting of online education, which meets their demand for fragmented and diverse learning. Micro-education, Baidu education, NetEase open course, Tencent micro-classroom, Taobao students, and other companies in China are all interested in putting their skills to the test in the field of online education [11–13].

Tsinghua University’s president Chen Jining stated that online education provides a new paradigm of knowledge transmission and learning, which would result in a significant shift in global higher education. This significant modification differs significantly from past network teaching. It not only brings about educational technology innovation but also brings about significant changes in educational conceptions, educational systems, teaching methods, and the talent development process, among other things. He believes that the emergence of online education has broken down the wall between universities and society, so we must rethink and reshape the relationship between universities and society in order for universities to better fulfill their essential function. As an essential strategy for the internationalization of higher education, online education will undoubtedly become a significant factor in the future competitiveness of higher education in a variety of countries.

Yuan Sitian, vice president of Tsinghua University, stated that the “flipped classroom” has become a reality with the advent of MOOC. MOOC is a revolutionary method for continuously exploring the reform of new education and teaching mode based on new technology and enhancing the quality of talent training. It is causing a fundamental shift in the university’s traditional learning structure. Reportedly, discussions have begun regarding the mutual recognition of course credits, inter-school course cooperation, and independent enrollment in relation to MOOC. Due to the credit mutual recognition agreement of the C9 Alliance (China’s first top inter-university alliance), the mutual credit recognition of “online Tsinghua School” may become the first significant advancement.

2.2. The Data Mining Technology. The process of collecting hidden, unknown, but potentially relevant information and
knowledge from a large volume of incomplete, noisy, ambiguous, and unexpected data from real-world applications is known as data mining. Data mining tries to reveal hidden patterns in the process of knowledge discovery. Data mining is the first step in the knowledge discovery process. As is commonly understood, data mining emphasizes the large-scale dataset as its object, independent of how these data are stored and managed [14]. Data mining encompasses not only a database in the traditional sense but also a data warehouse, file system, or any other organized data collection, such as WWW information resources. As a result, data mining is, in a broad sense, a decision-support method for discovering important knowledge and patterns in large-scale data, such as fact collections or observation data.

Data mining is a process that identifies potential rules and extracts useful information from massive amounts of data. Database knowledge discovery is an alternative moniker for it (KDD). During the eleventh International Joint Academic Conference in August 1989, the term KDD was first used. With the advancement of human research since 1989, the definition of KDD has been continuously revised. According to a more precise definition, data mining is the process of extracting useful information from massive amounts of data stored in databases, data warehouses, or other data repositories. Clustering, classification, prediction, association analysis, and time series analysis are among the most prevalent data mining operations.

Various perspectives allow for the classification of data mining algorithms into numerous categories [15].

Classification or prediction model discovery, data summarization, grouping, association rule discovery, sequence pattern discovery, dependency or dependency model discovery, anomaly and trend detection are among the mining occupations.

Relational, transactional, object-oriented, active, spatial, temporal, textual, multimedia, and heterogeneous database types underpin all database and legacy systems (WWW).

2.2.1. Classification according to Adopted Technology. The technology itself is described from different angles: (1) according to the degree of user participation. It is divided into the autonomous system, interactive exploration system, and query system; (2) depending on the data analysis methods used, they are classified as database or data warehouse focused technology, pattern recognition, statistical analysis, visualization technology, neural network, machine learning, and so on.

2.2.2. Evaluation Criteria for Data Mining Algorithms. It is not very easy to give a complete comparison and evaluation of data mining, but there are still many public principles and a series of measures, which is very comprehensive. The overall effectiveness of data mining can be measured from the following three aspects [16]:

(1) Precision: the accuracy will directly affect the accuracy and availability of the mining results. The higher the accuracy, the stronger the availability, and the more conducive to make the right decision. Accuracy will depend on the algorithm design and historical data volume, and user expectations, so sometimes, you have to compromise between accuracy and speed.

(2) Speed: although decision support needs to operate huge amounts of historical data, speed is not the main factor, but speed is still a factor to consider. After all, the amount of data is constantly expanding. Therefore, the algorithm must be practical, and parallel data processing, distribution, and efficient data fragmentation are all effective ways to improve the speed.

(3) Overheads: overheads will ultimately determine whether to use data mining for decision support. Good algorithms should not be expensive, there should be good portability, and not rely on specific environments and hardware.

2.3. The Commonly Used Classification Algorithms

2.3.1. Decision Tree. A tree has many analogies in real life, and it has influenced many aspects of machine learning, such as regression and classification. In indecision analysis, a decision tree can be used to visually depict decisions and decision making. As the name suggests, it uses a decision tree-style model. It is widely used in machine learning, though it is most commonly used in data mining to devise a strategy for achieving a specific objective [17].

As shown in Figure 1, the root of the decision tree, which is displayed inverted, is at the top. The figure on the left depicts an internal node or condition that causes the tree to split into branches/edges in bold black text. In this case, the decision/leaf appears as red and green text at the end of the branch that no longer divides, indicating whether the passenger died or survived.

Even though a real dataset would have many more features and this is only one branch of a much larger tree, the ease with which this technique can be implemented cannot...
be overemphasized. The significance of each component and the relationships between them are readily apparent. Because the objective is to classify passengers as alive or dead, the aforementioned tree is known as the classification tree, and the corresponding process is known as the learning decision tree from data. Using a comparable method, regression trees are depicted. They simply predict continuous numbers, such as the house price. CART stands for decision tree methods (classification and regression trees).

So, what is actually occurring? Determining which features to use and under what conditions to split, as well as knowing when to stop, is a part of the process of growing a tree. Because they develop at their own rate, trees must be pruned to maintain their aesthetic appeal. Let us begin with a common method of splitting.

2.3.2. Support Vector Machine. The support vector machine is another simple approach that any machine learning expert should be familiar with. The support vector machine is popular because it achieves high accuracy while consuming less computing power. Support vector machine (SVM) is a machine that can be used for regression as well as classification. However, it is widely used in categorization objectives.

To divide the two classes of data points, there are a variety of hyperplanes to choose from, as shown in Figure 2. The goal is to find the plane with the largest distance between data points in the two classes. The maximum margin distance plays a reinforcing role, making the subsequent data points easier to classify.

Hyperplane is a type of boundary decision. This helps to classify the database, and different classes can be assigned to data points. The edges of the hyperplane, and the characteristics of the hyperplane also depend on their number. The hyperplane is just a line if there are only two input features. When the number of input features reaches 3, the hyperplane becomes a plane. It is unimaginable when there are more than three features.

We use the edge of the maximum support vector machine classifier if support vector machine (SVM) is deleted, super plane position will be changed. Support vector machine (SVM) is a hyperplane of data points, closer to the hyperplane, which have influence on the position and direction of hyperplane.

The SVM method aims to reduce the distance between the data points and the hyperplane as much as possible. Equation (1) can be used to derive the hinge loss function, which aids in maximizing the margin.

\[
c(x, y, f(x)) = \begin{cases} 
0, & \text{if } x \ast f(x) \geq 1, \\
1 - y \ast f(x), & \text{otherwise.}
\end{cases}
\]

(1)

The cost is zero if the projected and actual values have the same sign. The loss value is computed if they are not. For the cost function, we additionally include a regularization parameter. The goal of the regularization parameter is to strike a balance between maximization of margins and loss. After using the regularization parameter, the cost functions are shown in the following equation:

\[
\min_w \lambda w^2 + \sum_{i=1}^{n} (1 - y_i < x_i, w >),
\]

(2)

Now that we have the loss function, we can use partial derivatives in relation to the weights to find the gradients. Using the gradients (equations (3) and (4)), we can update our weights.

\[
\frac{\partial}{\partial w_k} \lambda w^2 = 2\lambda w_k,
\]

(3)

\[
\frac{\partial}{\partial w_k} (1 - y_i < x_i, w >) = \begin{cases} 
0, & \text{if } y_i(x_i, w) \geq 1, \\
-\lambda y_i x_i k, & \text{otherwise.}
\end{cases}
\]

(4)

When there is no misclassification, that is, when our model correctly predicts the class of our data point, all we need to do is update the gradient from the regularization parameter using the following equation:

\[
w = w - \alpha \cdot (2\lambda w).
\]

(5)

When there is a classification discrepancy, that is, when our model incorrectly predicts the class of our data point, we conduct a gradient update (as given in equation (6)) that includes the loss as well as the regularization parameter.

\[
w = w + \alpha \cdot (y_i \cdot x_i - 2\lambda w).
\]

(6)

2.3.3. Neural Network. Artificial neural network, or ANN, is a common term in machine learning, especially in the field of deep learning.

Neural networks use the bionics concept to achieve modeling by imitating the structure and function of a biological brain network.

Dendrites and axons are distributed on both sides. Dendrites are used to receive signals transmitted by other neurons, while axons are used to transmit signals to other neurons. Signals are transmitted between multiple neurons to form a neural network. Many neuronal cells constitute the nerve center, which is used to respond to stimuli.
Referring to the biological structure of neurons, McCulloch and Pitts proposed the artificial neuron model, i.e., the M-P neuron model, in 1943. The structure is shown in Figure 3.

Different signals in the input layer are first summarized through a linear summation model, and each signal has a different weight, and then, an activation function is used to judge whether the output is required. Activation functions can take many forms.

The relationship between the activation function and the linear combination can be calculated by the following equation:

\[
y = f \left( \sum_{i=1}^{n} w_i x_i - \theta \right),
\]

where \(\theta\) is the threshold and \(w\) represents the weight. In the MP neuron model, the weight and threshold are fixed values, which is a model without learning.

To make the machine have the ability to learn, based on the MP neuron model, the earliest neural network model, single-layer perceptron, is proposed. The structure is shown in Figure 4.

A two-layer neural network is used. The input layer is the first layer, while the output layer is the second. Because there is only one computation layer, only the output layer requires calculation. A single-layer perceptron is what it is called. Formally, the input signal in the MP model is only regarded as an independent layer of neurons, but it is very different in essence. The weights and thresholds in the perceptron model are no longer fixed but the result of computer “learning.” The concept of the loss function is introduced, and the weight and threshold are continuously adjusted through iteration to minimize the loss function so as to find the best weight and threshold.

The number of parameters in the model dramatically grows with each new layer, as can be shown, so the requirements of deep learning on computing resources are particularly high. In practical use, the training time of the model is very long. Although it consumes computing resources, the advantages of deep learning are also prominent. When compared to machine learning, the model completes feature extraction without the need for manual feature engineering, which is especially significant when dealing with high-dimensional data. The following is a comparison diagram of the two (see Figure 5).

A feedforward neural network is made up of three typical structures: an input layer, a hidden layer, and an output layer. The back-propagation algorithm iteratively updates the parameters. There are also various versions, such as convolutional neural networks, cyclic neural networks, and generative countermeasure networks, that are useful in disciplines including computer vision, natural language processing, and picture production.

### 3. The Proposed Method

#### 3.1. Association Rules

Association rules are one of the most significant methods in data mining. They possess unique advantages for discovering hidden information in the database of specified things. Before data mining, the relationship between attributes is unknown. Even if some behavior is known in advance, it is impossible to predict the outcome of data mining. Association rule mining is an ongoing learning process. By utilizing association rule mining, people are able to locate the content they are unaware of in advance, and even the unearthed content can be useful.

Some researchers created conceptual definitions of the association rule mining problem in order to provide a clearer and more accurate description of association rule mining, and then introduced the concepts related to association rules in depth.

Transaction: all of the data items to be mined during the mining process are transactions. Each transaction is distinguished by its unique identifier.
Transaction database: $D = \{t_1, t_2, \ldots, t_n\}$, the transaction database is composed of these uniquely identified transactions.

Itemset: a collection of several different data items.

Itemset dimension: there are a number of data elements in each itemset. Because each item has a dimension, the number of items in the itemset is referred to as the dimension of the itemset. The term $k$-item refers to a collection of items with a dimension of $k$.

Frequent itemset: an itemset $X$ is called the frequent itemset if its support passes the minimal support threshold, that is, if its support is not less than the minimum support, $\text{Support}(X) \geq \text{min\_sup}$, the frequent item collection is referred to as $X$.

Non-frequent itemset: an itemset $X$ is considered a non-frequent itemset if its support does not match the minimum support threshold, that is, if its support is less than the minimum support, namely, $\text{Support}(X) < \text{min\_sup}$, the non-frequent item collection is referred to as $X$.

In association rule mining, there is the following theorem: let $X$ and $Y$ be the itemsets in dataset $D$, then, there are the following contents:

1. If $X \subseteq Y$, then, $\text{support}(X) \geq \text{support}(Y)$.
2. If $X \subseteq Y$, if $X$ is an infrequent itemset, then, $Y$ is an infrequent itemset as well.
3. If $X \subseteq Y$, if $Y$ is a frequent itemset, then, $X$ is a frequent itemset as well.

Support of itemset: assuming that $X$ is an itemset and $D$ corresponds to a transaction database, the ratio between the number of $X$ in $D$ and the total number in the database is called the support of $X$ in $D$, which is recorded as $\text{support}(X)$, as shown in the following formula:

$$\text{support}(X) = \frac{|\{d \in D | X \in d\}|}{D}. \quad (8)$$

The ratio between the number of transactions having both $X$ and $Y$ and all transactions, which is recorded as $\text{support}(X \Rightarrow Y)$, is referred to as rule support, as shown in the following formula:

$$\text{support}(X \Rightarrow Y) = \frac{|\{T | (X \cup Y) \subseteq T, T \subseteq D\}|}{D}. \quad (9)$$

3.2. Apriori Algorithm Based on Multidimensional Association Rules Has Been Improved. The Apriori technique has a number of drawbacks: it generates a large number of candidate item sets, and it scans the transaction database frequently during the mining process, which consumes a great deal of processing resources [4, 7].

Researchers have successively improved the Apriori algorithm, resulting in distinct algorithms. The following is a summary of the final method: reduce the generation of candidate itemsets and database scanning by optimizing the Apriori process using various statistical methods or knowledge of data structure. Indeed, these methods are very useful for the generation of association rules, but there may be other instances where special data are involved. For instance, when multivalued attribute data is encountered, different attribute values of the same attribute will be connected. In association rules, however, the value of the same attribute will appear only once. This repeated relationship does not meet the criteria for association rules.

Multivalued attribute data is distinct from Boolean-only association rules. The values of attributes in rules are not simply a yes-or-no relationship. Some values are continuous, such as age, income, etc. When confronted with these attributes, Boolean association rules are inadequate for processing these data. These multi-attribute data can only be processed via other association rules. Table 1 attributes with multiple values.
The data comes from the hospital’s medical data, which is used to record the patient’s medication information and the situation after medication. It can be found from the data that this is a data table containing multiple attributes. Each attribute has different representation methods when taking values, such as gender, age, item code, drug number, medication dose, and impact after medication. It is convenient to explain the changes and impact of some indicators in a patient’s body after using an important drug.

Through simple data preprocessing technology to sort out the original data, mainly to quantify the age and process the specific age into age groups. The processed data are shown in Table 2.

The objective of multivalued attribute association rules is to mine multidimensional, frequently occurring itemsets. For multivalued attribute data, it is discovered that each rule contains multiple attributes, but only one value corresponds to each attribute. In the event that two or more attribute values correspond to the same attribute in a rule, the mined data information is illogical.

In contrast to other Boolean association rules, because there are numerous attributes in the data and a large number of attribute values for each attribute, the connection between attribute values in the mining process may involve different attribute values for the same attribute, which is obviously an inappropriate mining result. If the conventional method is utilized, the mined information will be scanned and compared to the original database content, and mining information with different attribute values for the same attribute will be discarded. However, this method will consume a substantial amount of computing resources and reduce the efficiency of mining. This paper discusses how, following the connection step, it is possible to automatically determine whether there is a connection with repeated attribute values, thereby eliminating the need for repeated connections, while conserving computational resources by eliminating the need to check and compare database data. It is possible to enhance mining productivity.

The following algorithm stages are used to avoid connecting different attribute values of the same attribute multiple times. Continue to employ the Apriori algorithm’s structure and hierarchy in the main algorithm structure. Scanning the database, calculating the number of data items, and setting the data items that meet the minimal support as frequent itemset, $L_1$, is the first step. Then, use the connection step to find frequent itemset $L_2$. Continue to find $L_3, \ldots, L_k$ until the end, the proposed algorithm is shown in Algorithm 1.

In the process of the algorithm, the detection of the connection with the same attribute value is added. By comparing whether the code corresponding to the attribute of the new connection coincides with the code corresponding to the attribute already existing in the frequent itemset, if the coincidence indicates that the attribute of the new connection already exists, the new connection will be deleted; if the codes do not coincide, it indicates that the connection can form a new candidate itemset until a new frequent itemset cannot be found. By judging whether the candidate itemset meets the properties of multivalued attribute data in advance before scanning the data, that is, multiple attribute values of the same attribute can only appear once, preventing the linkage of distinct attribute values of the same attribute and therefore improving mining efficiency.

4. Experiment and Results

In this paper, the Python programming language is used to obtain a total of 1214 vocal music teaching-related video courses from the MOOC website. In addition to the course name, the data includes information regarding the course’s intended audience, class hours, course introduction, object-oriented, etc., This is the experimental portion of this paper’s dataset.

In order to complete the experiment, the author divides the data into training set, verification set, and test set. The verification set is used to select the model and super parameters, whereas the training set is used to train the model.
The final operation effect of the algorithm is evaluated using an independent test set. AdaBoost, SVM, and ANN were selected as comparative classification algorithms to evaluate the approach proposed in this study.

Figure 6 depicts the loss function curve during model training:

The algorithm described in this paper has a quick convergence speed, as seen in Figure 6. The classification accuracy of the model on the test set is shown in Table 3.

The algorithm developed in this paper has a greater classification accuracy than the comparison algorithm, as shown in Table 3.

5. Conclusion

Data mining, also known as database knowledge discovery, has transcended the limitations of conventional data analysis and is applicable to a wide range of industries. It can be found in vast quantities of data, information that is novel or potentially useful.

Association rules are an important type of algorithm used in data mining technology to identify associations between data that are of interest.

Education derived from data mining from the unique data found in the knowledge of education environment facilitates a greater understanding of the students’ learning behavior and aids in directing the student to study the arrangement.

Based on association rules and education data, this paper focuses on the following aspects of work:

(1) An introduction to association rules technology with an emphasis on the data mining process, including data collection, preprocessing, and related mining algorithms.

(2) There are typically more meaningful hierarchical structures and dimensions for education data. The paper chose multi-dimensional layers of the SP association rules algorithm for data mining based on this information.

(3) The MMSP algorithm is applied to actual data, conclusive results are obtained, the data is analyzed, and the corresponding suggestions are provided.

In the future, we will try to introduce deep learning models to use the powerful representation capabilities of deep learning to improve classification accuracy and better handle complex data in reality.

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 he has no conflicts of interest.

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