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Retraction

Retracted: An Empirical Analysis of Piano Performance Skill Evaluation Based on Big Data

Mobile Information Systems

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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

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

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

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

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

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

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[1] Y. Zhang, "An Empirical Analysis of Piano Performance Skill Evaluation Based on Big Data," *Mobile Information Systems*, vol. 2022, Article ID 8566721, 9 pages, 2022.

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Research Article

An Empirical Analysis of Piano Performance Skill Evaluation Based on Big Data

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Teachers often guide the rhythm and coherence of piano performance in the teaching process. It is of great significance to use computer technology to automatically evaluate piano performance skills. In this paper, computer technology is used to automatically evaluate the accuracy of piano music classification based on the high-dimensional data collaborative filtering recommendation algorithm, and the K-means model algorithm is used for comparative testing. By comparing the classification results of the high-dimensional data collaborative filtering recommendation algorithm with the piano music classification results of the K-means algorithm, the piano learning burden can be reduced and the piano learning effect can be improved. The research results of this paper show that the accuracy rate of the automatic piano performance evaluation system based on the high-dimensional data collaborative filtering recommendation algorithm reaches 95%, which has a good evaluation effect.

1. Introduction

With the continuous development and deepening of China's reform and opening up, people's material living standards are rising, and people's pursuit of spiritual quality of life is also getting higher and higher, and piano learning is also sought after by more and more people [1–3].

According to the survey, about 20% of parents in the city want their children to learn to play piano, and the number of piano grade examinations is growing at a rate of 20% per year. It is difficult to improve the supply and demand of piano teachers in China in a short period of time.

Although many parents in China would like their children to learn to play piano, the cost of piano education is actually high, and not only does an ordinary piano cost tens of thousands of dollars but piano instruction costs hundreds of dollars per hour. As a result, parents are often able to hire a teacher for only one hour a week, while the rest of the time, students are left to learn blindly, which leads to unsatisfactory piano learning results [4, 5].

With the development of information technology, computers have been widely used in the field of music. From the early phonograph to the current electro-acoustic band are the products of the development of electronic technology [6]. At present, piano learners can download various piano scores, sound samples, and other piano learning materials from the Internet, which can reduce the pressure of piano learning and enhance the effect of piano learning. When learning piano, although you can use some piano learning materials to learn the basics and improve your playing proficiency by making more connections, these learning materials are not very helpful in grasping the emotion and timbre of the music when learning piano. Compared to teacher learning, music learning through computer-based learning materials is less interactive [7]. It is not only the accuracy of the notes played that makes a piano performance good or bad but also the rhythm and coherence of the piano performance that is usually instructed by the teacher in the process of teaching. Therefore, it is very important to use computer technology to automatically evaluate the piano playing technique so as to reduce the burden of piano learning and improve the piano learning effect [8].

The computer recognition and automatic evaluation of piano performance involves various aspects of music theory, signal processing, pattern recognition, and piano performance technology, and it involves many fields such as music theory, electronics, computers and physics. At the same time, the automatic evaluation system of piano performance is also useful for the development of computerized composition, automatic score, and music feature recognition [9, 10].

With the increasing popularity of computers, we develop a piano automatic identification and evaluation system by computer to automatically evaluate the performance level of piano players and replace professional music educators with "electronic teachers," thus helping piano learners to understand piano music and improve their knowledge of music with the assistance of computers, and the system identifies and analyzes the piano performance music, extracts and processes the features, and compares them with the features of the music score to obtain the final evaluation results, thus giving the most realistic evaluation of the player's piano level and allowing the piano learner to recognize the shortcomings of the performance more clearly.

2. Related Work

The Moorer system was the first polyphonic recognition system that supported the input of two voices. The early Moorer system required that the ranges of the two voices be staggered and that the fundamental frequency (pitch) ranges of the two voices to be input do not overlap with each other. By the late 1980s, efforts were made to develop the perception and extraction of music signals with the aim of creating a system similar to the one used by the human ear to perceive music. This project resulted in the design of two systems, one of which was able to perform recognition of three input voices while tolerating more errors, and the other was able to recognize monophonic melodies of Japanese folk songs and to recognize inaccurate or erroneous content in music according to the characteristics of Japanese music. In 1993, Blanco-Piñeiro et al. [11] proposed an algorithm for multipiano work recognition based on computer auditory pathway analysis and proved by practice that the algorithm has good performance of multipiano work recognition. Wallerstedt and Pramling [12] studied a music recognition system using the heuristic signal processing method, which can recognize organ ensemble music with as many as eight inputs. However, the system placed more emphasis on the perceptual consistency of the system recognition results by listening to input music and was not able to accurately identify the notes in the music. Gibson et al.'s [13] research group made a significant contribution to automatic music recognition by clearly analyzing the human auditory discrimination mechanism for the first time as well as introducing a process-based pitch modeling process, proposing an automatic pitch modeling algorithm and was able to automatically extract from the signal. The system was introduced in 1995.

In 1995, the system was further improved by adopting the blackboard structure, which abandoned the global control module, and the organic integration of various types of prior knowledge greatly improved the effect of music recognition and made the system have better prior knowledge through the application of the blackboard structure in Bayesian probabilistic networks. Greenberg [14] also used the blackboard structure to study the music recognition system although the study did not establish the propagation network and probabilistic information, nor did it perform automatic pitch modeling, that is, by adding a perceptually weighted front-end and analyzing the correlation graph, thus supporting the analysis of multiple music signal inputs with a maximum number of pronunciations of four. Because of the short development time of computer technology in China, there is a lack of domestic research on piano music recognition. The research on piano music recognition, feature extraction, and automatic evaluation is lacking in China. However, in the field of automatic speech recognition, which is related to automatic piano recognition, many universities and research institutes have started to research on automatic speech recognition technology due to the high attention of the state.

Due to the sensitivity of the human ear to sound and the ambiguity of emotion, it is not a perfect performance that requires the piano music to be exactly the same as the music in the score. Therefore, after extracting the characteristics of piano music, some intelligent evaluation methods are usually used to classify the performed piano music for the purpose of piano music evaluation. At present, the main classification and evaluation methods are neural network algorithms. The development of neural network can be traced back to 1890, Katayose et al. [15] clarified about the structure of human brain and its functions. In his academic journal, and Zhen[16] proposed a mathematical model for processing information by neuronal networks (i.e., the M-P model), which unveiled the research on neural networks to the world for the first time, and the research on neural networks entered the main topic. The learning rule emphasizing the change of connection strength between artificial neurons created a new situation in the research of neuronal networks and marked the period of neural networks entering the application [17].

A system with self-learning capability was successfully developed, which started the first research boom of artificial neuronal networks [18, 19]and developed an adaptive linear unit Adaline. Adaline a two-layer variant of Adaline Madaline was applied in various fields, including speech recognition, character recognition, atmospheric forecasting, and adaptive control functions. This was the first application of neural networks to a practical problem. Katayose et al. [15] proposed a neural network for visual recognition called "Neocognitron," which was compatible with biological vision theory and could perform pattern recognition without guidance, but the network structure was too complex to be generalized. The PDP group led by Wright et al. [18] developed a backpropagation network, which has been more widely used. This model introduced the LyaPunov function (i.e., computational energy function) gave the basis for determining the stability of the network and proved the principle that a neural network system with interconnected units would achieve minimum energy loss. The Hopfield model successfully solved the complex NP problem; that is, the Hopfield model successfully solves the complex NP problem, namely, the "salesman's travel path" problem (computation increases exponentially with the number of cities N).

Moreover, the model can be implemented by integrated circuits, which provides the basis for neuronal computers. Rumelhart and McClelland proposed an error propagation learning algorithm for multilayer networks which is referred to as the B-P model. This model introduced multilayer nodes to solve the problem of nonlinear samples. Many successful neural network models were also proposed by many researchers in the same period. These results have greatly contributed to the development of neuronal networks.

3. Architecture

The computerized evaluation system of the piano performance is a computerized system that automatically discriminates a piece of piano performance music, evaluates whether it meets the requirements of music performance according to the requirements of music performance and logic, and scores the performance according to certain rules.

Of course, in the future further development work, the system will give textual evaluation of the performer's performance and suggest improvements.

Based on the system design idea, the overall framework of the designed system is shown in Figure 1.

The detection of the end frame of piano music is similar to the detection of the beginning frame of piano music: search from the sound file backward to forward, find the first frame whose average amplitude or average energy exceeds ETL, and if the average amplitude or average energy in this frame forward does not have the next frame whose average amplitude or average energy drops below ETL before it exceeds ETU, then mark this frame as N2; if there are some consecutive frames in the 25-frame period in which the zero rate exceeds ZT, the last frame that meets $Z > \mathrm{ZT}$ is the end frame of the piano tone (Ne) [20–22]; otherwise, N2 is the end frame of the piano tone. The endpoint detection flow of piano tone is shown in Figure 2.

As shown in Figure 2, in the practice of automatic piano sound evaluation, if the input signal is a piano sound signal collected directly through a microphone, the piano sound signal can still be detected very accurately by the method shown in Figure 2 under the interference of piano sound background noise.

4. Introduction to Collaborative Filtering Recommendation Algorithms for High-Dimensional Data

In the process of solving the similarity between high-dimensional data, the spatial vector method is mainly used to determine the value of weight information between high-dimensional data information [19] which set the corresponding threshold value according to the weight information to prevent the weight threshold value of high-dimensional data information from being too high, resulting in low similarity. The formula for calculating the weight of high-dimensional data information is as follows:

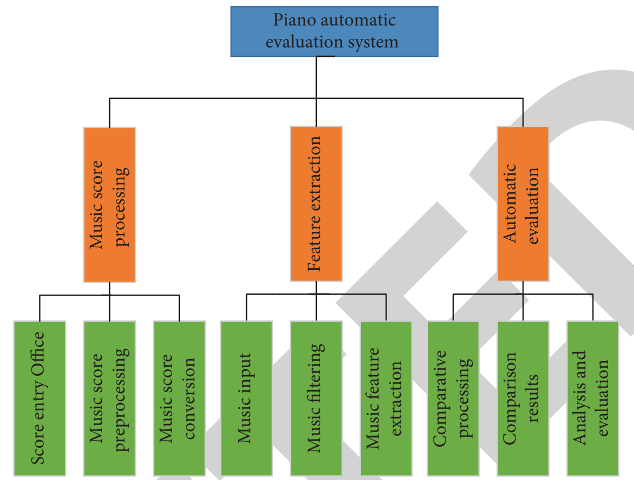

Figure 1: Overall system structure.

$$\mathrm{Weight}(t)_d = [\alpha(t)_d + \beta(t)_d] \times \mathrm{TFIDF}(t), \quad (1)$$

where $\mathrm{Weight}(t)_d$ denotes the weight of a data information t in the high-dimensional data d. The initial and ending weights of data information t in the data set d are $\alpha(t)_d$ and $\beta(t)_d$, respectively, for the TFIDF value of data information t in the data set d can be calculated by

$$\mathrm{TFIDF}(t)_d = \frac{TF(t)_d \times \log 10(N_k/n_i + 0.01)}{\sqrt{\sum_{xd}[TF(t)_d \times \log 10(N_k/n_i + 0.01)]^2}}. \quad (2)$$

In the above equation, N_k denotes the amount of features in the information set of high-dimensional data, $TF(t)_d$ denotes the probability of existence of high-dimensional data t in dataset d, and n_i denotes the number of all high-dimensional data in dataset d.

By using the adaptive analysis method, the similarity between high-dimensional data is defined as

$$\mathrm{Sim}(s_i, s_j) = \frac{|C_i \cap C_j|}{|C_i \cup C_j|}. \quad (3)$$

In the above equation, C denotes the set of feature information between high-dimensional data. By solving the two high-dimensional data feature vectors s and s, we can obtain the contrast value about the high-dimensional data feature vectors so as to determine the similarity between high-dimensional data. The similarity between high-dimensional data can be determined by equtaion (3), where 0 means that there is no similarity between the two high-dimensional data information, and 1 means that the high-dimensional data information is completely similar.

By calculating the similarity of high-dimensional data, the distribution of similarity of different high-dimensional data in the dataset is obtained, and the following matrix is used to express the meaning:

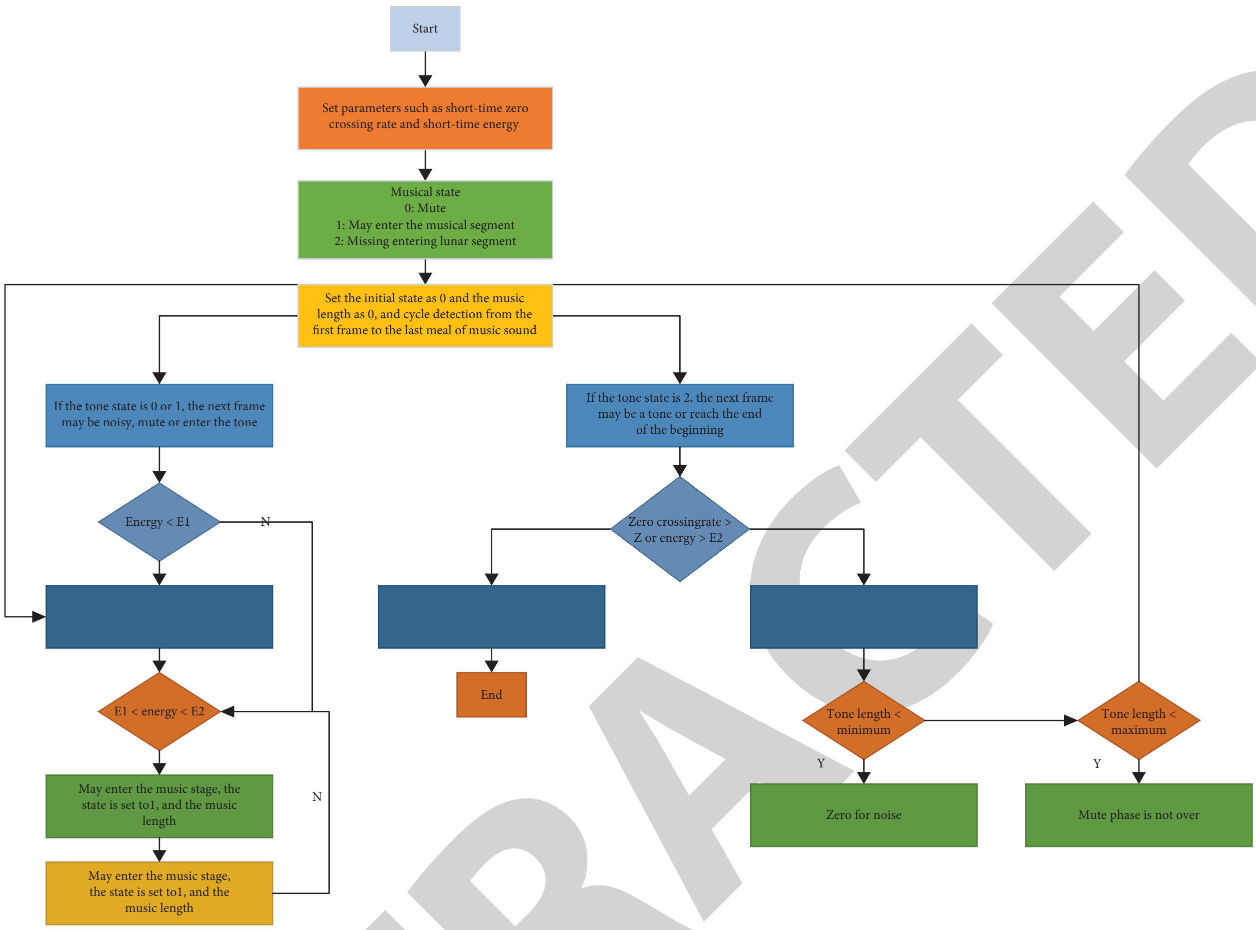

Figure 2: Endpoint detection flow chart for piano music.

$$S = \begin{bmatrix} s_{11} & s_{12} & \cdots & s_{1n} \\ s_{21} & s_{22} & \cdots & s_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ s_{n1} & s_{n2} & \cdots & s_{nm} \end{bmatrix}, \quad (4)$$

where s_{nm} denotes the similarity between s_n and s_m different high-dimensional data in the dataset.

By analyzing the similarity of different high-dimensional data in the dataset, we set the similarity weight threshold value of high-dimensional data, obtain the similarity between high-dimensional data in the dataset by calculating the weight value, get the distribution of similarity between high-dimensional data information, and complete the calculation of similarity value between high-dimensional data [23–25].

Using data mining technology, we preprocess the high-dimensional data information to realize the classification of information (2). We construct a collaborative filtering scoring model, which is expressed by the $m \times n$ collaborative filtering scoring matrix, as follows:

$$R(m, n) = \begin{Bmatrix} r_1 & r_2 & \cdots & r_n \\ r_{11} & r_{12} & \cdots & r_{1n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{Bmatrix}. \quad (5)$$

In the above equation, m represents the number of rows of the scoring matrix in the collaborative filtering process for high-dimensional data, n is the number of columns of the scoring matrix in the collaborative filtering process, and the scoring result of high-dimensional data i on target data j is expressed as R_{ij}. The evaluation level of the high-dimensional data is expressed by a constant from 0 to 5, which represents the rating of the collaborative filtering of the high-dimensional data.

According to the collaborative filtering scoring model for high-dimensional data, the prediction of users' preference scores is obtained by collaborative filtering for each collected high-dimensional data sample $T = \{(q_1, u_1), \cdots (q_n, u_n)\}$, where $q_i = (q_{1i}, \cdots, q_{ni})$, the jth high-dimensional data attribute of the first collaborative filtering training sample is denoted as q. According to the users' evaluation system, the conditional probability of users' collaborative filtering of high-dimensional data $P(c_k)$ is calculated using (6) and (7):

$$P(c_k) = \sum_{i=1}^{N} \frac{I(c_k)}{N}, \quad (6)$$

$$P\left(q_i^i | c_k\right) = \frac{\sum_{i=1}^{N} I\left(q_i^j, c_k\right)}{\sum_{i=1}^{N} I(c_k)}, \quad (7)$$

where N denotes the frequency of users clicking on preferences, $I(c_k)$ denotes the probability between users' search results and ratings, and $I(q_i^j, c_k)$ denotes the conditional probability of users' search; $\sum_{i=1}^{N} I(c_k)$ denotes the probability of similarity between the training samples and users' preferences in collaborative filtering of high-dimensional data. After training the model, the collaborative filtering inference can be performed on the high-dimensional data q^j:

$$U = P(c_k)\prod_{j=1}^{n} P\left(q_i^j \mid c_k\right). \tag{8}$$

In the above equation, different user preferences are obtained depending on the characteristics of the high-dimensional data, and this value represents the relationship between user preferences and recommendation results [26–28].

In the high-dimensional data collaborative filtering recommendation process, suppose $\{(u_1, a_1), \ldots, (u_n, a_n)\}$. denotes the data node information, where n recommendation results and m users search high-dimensional data bipartite graph as G, a_i is the predicted value of high-dimensional data collaborative filtering results, then the user preferences collaborative filtering a_i, summation, is

$$w_{qi} = \sum_{j=1}^{n} \frac{a_j}{k\left(u_j\right)}, \tag{9}$$

where $k(u_j)$ denotes the number of collaborative filtering of high-dimensional data, and a_j denotes the predicted value of the collaborative filtering result. The prediction of the recommendation list according to the user's preference is

$$w_{qi} = \sum_{j=1}^{n} \frac{a_j}{k\left(u_j\right)} \frac{\text{click}\left(u_j, q_i\right)}{N}, \tag{10}$$

where $\text{click}(u_j, q_i)$ denotes the probability of high-dimensional data q_i being recommended.

In the final list of high-dimensional data recommendations, there are

$$v_{qi} = \left[\sum_{j=1}^{n} \frac{\text{click}\,(u_i, q_i)}{\text{Num}\,(q_i)} + \alpha \frac{\left|q \cap q_i\right|}{\left|q \cup q_i\right|}\right], \tag{11}$$

in which α represents the time influence factor, and different time factors are set according to different users' preference coefficients. By collaborative filtering of user preferences q_i, the high-dimensional data with the highest similarity are recommended to users:

$$N = \sum_{j=1}^{n} t\,(q, q_i), \tag{12}$$

where $t(q, q_i)$ indicates the correlation of q with q_i.

According to the above process, a collaborative filtering recommendation algorithm for high-dimensional data is designed to achieve collaborative filtering recommendation for high-dimensional data.

5. Results

In order to compare the accuracy of piano music classification based on the high-dimensional data collaborative filtering recommendation algorithm, the K-means model algorithm is used to verify the accuracy and feasibility of piano performance music classification using the high-dimensional data collaborative filtering recommendation algorithm and K-means algorithm.

According to the requirements of the high-dimensional data collaborative filtering recommendation algorithm, the 1000 music works were divided into two data sets, train and test, which contain 400 piano music works and 600 piano music works, respectively.

In order to obtain a better classification effect, the high-dimensional data collaborative filtering recommendation algorithm was tested four times; that is, 400 piano performance music were selected four times from 1000 piano works, respectively, and each time the piano performance music was demanded, in order to ensure the distribution of piano music evaluation after each random selection, the 1000 piano works were divided into five categories according to the evaluation, and each time when the selection was made, then in each category in order to ensure the distribution of piano music evaluation after each random selection, the 1000 piano works were divided into five categories according to the evaluation, and 80 piano works were selected in each category, thus ensuring that each randomly selected piano music collection contains 80 piano music with good evaluation, 80 piano music with average evaluation, 80 piano music with qualified evaluation, 80 piano music with unqualified evaluation, and 80 piano music with poor evaluation [29].

In each test, the high-dimensional data collaborative filtering recommendation algorithm was trained to classify the remaining 600 piano performance music, and the error between the high-dimensional data collaborative filtering recommendation algorithm and the real evaluation of piano works was calculated for each test by comparing the design evaluation of these 600 piano performance music. The objective matrix of each test data set is shown in Table 1.

As shown in Table 1, the horizontal rows represent the actual evaluation results of piano music, and the vertical rows represent the evaluation results of piano music by the high-dimensional data collaborative filtering recommendation algorithm. In the correct evaluation process, piano music with good evaluation is evaluated as good, piano music with average evaluation is evaluated as average, piano music with fair evaluation is evaluated as qualified, piano music with unqualified evaluation is evaluated as unqualified, and piano music with poor evaluation is evaluated as poor.

In order to verify the effect of piano performance music classification based on the high-dimensional data collaborative filtering recommendation algorithm designed in this paper, the K-means clustering algorithm and high-dimensional data collaborative filtering recommendation algorithm were used for comparison and analysis in this research project. The k-means clustering algorithm trained by four

Table 1: Objective matrix.

	Good	Commonly	Qualified	Unqualified	Difference
Good	1	0	0	0	0
Commonly	0	1	0	0	0
Qualified	0	0	1	0	0
Unqualified	0	0	0	0	1
Difference	0	0	0	1	0

Table 2: Error of the first test result matrix and the actual situation.

	Good	Commonly	Qualified	Unqualified	Difference
Good	0.024	1.24	1.39	0.68	0.68
Commonly	−1.32	0.03	−0.32	1.13	1.32
Qualified	1.83	−0.82	0.04	−1.31	−0.21
Unqualified	−0.82	−0.21	0.82	0.04	−0.04
Difference	0.32	−0.04	−0.32	0.82	−0.02

Table 3: Error between the result matrix of the first test and the actual situation.

	Good	Commonly	Qualified	Unqualified	Difference
Good	0.075	0	0.27	0	1.83
Commonly	−0.54	−0.005	1.34	0.34	−0.82
Qualified	1.32	1.21	0.001	2.44	0.82
Unqualified	−0.23	−0.004	−0.67	0.08	−0.31
Difference	1.34	0.60	−0.42	0.26	−0.01

randomly selected piano music training sets was used to classify the remaining 600 piano performance music in the following matrix. The result matrix obtained from the first K-means clustering algorithm test and the target matrix error are shown in Table 2.

As shown in Table 2, the error between the results of the first K-means clustering algorithm test and the actual situation was calculated as error $1 = 3.2366$.

The error between the result matrix and the target matrix obtained from the second K-means clustering algorithm test is shown in Table 3.

As shown in Table 3, the error between the second K-means clustering algorithm test results and the actual situation is calculated as error $2 = 1.6053$.

The error between the result matrix and the target matrix obtained from the third K-means clustering algorithm test is shown in Table 4.

As shown in Table 4, the error between the results of the third k-means clustering algorithm test and the actual situation was calculated as error $3 = 1.7832$.

The error between the result matrix and the target matrix obtained from the fourth K-means clustering algorithm test is shown in Table 5.

As shown in Table 5, the error between the test results of the fourth K-means clustering algorithm and the actual situation was calculated as error $3 = 1.6472$.

The classification result matrix of the remaining 600 piano performance music by the high-dimensional data collaborative filtering recommendation algorithm trained by the four randomly selected piano music training sets is shown in the Table 6. The result matrix obtained from the first test of the high-dimensional data collaborative filtering recommendation algorithm with the target matrix error is shown in Table 6.

As shown in Table 6, the error between the results of the first test of collaborative filtering recommendation algorithm for high-dimensional data and the actual situation is calculated as error $1 = 0.6539$.

The error between the result matrix and the target matrix obtained from the second test of the collaborative filtering recommendation algorithm for high-dimensional data is shown in Table 7.

As shown in Table 7, the error between the results of the second test of collaborative filtering recommendation algorithm for high-dimensional data and the actual situation is calculated as error $2 = 0.4076$.

The error between the result matrix and the target matrix obtained from the third test of high-dimensional data collaborative filtering recommendation algorithm is shown in Table 8.

As shown in Table 8, the error between the results of the third test of collaborative filtering recommendation algorithm for high-dimensional data and the actual situation is calculated as error $3 = 0.2652$.

The error between the result matrix and the target matrix of the fourth high-dimensional data collaborative filtering recommendation algorithm test is shown in Table 9.

As shown in Table 9, the error between the test results of the fourth high-dimensional data collaborative filtering recommendation algorithm and the actual situation is calculated as error $3 = 0.1606$.

Finally, the average error value of the K-means piano performance music classification was calculated with all data. It is shown that the piano music classification results by

Table 4: Error between the result matrix of the third test and the actual situation.

	Good	Commonly	Qualified	Unqualified	Difference
Good	−0.021	1.33	−0.31	−1.32	0.78
Commonly	1.21	0.08	−0.18	1.84	0.82
Qualified	−0.001	−0.312	0.08	−0.721	−0.312
Unqualified	1.21	0.82	0.82	0.026	0.82
Difference	0.60	−0.19	−0.42	0.31	0.027

Table 5: Error between the result matrix and the actual situation for the fourth test.

	Good	Commonly	Qualified	Unqualified	Difference
Good	0.025	0.78	1.32	1.27	1.21
Commonly	−0.31	0.01	−1.32	1.34	−0.004
Qualified	0.82	−0.31	0.13	0.78	1.21
Unqualified	0.26	0.82	0.60	−0.12	1.21
Difference	1.85	−0.31	0.11	−0.004	0.03

Table 6: Error between the result matrix and the actual situation for the fourth test.

	Good	Commonly	Qualified	Unqualified	Difference
Good	0.025	−0.19	1.01	0.82	0.83
Commonly	0.56	0.023	0.60	1.83	−0.42
Qualified	0.82	−1.32	0.024	−0.823	1.831
Unqualified	−0.004	0.82	−0.82	0.012	-0.312
Difference	−0.002	1.31	0.32	0.60	0.033

Table 7: Error between the result matrix of the second test and the actual situation.

	Good	Commonly	Qualified	Unqualified	Difference
Good	−0.031	1.56	−0.82	0.23	1.83
Commonly	0.82	0.01	1.212	0.60	1.82
Qualified	1.32	0.82	0.085	2.44	0.83
Unqualified	1.83	1.21	−0.67	0.047	0.82
Difference	0.60	0.61	1.42	0.26	0.068

Table 8: Error between the result matrix of the second test and the actual situation.

	Good	Commonly	Qualified	Unqualified	Difference
Good	−0.02	0.89	−0.31	0.78	1.31
Commonly	0.82	−0.03	−0.19	0.82	1.14
Qualified	1.38	0.82	0.09	−0.31	1.21
Unqualified	−0.31	0.23	1.83	0.012	0.82
Difference	0.82	0.31	0.912	0.60	−0.119

Table 9: Error of the fourth test result matrix and the actual situation.

	Good	Commonly	Qualified	Unqualified	Difference
Good	1.12	1.32	1.21	0.61	−0.32
Commonly	−0.004	1.005	0.82	2.44	0.82
Qualified	1.21	1.24	0.79	−0.31	1.36
Unqualified	1.72	0.82	0.802	0.82	1.84
Difference	0.26	1.32	1.34	0.87	0.60

the high-dimensional data collaborative filtering recommendation algorithm are closer to the actual piano music classification results; that is, the classification results by the high-dimensional data collaborative filtering recommendation algorithm are better than the classification results by the K-means clustering algorithm.

The piano music classification model designed by the high-dimensional data collaborative filtering recommendation algorithm is more accurate and allows better attention to the risks of piano music.

6. Conclusions

In order to compare the accuracy of piano music classification based on the high-dimensional data collaborative filtering recommendation algorithm studied in this paper, the K-means model algorithm was used to conduct a comparison test to verify the accuracy of piano performance music classification using the high-dimensional data collaborative filtering recommendation algorithm and K-means algorithm in this paper. The final results of the comparison experiments show that the piano music classification by the high-dimensional data collaborative filtering recommendation algorithm is not only accurate but also feasible. The final results show that the piano music classification model designed by the high-dimensional data collaborative filtering recommendation algorithm can improve the accuracy of the piano music classification results by more than six times, which can meet the demand of automatic piano evaluation.

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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