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A study on assessing students' skill levels through pattern recognition techniques in piano teaching

Le He[1], Qian Yang[2] and Linjing Tang[1,*]

[1] School of Arts, Jinan Preschool Education College, Jinan, Shandong, 25030, 7China
[2] College of Music and Dance, Chongqing Preschool Education College, Wanzhou, Chongqing, 404100, China
[3] The Department of Music, College of Arts, Xiamen University, Xiamen, Fujian, China

Corresponding authors: (e-mail: 15805921683@163.com).

Abstract Traditional assessment methods rely on teachers' subjective judgment and lack objective quantitative standards. With the popularization of piano education, scientific assessment of students' piano skill level has become particularly important. This study proposes an automatic piano skill assessment framework based on computer vision motion tracking and ID3 decision tree classification model to capture the motion characteristics of piano playing and analyze them quantitatively. The research methodology captured feature data such as keystroke and tone control, pedal technique, and musical expression through visual recognition assessment of 42 piano performers of different levels, and established an ID3 decision tree classification model to automatically assess students' piano skill level. The results showed that: the accuracy of the visual recognition-based assessment reached 81.7%, with a Wilks' Lambda value of 0.25; the ID3 decision tree classification model reached 95.8% accuracy on the training set and 74.5% on the test set; it was found by Pearson's correlation coefficient analysis that keystroke and tone control (0.411) and pedal technique (0.408) were the most important features for discriminating the the most important characteristic parameters of piano skill level. Upon comparison with other methods, the assessment framework proposed in this study outperformed the existing methods in terms of accuracy, with an assessment accuracy of 84.86%. The study shows that the pattern recognition technology combining computer vision and ID3 decision tree can effectively realize the objective assessment of piano skill level and provide a scientific and quantitative evaluation system for piano teaching.

Index Terms Piano skill assessment, Pattern recognition, ID3 decision tree, Visual recognition, Keystroke and tone control, Musical expression

I. Introduction

Piano is called the king of musical instruments, the pearl of musical instruments, and also called the aristocrat of musical instruments [1]. In piano teaching, the skill level of students is an important criterion reflecting the teaching level of teachers, and at the same time, it is not only the teacher's responsibility to assess the skill level of students, but also to take corresponding teaching measures for the level [2]-[4]. However, the traditional assessment method is mainly based on the viewpoints between teachers and classmates, which has problems such as strong subjectivity and bias, while with the development and application of artificial intelligence, pattern recognition technology gradually plays a role in teaching assessment [5]-[7].

Pattern recognition technology refers to the technology of learning and analyzing the data, from which the hidden laws and patterns are found [8]. In piano teaching, pattern recognition technology can be used to assess the piano skill level of students by collecting and analyzing their learning data and extracting their learning patterns and characteristics from them [9], [10]. Specifically, the applications of pattern recognition technology in piano teaching are learning behavior pattern analysis, learning process monitoring and analysis, and learning outcome prediction and assessment [11], [12]. Through the analysis of students' learning behavior data, we can discover the patterns of students' learning habits, learning styles, and learning process, and we can monitor students' learning process in real time and record students' learning behavior data, such as learning time, learning duration, and learning content [13]-[16]. Through the analysis of these data, pattern recognition and analysis of students' learning data can be carried out to achieve the prediction of students' skill levels, in order to help teachers better understand students' learning and provide students with personalized learning support and guidance [17]-[19].

As an important form of musical art expression, the piano's teaching quality assessment has long relied on teachers' professional experience and subjective judgment. In traditional piano teaching, teachers usually evaluate students' abilities by observing their playing postures, listening to musical effects, and evaluating technical details, which has its value but is difficult to form a standardized and quantitative assessment system. Experts in the field of music education have found that effective assessment of skills requires the simultaneous consideration of multiple dimensions of performance, including technical performance, musical expression, and improvisation. Modern music education gradually recognizes that objective, accurate, and multi-dimensional skill assessment of piano learners is a key part of improving teaching effectiveness. However, the lack of objective quantitative indicators in traditional assessment methods makes it difficult to accurately reflect the true level of learners, which limits the precision and relevance of teaching feedback. The rapid development of computer technology and artificial intelligence provides new possibilities for solving this problem. Pattern recognition technology has shown great potential in many fields through the automated recognition and analysis of human behavior patterns. Especially in the field of education, this technology is able to capture subtle but critical features of learner behavior and provide data support for teaching evaluation. Music education researchers have begun to explore how this technology can be applied to piano teaching assessment by algorithmically analyzing learners' performance characteristics and establishing objective evaluation criteria. Decision tree algorithms have become an important research direction in this field due to their strong interpretability and outstanding ability to handle multi-category problems. Based on the above background, this study proposes an innovative framework for assessing piano skill level based on computer vision and ID3 decision tree classification model. The framework captures the piano player's motion features, including key touch and tone control, pedal technique, musical expression, and other key parameters, through visual motion tracking; constructs a classification model using the ID3 decision tree algorithm to automatically identify and evaluate piano players with different skill levels; and realizes efficient and accurate skill level discrimination by transforming high-dimensional image information into low-dimensional motion features. In this study, we designed an evaluation procedure and recruited piano performers of different levels for testing, and verified the effectiveness of the proposed method by comparing and analyzing the training and testing results. The study also explores the importance of different parameters for piano skill assessment, which provides a theoretical basis for the establishment of a perfect assessment system.

II. Computer-assisted assessment of students' piano skill levels

II. A. ID3 Decision Tree Classification Model

II. A. 1) ID3 algorithm

The ID3 algorithm is an algorithm that utilizes information theory principles for decision tree construction. The core goal of the algorithm is to find a feature that gives the highest information gain to the classification result of the dataset under that feature. Where each internal node represents a judgment condition on an attribute, each branch represents an output of the judgment result, and each leaf node represents a category label. A decision tree represents the classification rules by a path from the root node to the leaf nodes. When constructing a decision tree, the goal is to select an optimal partition attribute, so that the subset of the partition belongs to the same category as much as possible, i.e., the nodes are more and more “pure”. Commonly used segmentation criteria are information gain, gain rate, Gini index and so on. The information gain represents the contribution of features to the classification result, and is calculated as the reduction of the entropy of the dataset after the introduction of features.ID3 algorithm starts from the root node, and recursively splits the dataset until it meets the stopping conditions, such as reaching the maximum depth of the tree, all instances belonging to the same category, or the information gain is less than the preset threshold value [20].

The ID3 algorithm mainly involves the concept of entropy and the calculation of information gain.

(1) Entropy represents the uncertainty of a random variable. Let X be a discrete random variable taking a finite number of values with probability distribution $P\left(X=x_i\right)=p_i$, $i=1,2,\ldots,n$, then the entropy of the random variable X is defined as:

$$H(X)=-\sum_{i=1}^{n}p_i\log_2 p_i \tag{1}$$

where p_i is the probability that the i th class occurs in the dataset, i.e., $p_i=\frac{|C_i|}{|D|}$; C_i is the set of samples in the dataset belonging to the i th class, and $|C_i|$ is its number of samples; $|D|$ is the total number of samples in the dataset.

(2) Iterate over all the feature attributes and compute the information gain $g(D,A)$ of each attribute, for the feature attribute A, its conditional entropy $H(D|A)$ is defined as:

$$H(D \mid A) = \sum_{v \in V_A} \frac{|D_v|}{|D|} H(D_v) \tag{2}$$

where V_A is the set of all possible values of attribute A; D_v is the subset of samples whose corresponding value of attribute A is v; and $H(D_v)$ is the entropy of the subset D_v.

(3) Information gain: $g(D, A)$ is then computed as $g(D, A) = H(D) - H(D \mid A)$, where D is the dataset; A is a feature attribute. The greater the information gain, the greater the "purity improvement" obtained by using this feature attribute for segmentation.

II. A. 2) Derivation process

The process of constructing a decision tree is the process of generalizing a set of classification rules from a training data set. This process usually adopts a top-down recursive approach, starting from the root node to select the optimal division attributes for division until the stopping conditions are met (e.g., all samples belong to the same category, no attributes can be further divided, etc.). The specific steps are as follows:

(1) Calculate the entropy $H(D)$ of the dataset;

(2) Iterate over all feature attributes and calculate the information gain $g(D, A)$ for each attribute;

(3) Select the attribute with the largest information gain as the optimal segmentation attribute;

(4) Divide the dataset into a number of subsets according to the optimal division attribute, and recursively execute steps 1-3 for each subset until the stopping condition is satisfied;

(5) Label each leaf node as the category with the most samples in the current subset.

A complete decision tree model for categorizing students' skill levels can be constructed by the above steps.

II. B.Application of the ID3 algorithm to student skill assessment

In student skill assessment, the ID3 algorithm can be applied to construct a classification model. The model is able to predict a student's skill level based on various learning characteristics. The steps for constructing a decision tree model are as follows.

II. B. 1) Data pre-processing

The raw data is first preprocessed for use in decision tree construction. This includes data cleaning, converting categorical variables to numeric type (if needed), handling missing values, etc. In this example, the data is already numeric and there are no missing values, so it is straightforward to proceed to the next step.

Define "high skill level" as a label, assuming that a piano skill level of 85 or more is considered "high skill level", otherwise "low skill level". Based on this criterion, a label column can be added to each piece of data.

II. B. 2) Calculating entropy

For the entire dataset, its entropy is first calculated. The entropy is calculated based on the distribution of high and low skill levels.

II. B. 3) Selection of optimal segmentation attributes

Next, an optimal segmentation attribute has to be selected to build the decision tree. In this example, the piano playing level (key touch and tone control, pedal technique, musical expression, sight-reading and improvisation, pedal technique, wrist technique, arm technique, fingering and chords) situation can be considered as a candidate segmentation attribute.

The value of each attribute is divided into intervals and the information gain for each interval is calculated. For example, for piano playing level, it can be divided into several intervals (e.g., below 60, 60-70, 70-80, 80-90, 90 or above) and then calculate the information gain for each interval.

The attribute with the largest information gain is selected as the best dividing attribute. Assuming that "intellectual achievement" is found to have the greatest information gain, then "piano playing level" will be used as the first attribute.

II. B. 4) Recursive Construction of Decision Trees

After dividing the data into subsets using the selected optimal segmentation attribute "Piano Skill Level", the above steps are performed recursively for each subset. In each subset, the entropy is recalculated, the optimal segmentation attribute is selected, and the data continues to be segmented until the stopping condition is met.

For example, in a subset of piano skill level, "piano skill level" may be selected as the next segmentation attribute. This process continues until each leaf node contains only samples of the same category (high or low skill level), or until the tree depth is reached, or until the number of samples in the subset is less than a predetermined threshold.

II. B. 5) Pruning and Optimization

In order to prevent overfitting and improve the generalization ability of the model, the decision tree can be simplified using pre-pruning techniques. A validation set is used before division to assess whether the performance improvement after division is significant. If the performance improvement is not significant or even decreases, the division is stopped and the current node is labeled as a leaf node.

II. B. 6) Application of models for prediction

After constructing the decision tree model, it can be used to predict whether the new student data is of high skill level or not. By entering the attribute values of the student data into the decision tree and following the path of the tree, the final leaf node reached will give the prediction.

II. C. Overall program design for the assessment

This paper investigates a computer-assisted student piano skill level assessment method, which can be applied to real-time stage recognition and online assessment. The motion features of the end tool including trajectory, velocity and acceleration are captured, and the captured piano playing motion features are analyzed, which are required to accurately identify the skill level from the piano playing motion features. Finally, the ID3 decision tree classification model was used to classify the captured features in a supervised manner to quantify the skill level, and the evaluation results were fed back to the teachers for more efficient training. In order to optimize the motion feature dataset for automatic assessment, the method investigates a kernel correlation filter algorithm for motion tracking, and establishes a visual motion tracking model, which converts high-dimensional image information into low-dimensional motion features to reduce computational overhead and ensure the timeliness of the assessment. In order to achieve efficient evaluation of piano skills, the evaluation method is based on the ID3 decision tree classification model and uses the optimized motion feature dataset as input. In order to realize the accurate assessment of piano skills, this assessment method effectively combines the advantages of visual efficiency and kinematic data accuracy to improve the accuracy of surgical skill assessment. The framework of the assisted piano skill assessment method based on computer vision motion tracking and deep neural network model is shown in Fig. 1.

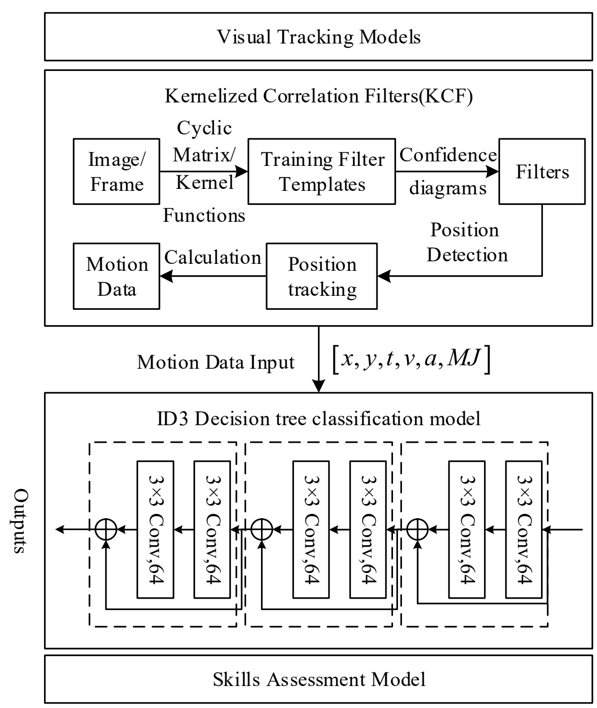

Figure 1: Skill assessment framework

III. Experimental Study on Assessment of Students' Piano Skill Level

III. A. Assessment procedures

Forty-two participants were involved in this study, categorized into advanced level, intermediate level, and beginner level groups. Participants in the advanced level group (n=11) were professional performers who had been playing piano for 5 years and had excellent piano skills and knowledge. Participants in the intermediate level group (n=16) were performers who had been playing piano for at least one to two years and had relatively perfect piano skills and abilities. Participants in the beginner level group (n=15) were beginning performers with minimal piano knowledge and experience. Data for the ID3 decision tree classification model and discriminant analysis were obtained from a visual recognition-based assessment program. Each set of assessment questions consisted of five visual recognition-based questions, and the overall horizontal assessment program consisted of more than ten question sets. Participants were first shown different movie clips of a piano performance in progress.

With the help of the judgment and opinion of a professional piano instructor, the results of the above assessment procedure were weighted to achieve a level assessment for each participant.

$$\text{Assessment score} = \frac{12.0}{TIME} \times \text{Answer score} \tag{3}$$

In equation (3), TIME is the combined time that the participant took to answer all five questions. The answer score is the total score for each correct answer in each of the five questions. Pianist skill level is a dichotomous variable.

The ID3 decision tree classification model and discriminant analysis used to assess pianist skill level consisted of three different dependent variables: key touch and tone control, pedal technique, musical expression, sight-reading and improvisation ability, pedal technique, wrist technique, arm technique, fingering, and chords (1 to 9).

III. B. Assessment of results

The results of the ID3 decision tree classification model based on the training dataset complete with parameter learning to classify the data samples based on visual recognition assessment are shown in Table 1.

Table 1: Data sample classification results

		Predictive result			Accuracy
		1	2	3	
Training data set	Primary level	10	1	0	100%
	Intermediate level	0	6	1	100%
	High level	1	1	9	100%
Test data set	Primary level	5	2	1	84.2
	Intermediate level	4	0	7	55.6
	High level	2	0	1	0
	Overall percentage	52.8	36.9	10.3	58.6

The ID3 decision tree classification model uses a hyperbolic tangent function for the hidden layer and a softmax function for the output layer. The dotted connection line in the figure indicates that the connection weight between two neural units is less than zero, and the solid connection line indicates that the connection weight between two neural units is greater than zero.

Table 2: The classification results of the adaptability of neural network

		Predictive result			Accuracy
		1	2	3	
Training data set	Primary level	8	1	0	90%
	Intermediate level	0	6	1	100%
	High level	1	0	9	100%
	Overall percentage	36.5%	22.8%	41.1%	95.8%
Test data set	Primary level	10	0	1	91.2%
	Intermediate level	4	2	2	50.4%
	High level	0	1	4	100%
	Overall percentage	64.5%	16.2%	21.4%	74.5%

The classification results of motion adaptation based on ID3 decision tree classification model are shown in Table 2. From the data in the table, it can be seen that the training accuracy and testing accuracy of motor adaptation classification are 95.8% and 74.5%, respectively.

The quantitative values of the extent to which the three mutually independent parameters in the visual recognition-based level assessment affect the total assessment score are shown in Table 3. The table indicates that the most important discriminative parameters in the ID3 decision tree classification model analysis were keystroke and tone control and pedal technique.

Table 3: The importance of the level evaluation of visual recognition

	The importance of independent parameters	
	Proportion of fraction	Magnitude
Touch and tone control	0.411	100%
Music expression	0.408	99.8%
Vision and improvisation	0.196	44.8%

The use of discriminant-based functions was also effective in differentiating athletes' skill levels during visual recognition-based testing, but this differentiation was biased during motor adaptation testing. The overall correct rate for the adaptive test was 74.6%, and the ratio of the within-group sum of squares to the total sum of squares (Wilks' Lambda) was 0.398, $p<0.001$. The overall correct rate for the visual recognition-based test was 81.7%, and the Wilks' Lambda was 0.25, $p<0.001$. The mean and standard deviation of the results of the adaptive test are shown in Table 4. Shown. From the data in the table, it can be seen that in the data of the mean and standard deviation of the keystroke and tone control, pedal technique, and musical expressiveness, the participants with higher levels of piano locomotion showed higher scores in the keystroke and tone control, and pedal technique tests, and lower scores in the musical expressiveness.

Table 4: The average of the adaptive test of the test function(SD)

	Touch and tone control	Music expression	Vision and improvisation
Primary level	4.42(0.39)	7.82(2.03)	58.71(9.46)
Intermediate level	3.94(0.33)	8.75(1.92)	64.87(6.92)
High level	3.45(0.22)	9.86(1.32)	68.14(0.63)

The classification accuracy of the judgment function-based motor adaptation test is shown in Table 5. In this judgment function model, the classification accuracy for the three skill level groups was 74.6%, which was slightly lower than the accuracy of the ID3 decision tree classification model.

Table 5: The classification of the adaptive classification of the function

		Predictive result			Total
		1	2	3	
Quantity statistics	Primary level	13	4	0	17
	Intermediate level	3	11	5	19
	High level	0	3	9	12
Percentage statistics(%)	Primary level	76.47%	23.53%	0%	100%
	Intermediate level	15.79%	57.89%	26.32%	100%
	High level	0%	25%	75%	100%

The mean and standard deviation of the three statistical results of pedal technique, fingering, and chord for the visual recognition based test are shown in Table 6. From the table, it can be seen that higher skill levels scored higher between those with higher skill levels compared to lower skill levels. The lower answer time of those with higher skill levels reflected faster recognition.

Table 6: The average of the test results of visual recognition (standard deviation)

	Pedal technology	Finger technique	Chords
Primary level	1.82(0.98)	0.89(0.94)	90.12(39.12)
Intermediate level	5.13(1.45)	3.39(1.67)	72.36(16.08)
High level	6.22(1.49)	4.23(2.28)	41.89(21.14)

The classification accuracy based on the visual recognition test is shown in Table 7. Its classification accuracy is 81.7% with Wilks' Lambda of 0.25, $p<0.001$.

Table 7: Classification of visual recognition tests of the judging function

		Predictive result			Total
		1	2	3	
Quantity statistics	Primary level	13	2	2	17
	Intermediate level	2	14	3	19
	High level	1	4	8	12
Percentage statistics(%)	Primary level	76.47%	11.76%	11.76%	100%
	Intermediate level	10.53%	73.68%	15.79%	100%
	High level	8.33%	33.33%	66.67%	100%

Finally, Pearson correlation coefficients were calculated to assess the relationship between participants' skill levels and the dependent variable, which consisted of all three sets of test data. The results of the calculations are shown in Figure 2. Single underlining indicates $P<0.01$, while double underlining indicates $P<0.05$.

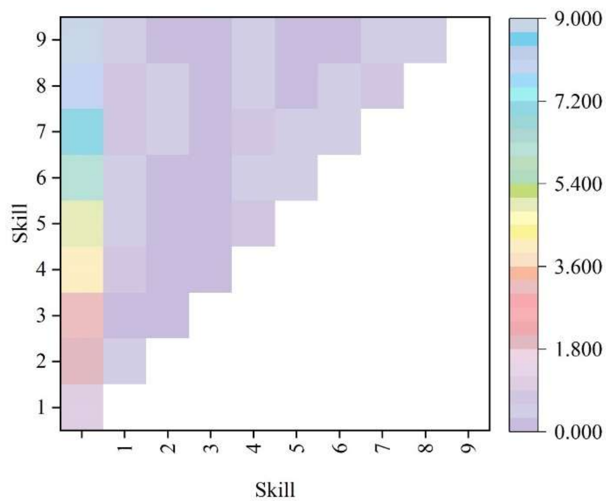

Figure 2: The calculation results of the Pearson correlation coefficient

III. C. Analysis of the validity of the assessment of skill level levels

In this study, a self-constructed student piano playing dataset at a university was used. An assisted automatic piano skill assessment framework based on visual motion tracking technique and deep ID3 decision tree classification model was validated in the dataset. The GRS in the dataset contains six scales from 1 to 5, including (1) technical difficulty, (2) movement, (3) time, (4) operation flow, (5) overall performance, and (6) final completion quality. The distribution of students' piano playing level is shown in Figure 3, thus reflecting the performance of the operation. Interquartile spacing (IQR) measures the degree of dispersion in the box plot. It can be seen that the intermediate level has the highest composite score with a median of 3.825, showing that the intermediate level has the best composite performance, followed by expert and novice. Thus, the labels in a university's self-constructed student piano performance dataset accurately differentiate between the three grades of assisted piano operating skill levels.

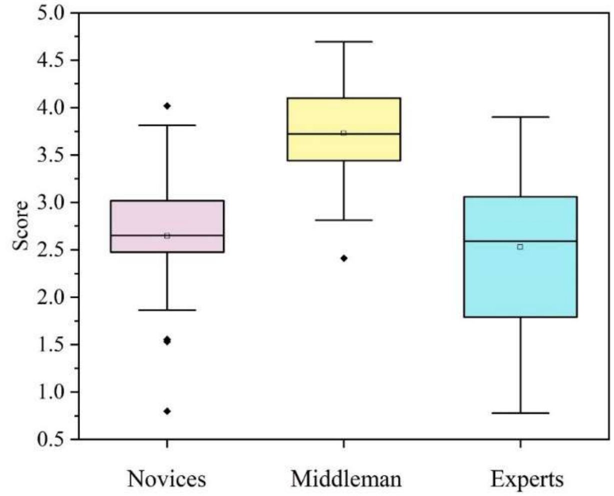

Figure 3: Boxplot of GRS for three skill levels

Whether the true label is consistent with the true skill level has a significant impact on the classification model. Most of the classification errors occur in the failure to accurately identify self-proclaimed intermediaries and experts in the dataset. The results are shown in Table 8, the more accurate the classification results of the ID3 decision tree classification model will be. In addition, the results of this study were compared with the most recent classifications. These studies use a self-constructed student piano playing dataset from a university as a video input source and conduct experiments under the LOSO scheme. It can be observed that the method of this paper produces results with an assessment accuracy of 84.86%, thus demonstrating the feasibility of the method proposed in this study for aiding piano skill assessment.

Table 8: The study was compared

Method	Results
STIP	80.12%
IDT	77.84%
CNN	80.74%
CNN-LSTM	81.63%
ResNet	81.94%
KCF + LSTM	78.05%
KCF + CNN-LSTM	80.12%
KCF + CNN	83.46%
The method of this article	84.86%

IV. Conclusion

The piano skill assessment framework based on computer vision motion tracking and ID3 decision tree classification model shows excellent performance. The experimental results demonstrated that the assessment framework has significant advantages in accurately distinguishing piano players of different levels, with an overall assessment accuracy of 84.86%, which exceeds existing methods such as STIP (80.12%) and CNN-LSTM (81.63%). Pearson's correlation coefficient analysis showed that keystroke and tone control (accounting for 0.411) and musical expressiveness (accounting for 0.408) were the key indicators for discriminating the skill level, which provides data support for the direction of focusing on training in piano teaching. It is worth noting that high-level players scored 3.45 in the key touch and tone control test, which was significantly lower than the 4.42 of the beginner level group, reflecting the precise control of key touch by professional players.The classification accuracy of the ID3 decision tree model in the visual recognition test was 81.7%, with a Wilks' Lambda value of 0.25, which indicated that the model had good discriminative ability. This assessment framework not only realizes an objective quantitative assessment of piano skill level, but also provides a data-driven guidance direction for piano teaching, which helps teachers to provide precise guidance for students' weak points, thus enhancing the science and effectiveness of piano teaching.

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