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A fuzzy logic modeling study on quantitative evaluation of students' skill level in piano teaching

Le He[1], Qian Yang[2], Linjing Tang[3,✉]

[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*

ABSTRACT

For a long time, the cultivation and assessment of the practical application ability of piano in music education has been an important issue that people are constantly concerned about and trying to solve. The research uses the evaluation method based on fuzzy neural network to conduct the study, first of all, from the basic skills, performance skills as well as creative skills in three aspects of the construction of the students' piano skills level index system, through the objective weight entropy weighting method to determine the weight of the index system on the students' piano skills were assessed and analyzed, and got the indexes of the importance of the order of the subjective weighting order of the creation of skills (C, 0.471) > performance skills (B, 0.384) > basic skills (A, 0.145). 0.384) > basic skills (A, 0.145). After the selection of sample data, standardization of sample data and simulation training of the network model, the experimental results show that the application of the fuzzy neural network model for the evaluation of piano skill level is effective and feasible. The temporal accuracy and cognitive accuracy of piano playing were fused to quantitatively assess the brain function. The experimental results show that the brain function scores obtained with this method can effectively indicate that the students' brain function increases with the increase of practice time and decreases with the increase of difficulty.

Keywords: fuzzy neural network, evaluation index, piano level skill, weighting coefficient

1. Introduction

Piano teaching plays an important role in higher music colleges and universities, helping to cultivate students to form basic music literacy, guiding students to develop good music learning habits, helping students to establish the basic knowledge of music, and improving students' music appreciation [1-4]. It can be said that piano teaching is indispensable to improve students' comprehensive musical quality

✉ Corresponding author.
E-mail address: 15805921683@163.com (L. Tang).
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[5]. However, in China's music teaching, although piano teaching plays its due role and has gained certain achievements through continuous development and reform, it still faces various problems and is difficult to adapt to the ever-changing social needs [6-8]. Therefore, piano teaching in colleges and universities still needs to continuously improve teaching strategies, and the teaching content needs to be upgraded, improved and supplemented, so that it can be more adapted to the current practice of music teaching in colleges and universities [9-11].

Teaching evaluation is an important part of piano teaching and an important link in assessing the quality of classroom teaching [12]. In piano teaching, teachers focus on building efficient piano teaching classroom at the same time, should also pay attention to the establishment of a sound and perfect piano teaching evaluation system, so as to comprehensively grasp the students' piano knowledge and skills, so as to facilitate the subsequent development of targeted teaching practice [13-16]. Ordinary colleges and universities majoring in music piano teaching assessment is mainly the end of each semester students to learn the piano repertoire to play, the teacher according to the difficulty of the students' piano performance works, completion, completion of the effect of scoring [17-19]. Under the influence of this examination system, many students tend to practice the examination repertoire or deliberately play some difficult piano repertoire in order to successfully complete the examination [20]. This single evaluation method can not truly reflect the students' learning situation, not to mention the comprehensive assessment of students' piano literacy, which affects the students' motivation to learn the piano [21-22]. With the continuous innovation of the piano teaching mode, if the traditional teaching assessment and evaluation mechanism is still used, it can not effectively meet the needs of the development of piano courses in art colleges and universities in the new period [23-24]. In this context, teachers should do a good job of teaching and research, to realize the innovation of the piano teaching evaluation mechanism, so as to ensure that the assessment and evaluation system is compatible with the development of piano course teaching.

Aiming at some shortcomings of the traditional quantitative evaluation method of students' skill level, the fuzzy neural network method is introduced into the field of students' ability evaluation. At the same time, the evaluation indexes for quantitative evaluation of students' skill level in piano teaching are constructed from three aspects, namely, basic skills, performance skills and creative skills, and the index system is combined and empowered by using the G1-entropy weighting method. The hierarchical evaluation method based on fuzzy neural network is then used to train the skill indexes with neural network and the non-student skill level indexes with fuzzy neural network, and a fuzzy neural network evaluation model is constructed to obtain the evaluation value of the students' skill level in piano teaching.

2. Quantitative Evaluation Model of Students' Skill Level in Piano Teaching

2.1. Construction of the evaluation index system

2.1.1. Evaluation principles. In order to ensure the science and practicality of the developed approach, the following principles were followed during the development of the assessment index system and quantitative coefficients, assessment scales, etc:

Principle of policy: The system is based on the piano outline for teacher education majors of the Ministry of Education, and is formulated to meet the requirements of the general objectives of teacher education, to satisfy the requirements of piano application skills for the future as a music teacher in primary and secondary schools, and to lay a foundation for lifelong learning.

Principle of combining qualitative and quantitative: The evaluation of music skills has always been based on qualitative evaluation, taking the approach of collective on-site scoring or discussion and ranking.

It plays a direct role in adjusting and guiding the teaching. Therefore, this talent training assessment system should be on the skills that must be mastered.

The principle of system theory: each single indicator is not isolated, it is a part of the overall skills composition, the quantitative assessment of a single skill content should be linked to the broader context of skills training, reflecting the “combination of points and surfaces”; At the same time, individual skills improve as other skills develop, reflecting continuity and systematicity in the various stages of assessment. Therefore, the development of the system must also take into account the relationship between the part and the whole, in accordance with the “principle of system structure”.

Principle of operability: The content of the assessment should be matched with a suitable form of assessment, using a three-point system of marking scales and evaluation coordinates, which is operable and generalizable. It can not only adapt to the assessment of school students, but also meet the assessment needs of in-service primary and secondary school music teachers, and should have a wide applicability and reflect the characteristics of teacher training skills.

Principle of proportionality: According to the policy requirements of "quality and ability, knowledge and skills, specialization and professionalism, combination of academic education and lifelong learning", according to questionnaires, literature statistics and analysis, practice evidence collection and other methods, the "principle of proportionality" in the formulation of index weight coefficients is used for reference, and the principle of combining "necessity, applicability, and narrow identity" is followed to carry out objective, reasonable and scientific weighting of indicators at all levels to obtain weight coefficients.

2.1.2. Evaluation indicator system. According to the requirements of the Piano Curriculum Guidelines for Teacher Education of the Ministry of Education, based on the contents of various competitions, combined with the actual needs obtained from the questionnaire survey according to the inclusion, progressive relationship, respectively, the three major segments - nine skills - specific requirements, such as the three-level Indicator system. According to the goal of cultivating “the ability to use piano comprehensively”, based on the music-oriented thinking, strengthening the instrumental nature of the piano, and taking the principles of refinement, comprehensiveness and sense of structure as the principles, we set up a rationalized skill system of “three major sections, nine skills and seven qualities”. The evaluation index system of students' piano skills is shown in Table 1.

Table 1. Student piano skill level evaluation index system

Target value	Primary indicator	Code	Secondary indicator	Code
Student piano skill level	Basic skill	A	Basic skill	A1
			Visual skill	A2
			Shift skill	A3
	Performance skill	B	Solo skill	B1
			Accompaniment	B2
			Singing skill	B3
	Creative skill	C	Improvisational solo skills	C1
			Improvisational accompaniment	C2
			Improvisation	C3

2.2. Calculation of evaluation index weights based on combination assignment

2.2.1. G1 method for determining subjective weights:

1) Ranking the importance of indicators. Assuming that the set of evaluation indicators in the system is $\{X_1, X_2, X_3, \cdots X_n\}$, the importance of the indicators is ranked, the most important indicator is recorded as X_1', and then continue to filter the most important indicators among the remaining indicators as X_2'. Repeat the above operation until X_n', so as to group the indicators into an ordinal relationship.

2) Assignment of relative importance. Set the ratio of importance between neighboring evaluation indicators X_{k-1} and X_k that form an ordinal relationship to R_k, where $R_k = \frac{W_{k-1}}{W_k}$.

3) Calculation of indicator weights. The weight of a single indicator is first calculated as W_m, and then

the weights of other indicators in the indicator set are calculated as W_{k-1}.

$$W_{\mathrm{m}}=\left(1+\sum_{m=2}^{n}\prod_{k=m}^{n}R_k\right)^{-1} \tag{1}$$

$$W_{k-1}=R_kW_k, k=m,m-1,\ldots,3,2 \tag{2}$$

2.2.2. Entropy weighting method to determine objective weights:
1) Construct judgment matrix. Assuming that there are n object and m indicators in the evaluation system, this multi-object, multi-indicator judgment matrix C is:

$$C=\begin{bmatrix} C_{11} & C_{12} & \cdots & C_{1m} \\ C_{21} & C_{22} & \ldots & C_{2m} \\ \cdots & \ldots & \vdots & \cdots \\ C_{n1} & C_{n2} & \cdots & C_{nm} \end{bmatrix} \tag{3}$$

2) Dimensionless processing and calculation of indicator ratios. All positive indicators within the evaluation system, to which the data are dimensionless processing, the formula is:

$$P_{ij}=\frac{C_{ij}}{\sum_{j=1}^{m}C_{ij}}(i=1,2,\cdots,n; j=1,2,\cdots m) \tag{4}$$

Calculate the weight of the i st evaluation object under the j nd indicator P_{ij} with the formula:

$$Z_{ij}=\frac{X_{ij}-\min\left(X_{ij}\right)}{\max\left(X_{ij}\right)-\min\left(X_{ij}\right)} \tag{5}$$

3) Calculate the entropy value of the indicator. Calculate the entropy value of the j st indicator e_i with the formula:

$$e_i=(1/\ln(n))\sum_{j=1}^{n}P_{ij}\ln\left(P_{ij}\right)(i=1,2,\ldots,n) \tag{6}$$

4) Calculate the weights of indicators. Calculate the weight of the j st indicator H, where $0\leq H\leq 1$, the formula is:

$$H=\frac{1-e_i}{\sum_{i-1}^{n}\left(1-e_i\right)} \tag{7}$$

2.2.3. Game theory to determine portfolio weights. The subjective and objective weights obtained through the G1 method and entropy weighting method are assembled together through the game theory idea to minimize the deviation between the subjective and objective weights, so that the final weighting results are more reasonable and balanced, and the calculation steps are as follows:
1) Construct index weight combination set. Assuming that there is k method for calculating the weights of the indicators, the set of weights is obtained as W_i, then $W_i=\left\{W_{i1},W_{i2},\ldots,W_{in}\right\}$, where $i=1,2,\ldots,n$. Let the set of combinations formed by all the methods be W:

$$W=\sum_{i=1}^{n}\alpha_iW_i^T \tag{8}$$

Where α_i is the linear combination coefficient.

2) Combining game theory ideas, optimization countermeasure model Combining game theory combination of related ideas, we get the optimization countermeasure model of linear combination coefficients as:

$$\min \left\| \sum_{i=1}^{n} \alpha_i W_i^T - W_i \right\|_2 \tag{9}$$

$$\begin{bmatrix} W_1 \cdot W_1^T & W_1 \cdot W_2^T & \cdots & W_1 \cdot W_n^T \\ W_2 \cdot W_2^T & W_2 \cdot W_2^T & \cdots & W_2 \cdot W_n^T \\ \vdots & \vdots & \ddots & \vdots \\ W_n \cdot W_1^T & W_n \cdot W_2^T & \cdots & W_n \cdot W_n^T \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_n \end{bmatrix} = \begin{bmatrix} W_1 \cdot W_1^T \\ W_2 \cdot W_n^T \\ \vdots \\ W_n \cdot W_n^T \end{bmatrix} \tag{10}$$

3) Normalization of combined coefficients. The set of combination coefficients, $\{\alpha_1, \alpha_2 \ldots, \alpha_n\}$, is normalized:

$$\alpha_i^* = \alpha_k \Big/ \sum_{i=1}^{n} \alpha_k \tag{11}$$

4) Calculate the final combination weights. Set the final combination weight of the evaluation indicators as W^*:

$$W^* = \sum_{i=1}^{n} \alpha_k^* W_k^T \tag{12}$$

2.3. Fuzzy Logic Neural Network Evaluation Model

2.3.1. Theory of fuzzy logic. Fuzzy set theory is an extended popularization of classical set theory. Because of its powerful ability to study uncertain things and solve fuzzy problems, scholars all over the world have widely used it in the fields of image recognition, artificial intelligence, medical diagnosis, geological evaluation, psychology, philosophical research and other fields, and have achieved remarkable results [25].

In classical set theory, let A be a subset of domain U, whether any element $u \in U$ and element u in the domain belong to the exact set A, there are only two absolute states, "belonging" and "not belonging", based on the mathematical description of the eigenfunction $C_A(u)$ such as equation (13), $C_A(u)$ has only two values, 0 and 1, and set $A = \{u \mid C_A(u) = 1\}$.

$$C_A(u) = \begin{cases} 1 & u \in A \\ 0 & u \notin A \end{cases} \tag{13}$$

However, such non-zero-or-one binary logic judgments are limited to events in scenarios with well-defined attributes, while classical set theory cannot be applied to express judgments for fuzzy scenarios that are more common in life. Therefore fuzzy sets and fuzzy logic, which are theories for solving fuzzy events and decision-making difficulties, have emerged. The theory of fuzzy sets takes fuzzy objects and expresses them mathematically and exactly, making up for the shortcomings of binary logic when describing the fuzzy containment relationship between elements and sets. The advantage of fuzzy logic is precisely to deal with fuzzy propositions, to generalize fuzzy conditions based on natural language, to apply fuzzy language rules, to model nonlinear functions on objects containing fuzzy concepts, and to reason to approximate fuzzy conclusions.

2.3.2. BP Neural Networks. The BP neural network not only simply transmits information, but also self-corrects itself through the back propagation of errors, mimicking the way the human brain learns

[26]. This mechanism makes the BP neural network have the ability similar to human learning, and can continuously adjust its own connection weights to minimize the error when facing complex tasks.
1) The network is initialized. Determine the number of neurons in each layer, where the number of nodes in the hidden layer Q determines the range, and randomly initialize all network connection weights and neuron thresholds:

$$Q=\sqrt{M+P}+a \tag{14}$$

where a is a constant from 1 to 10.
2) The sample data pre-processed by the fuzzy system form the training data set A, where any one of the training input data a is a M-dimensional vector; corresponding to the desired output set B, any one of the training output data b is a P-dimensional vector, and the training input data set and the desired output data set are inputted into the network for training.
3) Calculate the input and output values of each layer. The input signal is passed forward in the network, and the output of the current neuron is directly connected to the input of the connecting neuron in the lower layer. The neuron input is labeled as u, the output is labeled as v, and the weight is labeled as ω. For example, ω_{ij} represents the weight value of the neuron in layer I passed to the neuron in layer J.

The input of the neural network is the quantized evaluation value of all the second-level indicators, each of which contains five affiliation levels, and the affiliation degree of the level to which it belongs is multiplied by the affiliation score of the indicator to quantify the evaluation results, which is ultimately used as the input of the neural network system:

$$u^M = x_m \tag{15}$$

The input to the i st neuron of the hidden layer is:

$$u_i^I = \sum_{m=1}^{M} \omega_{mi} x_m \tag{16}$$

The input to the p st neuron of the output layer is:

$$u_p^p = \sum_{j=1}^{J} \omega_{jp} v_j^J \tag{17}$$

The output of the p st neuron of the output layer is:

$$v_p^P = f\left(\sum_{j=1}^{J} \omega_{jp} v_j^J\right) \tag{18}$$

The transfer function for the implicit layer usually uses the Sigmoid function:

$$y = \log \mathrm{sig}(x) = \frac{1}{1+e^{-ax}} \tag{19}$$

where a=1.
4) Error function $E(\omega,b)$, output error of the j rd neuron of the output layer:

$$E(\omega,b) = \frac{1}{2}\sum_{j=1}^{n-1}\left(d_j - y_i\right)^2 \tag{20}$$

Where: y is the number of iterations and d_j is the actual output of this neuron.
5) Correction of the weights of each layer. The error signal on its way to back-propagation modifies the weights ω and their corrections $\tilde{\omega}$ in turn, the learning efficiency is denoted as η, and the local gradient of the current neuron is denoted as δ. i.e:

$$\omega(n+1) = \omega(n) + \tilde{\omega}(n) \tag{21}$$

The amount of weight correction between implicit layer I and output layer P:

$$\omega_{ip} = \omega_{ip} - \eta_1 \cdot \frac{\partial E(\omega, b)}{\partial \omega_{ip}} = \omega_{ip} - \eta_1 \cdot \delta_{ip} \cdot x_i \tag{22}$$

$$b_p = b_i - \eta_2 \cdot \frac{\partial E(\omega, b)}{\partial b_p} = b_p - \eta_2 \cdot \delta_{ip} \tag{23}$$

The amount of weight correction between input layer M and implied layer I:

$$\omega_{mi} = \omega_{mi} - \eta_1 \cdot \frac{\partial E(\omega, b)}{\partial \omega_{mi}} = \omega_{mi} - \eta_1 \cdot \delta_{mi} \cdot x_k \tag{24}$$

$$b_i = b_i - \eta_2 \cdot \frac{\partial E(\omega, b)}{\partial b_i} = b_i - \eta_2 \cdot \delta_{mi} \tag{25}$$

After the weight adjustment is finished, the neural network continues to back propagate from the input signal until it meets the requirements of the set error value, at which time the fuzzy neural network training is finished.

2.3.3. Fuzzy Neural Network Construction:

1) Fuzzy neural network structure. The fuzzy neural network structure has 5 layers as shown in Fig. 1, which are input layer, fuzzification layer, rule layer, normalization layer, and output layer.

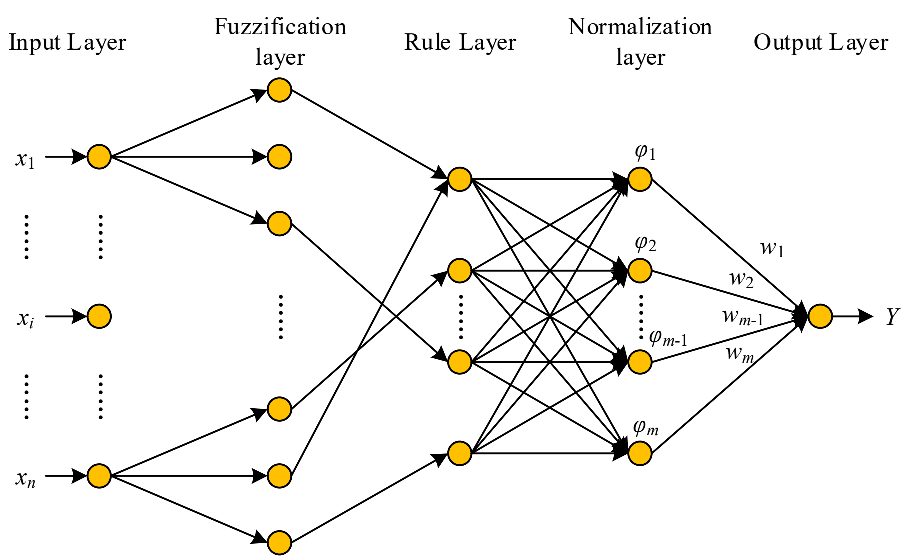


Fig. 1. Fuzzy neural network structure

(1) Input layer. The input data of the fuzzy neural network, i.e., the standardized indicator data vector $(x_1, \cdots, x_n)$, n are the number of input variables.

(2) Fuzzification layer. Each node represents an affiliation function, and the indicator vectors input from the input layer are transformed into the affiliation degree of each indicator to each indicator in the judgment set through the processing of the fuzzification layer, so as to realize the fuzzification of the indicator data. In this paper, Gaussian function is used as the affiliation function, which has good local characteristics and strong global mapping ability.

$$u_{ij}\left(x_i\right)=\exp\left[-\frac{\left(x_i-c_{ij}\right)^2}{\sigma_j^2}\right] j=1,2,\cdots,m \tag{26}$$

Where u_{ij} is the j rd affiliation function of x_i, c_{ij} is the center of the j th Gaussian affiliation function of x_i, σ_j is the width of the j th Gaussian affiliation function of x_i, and m is the number of affiliation functions i.e., the number of PV plant operation and maintenance quality evaluation classifications.

(3) Rule layer. Each node represents an RBF neuron and the basis function is a nonlinear Gaussian function:

$$v_j=\exp\left[-\frac{\sum_{i=1}^{r}\left(x_i-c_{ij}\right)^2}{\sigma_j^2}\right]=\exp\left[-\frac{\left\|x-c_j\right\|^2}{\sigma_j^2}\right], j=1,2,\cdots,m \tag{27}$$

where C_j is the center of the jth RBF neuron, i.e., the center of the j nd class; r is the number of fuzzy rules.

(4) Normalization layer. The output of the j th node is:

$$\varphi_j=\frac{v_j}{\sum_{k=1}^{m}v_j}, j=1,2,\cdots,m \tag{28}$$

(5) Output layer. Linearly weighted output of all input signals:

$$Y(X)=\sum_{K=1}^{m}w_k\varphi_k \tag{29}$$

where w_k is the connection weight of the k nd rule.

2) Fuzzy neural network training. The most important thing about D-FNN is to learn the appropriate network structure as well as the connection weight coefficients through training, and the model training process is shown in Fig. 2.

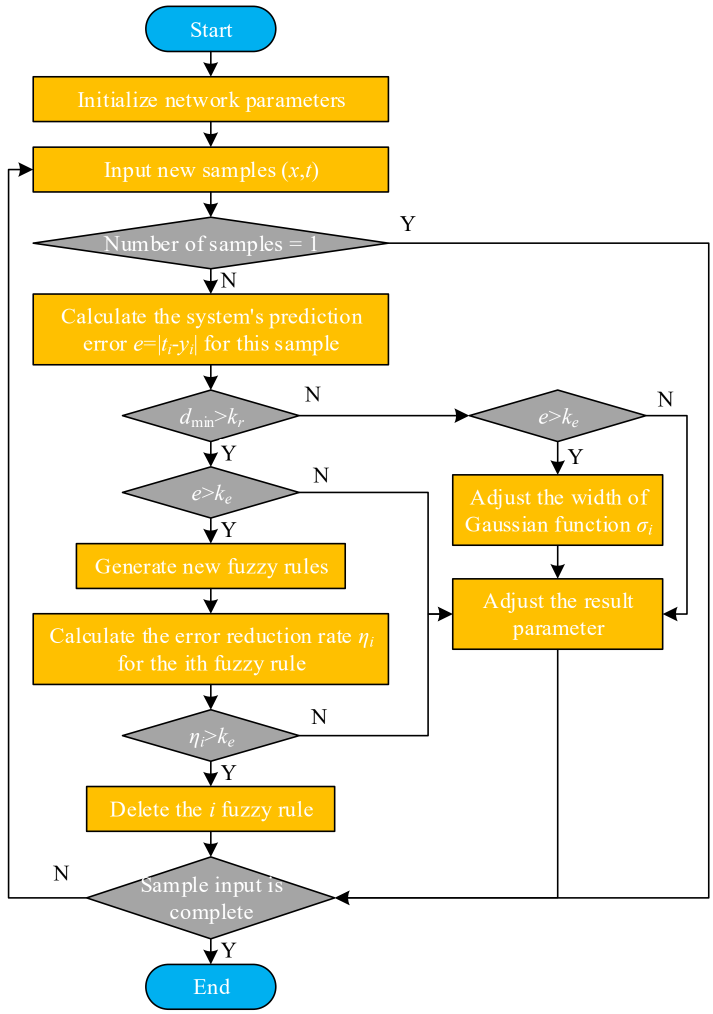


Fig. 2. The flow chart of the D-FNN model

3) Parameter adjustment. Each time a new sample is entered, its tolerable bound and systematic error are obtained, which are compared with the threshold value, and four cases exist, each of which is parameterized.

(1) Generating new rules. When $\|e_i\| > k_e$, $d_{\min} > k_d$, the new sample cannot be completely covered by the existing fuzzy rule, a fuzzy rule is generated, and the system needs to set the rule, that is, to adjust the parameters of each RBF unit. It has been shown that there is a close relationship between the width of the RBF unit and the generalization performance of the system, therefore, it is mainly necessary to adjust the width and the center of the newly generated rule, i.e., the RBF unit. Let the initial values of Gaussian center $C_1 = X_1$ and width $\sigma_1 = \sigma_0$ for the first learning be adjusted as follows:

$$C_i = X_i \tag{30}$$

$$\sigma_i = k \times d_{\min}, k > 1 \tag{31}$$

where X_i is the new sample for the i nd learning and k is the overlap factor. In this paper, we take $\sigma_0 = 2$, k=1.1.

(2) No parameter adjustment. When $\|e_i\| \le k_e$, $d_{\min} \le k_d$, at this time the existing network can fully accommodate the new sample, no need to adjust the parameters.

(3) Resulting parameter adjustment. $\|e_i\| \le k_e$, $d_{\min} \le k_d$: At this time, the RBF neurons of the existing network have better generalization ability and can cover the new sample, then adjust the

result parameters (weight coefficients) can be. Let the matrix of the output of the normalization layer be φ and the ideal output matrix be T, then the output matrix and error matrix are:

$$Y = W \times \varphi \tag{32}$$

$$E = \|T - Y\| \tag{33}$$

The resultant parameters are adjusted to find the optimal vector of weight coefficients W^* minimizing the error energy $E^T E$. Solve for $W^* = T\left(\varphi^T \varphi\right)^{-1} \varphi^T$ by linear least squares LLS approximation.

(4) RBF neuron adjustment. When $\|e_i\| \le k_e$, $d_{\min} \le k_d$, an RBF neuron covering this new sample is significantly less important, it is necessary to adjust the RBF neuron:

$$\sigma_j^i = k_w \times \sigma_j^{i-1}, k_w > 1 \tag{34}$$

where k_w is a preset constant, which is set to 1.2 in this paper.

3. Application of quantitative evaluation of students' piano skill level

3.1. Results of weighting of evaluation indicators

Combined with the above weight calculation method, the subjective and objective weights of each index are calculated, and then the comprehensive weights of students' piano skill level indexes are obtained based on the game theory viewpoint. The results of subjective weights, objective weights and comprehensive weights are shown in Table 2.

Table 2. Students' level of piano skills

Primary indicator	Subjective weight	Objective weight	Composite weight	Secondary indicator	Subjective weight	Objective weight	Composite weight
A	0.145	0.167	0.195	A1	0.451	0.396	0.377
				A2	0.378	0.284	0.351
				A3	0.171	0.320	0.272
B	0.384	0.296	0.417	B1	0.211	0.191	0.379
				B2	0.354	0.286	0.411
				B3	0.435	0.523	0.210
C	0.471	0.537	0.388	C1	0.119	0.387	0.158
				C2	0.237	0.314	0.375
				C3	0.644	0.299	0.467

According to the table, it can be obtained that the order of subjective weights in the three first-level indicators is: creative skills (C, 0.471) > performance skills (B, 0.384) > basic skills (A, 0.145). The subjective weights, objective weights, and combination weights of the first-level indicators are plotted as shown in Figure 3, which clearly shows that after the correction of the G1 method, the weight of the C indicator is still the maximum weight, and this problem is due to the fact that the actual score of the C indicator is higher, which leads to a larger entropy value obtained, and ultimately causes a larger impact on the overall system. This indicates that the combination assignment method used in this paper has a certain degree of rationality.

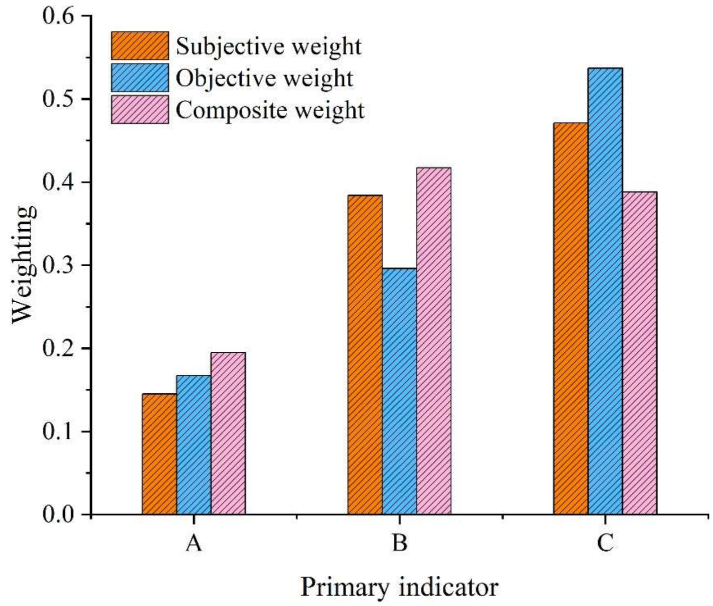


Fig. 3. First-level indicators subjective weight, objective weight, combined weight

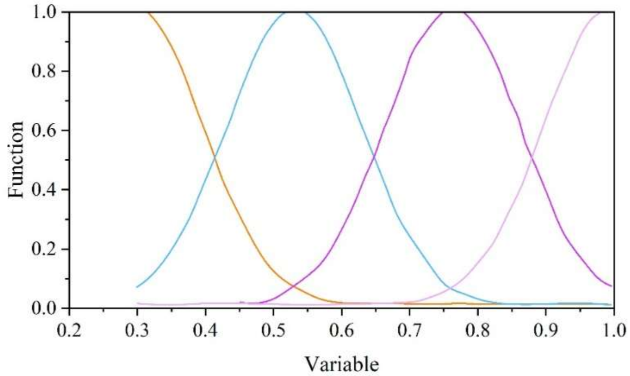
3.2. Typical case studies

3.2.1. Sample Selection. The size of the sample size directly affects the quality of the network model training and the generalization ability of the model. If the selected sample data size is large, the generalization ability of the network model may be stronger, but the local accuracy may be worse; if the data size is too large, it may increase the training time of the network; if the data size is too small, it will affect the generalization ability of the network model.

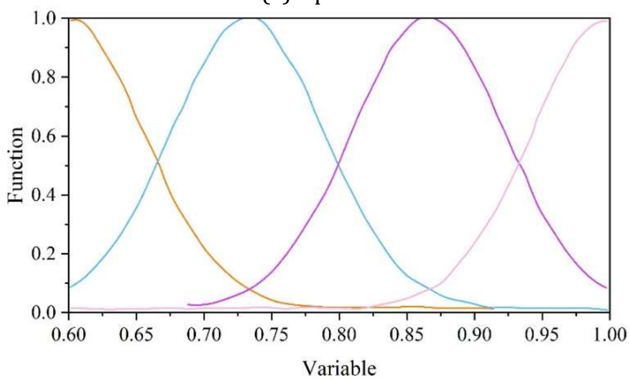
Based on the evaluation index system of students' piano skill level constructed in section 2.1, this paper selects 45 students from Shanghai Art School, and adopts the method of exam scoring to quantify the results of students' original piano skill evaluation as the expected output value of the model. After collecting and organizing a total of 100 groups of sample data, of which 60 groups of sample data as training data, 40 groups of sample data as test data.

3.2.2. Evaluation results. In this paper, the piano skill indicator model constructed by fuzzy neural network, the model structure consists of 6 skill indicators as inputs and 1 output, and the fuzzification layer has 28 neurons.

In this paper, during the training process of the above fuzzy neural network, the command function anfis provided in the MATLAB fuzzy toolbox is called, which can adaptively construct fuzzy rules and adjust the parameters in the affiliation function through the given sample data. Figure 4 shows the initial affiliation function curves of some input variables, and Figure 5 shows the affiliation function curves after 100 steps of training. The changes in the affiliation function curves of the input variables before and after training illustrate the self-learning ability of fuzzy neural networks. The root mean square error of the training data at this time is 0.0141.

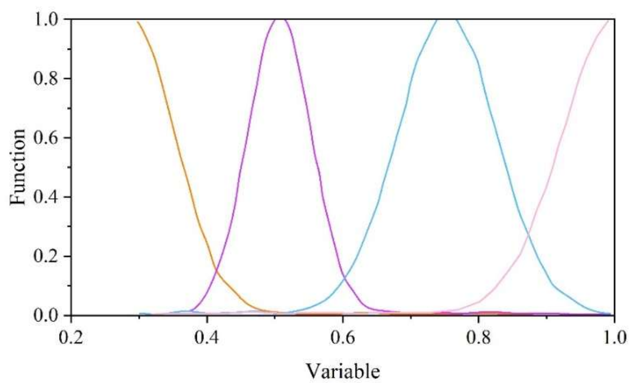


(a)Input 1

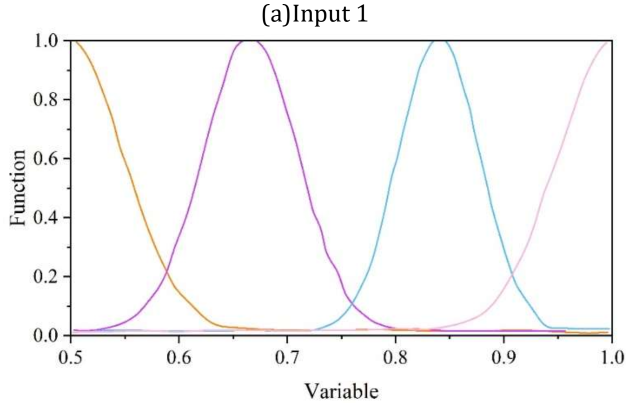


(b)Input 2

Fig. 4. The initial membership function curve of the partial input variable



(a)Input 1



(b)Input 2

Fig. 5. The partial input variables are subject to the function curve after 100 steps

Finally, the result value obtained from the training of the above model is used as the input of the evaluation model of students' piano skill level, then the number of inputs of the evaluation model is 2 (piano skill level and non-piano skill level, respectively), and the number of outputs is 1, which is the result of the evaluation of the students' piano skill level, and the defuzzification layer of the network contains 8 neurons, and the number of fuzzy rules is 16, so that the trained model of the students' evaluation of their piano skill level is The structure is shown in Fig. 6.

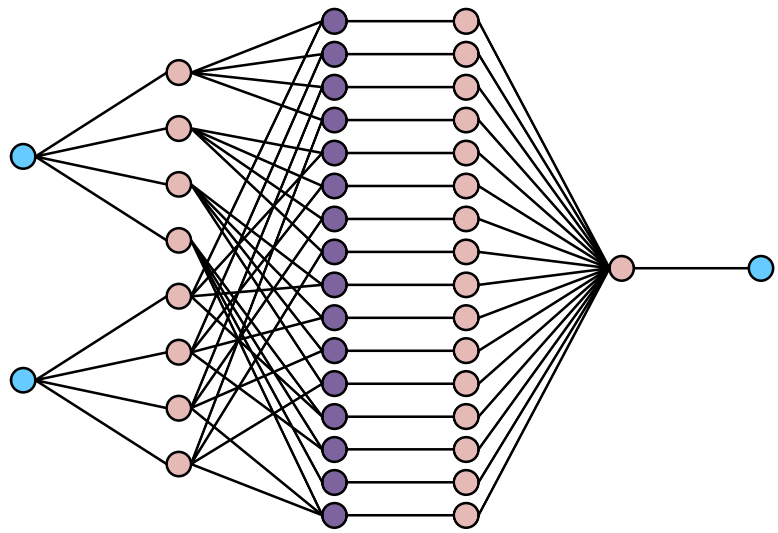


Fig. 6. Student piano skill level evaluation model

The mean square error curve of the training data is shown in Figure 7. From the figure, it is found that the mean square error curve of the training data of the students' piano skill level evaluation model is relatively smooth, and the mean square deviation reaches 7.7845e-005, and the network training effect is better.

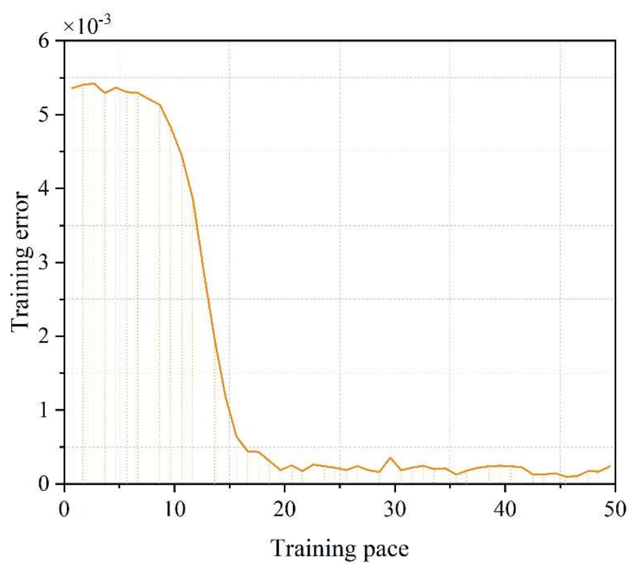


Fig. 7. The average variance curve of the training data

Finally, 40 sets of test sample data were input into the trained fuzzy neural network model for the evaluation of students' piano skill level, and the expected output of the test data and the actual output of the network model are shown in Figure 8.

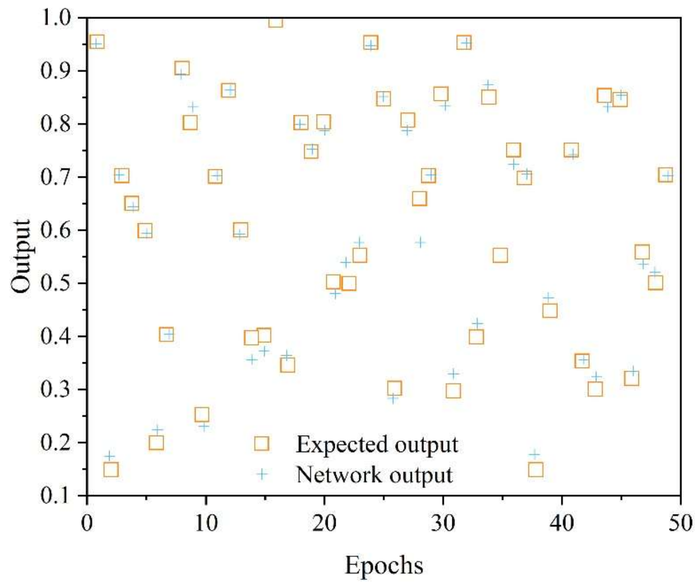


Fig. 8. The desired output and actual output of the network model test data

In this paper, we also categorize the students' piano skill level into four levels as shown in Table 3, then the level of piano skill level of the test sample data evaluated by the network is shown in Table 4.

Table 3. Grading criteria

Skill variable	Superior	Good	Medium	Difference
Fractional value	0.85⩽x<1	0.7⩽x<0.85	0.6⩽x<0.7	Below 0.6

Table 4. Partial test sample evaluation grade

Sample number	Piano skill level	The value of the network output	Network output rating
1	Superior	0.9783	Superior
2	Good	0.7257	Medium
3	Medium	0.6787	Medium
4	Difference	0.6375	Medium
5	Difference	0.2296	Difference
6	Superior	0.9154	Superior
7	Medium	0.6195	Difference
8	Good	0.8646	Good
9	Good	0.8611	Good
10	Medium	0.7087	Medium
11	Superior	0.9115	Superior
12	Difference	0.5294	Difference
13	Good	0.8697	Good
14	Medium	0.6812	Medium
15	Good	0.8177	Good
16	Good	0.7832	Good
17	Difference	0.4394	Difference
18	Difference	0.5526	Difference
19	Superior	0.9091	Superior
20	Superior	0.8892	Superior
21	Medium	0.4406	Difference

22	Good	0.8271	Good
23	Difference	0.4126	Difference
24	Superior	0.9503	Superior
25	Difference	0.3222	Difference

Table 4 shows the final evaluation grade classification of the testing samples of the student piano skill level evaluation model constructed in this paper. In order to test the network final evaluation grade results, here, an evaluation performance index is proposed: network evaluation result accuracy σ.

$$\sigma = \frac{H}{S} \tag{35}$$

where H denotes the number of network output evaluation results that match the students' piano skill level; and S denotes the total number of students participating in the evaluation. It may be worthwhile to analyze the reasons for the deviation between the network output evaluation grades and the students' piano skill level grades. the error between the network model's output evaluation values for samples 2, 4, and 7 and the grade boundary point values that we believe are delineated for the students is very small, and numerically it is basically possible to conclude that the network output evaluation values are in line with the actual performance, so that the network evaluation results accuracy σ revised can reach 0.97. At this point, it is Inevitably, it is more or less affected by human factors. Only the evaluation of sample 21, which belongs to one of the network's mis-assessments, is far from the students' piano skill level.

3.3. Analysis of changes in students' brain-computer capabilities

3.3.1. Scoring reference settings. In this section, the students' piano brain-computer abilities were analyzed using the model, and the statistical analysis of the students' brain-computer ability time accuracy is shown in Figure 9. In the data of students' brain-computer ability time accuracy, most of the students' time accuracy fell between -400 ms and 400 ms, and very few students' time accuracy fell outside of -500 ms to the left and outside of 500 ms to the right.

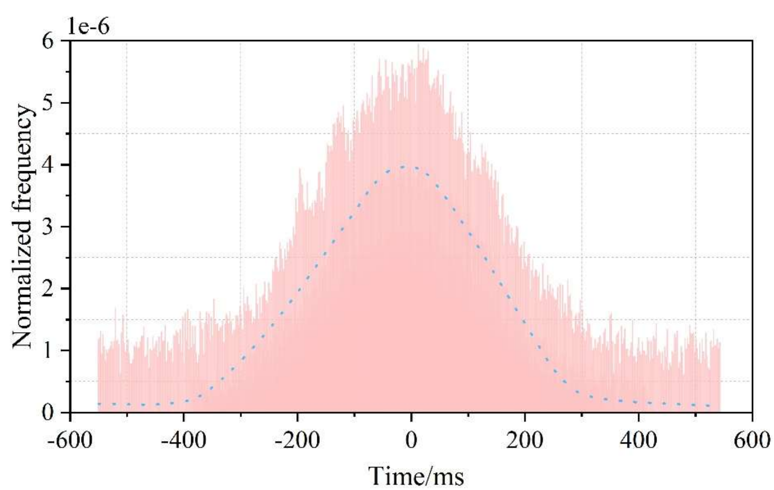


Fig. 9. Time accuracy distribution histogram

The histogram of the accuracy distribution is shown in Figure 10. From the figure, it can be seen that the overall data showed a bell shape with a high center and two short sides, and the peak of the data appeared at about 60 milliseconds. Therefore, according to the preliminary analysis of this paper, the distribution of students' time accuracy in this experiment can be approximated as a normal distribution.

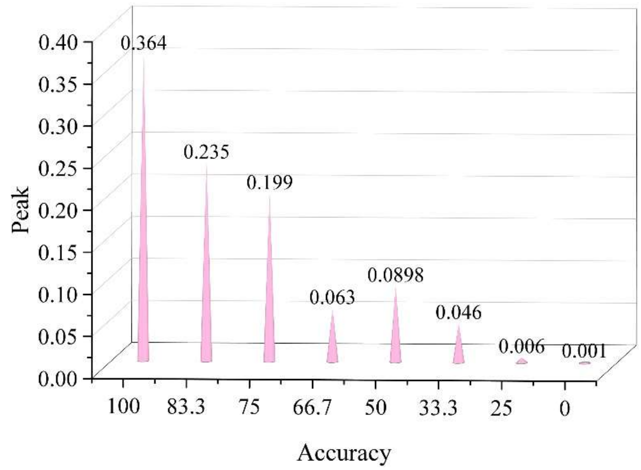


Fig. 10. Cognitive accuracy distribution histogram

According to the results of the statistical analysis of the strength accuracy of this experiment, this paper initially sets the piano cognitive accuracy scoring reference standard, the specific reference standard is as follows: the piano cognitive accuracy 100 is set as a full score of 100 points, then the time accuracy less than or equal to 25 is set to 0. A linear assessment method is used to score the strength accuracy that falls between 100 and 25, that is, strength accuracy and 100 is reduced by 1 point for every 0.75 interval. Based on this percentile scoring reference standard, it is possible to score and compare the cognitive accuracy of the piano in the experimental results.

From the histogram of the distribution of temporal accuracy shown in Figure 9, it can be seen that the student population showed some differences in temporal accuracy, which may be due to the fact that most of the student population did not have any learning experience in music. From the histogram of the distribution of cognitive accuracy shown in Figure 10, it can be seen that the student group has the highest frequency of cognitive accuracy falling in the highest scores.

3.3.2. Analysis of brain function results. Next, the changes in brain function of this student group under different levels of difficulty and prolonged measurements will be analyzed. The overall trend of brain function scores under prolonged testing for the left hand and for the right hand are shown in Figures 11 and 12. It can be seen that for the left hand, with the growth of time, there is a clear trend of slow growth in brain function under each difficulty level; for the right hand, with the growth of time, there are fluctuations in the change of brain function under each difficulty level, but the overall trend is still growth. Due to the short time span of this experiment, there are some fluctuations and instability, but overall, the results show that repeated practice can improve brain function, which is consistent with our basic knowledge of brain function development.

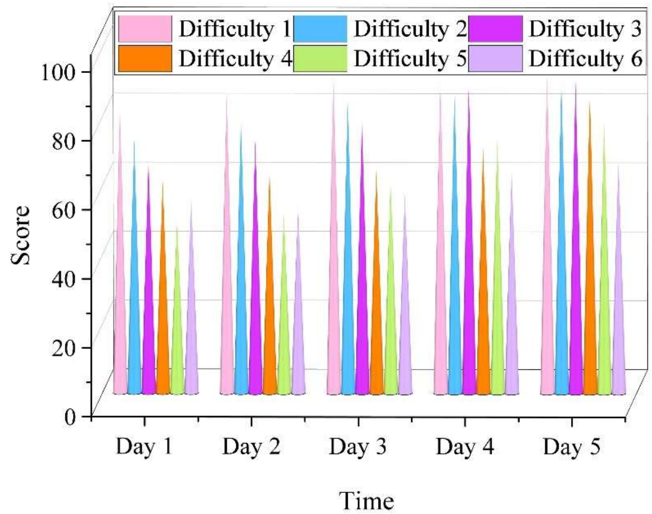


Fig. 11. The overall variation of brain function scores in the left hand

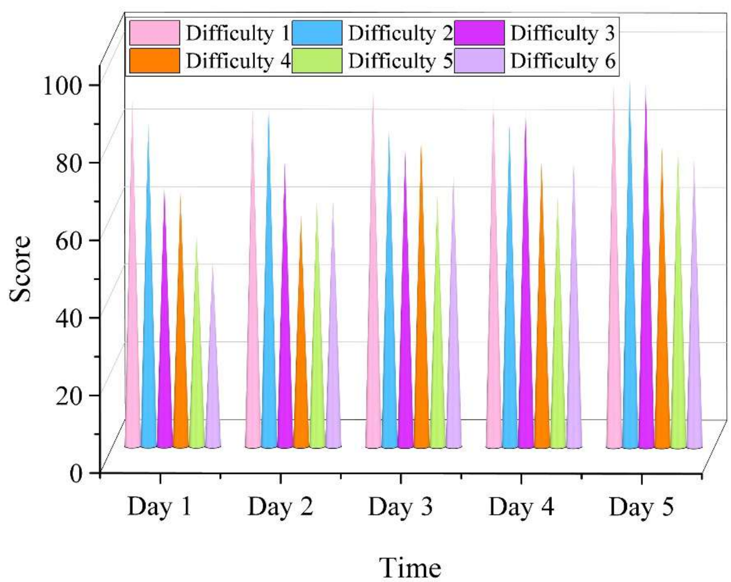


Fig. 12. The overall brain function scores of the right hand

The overall trend of the left and right hand brain-function ability scores under different difficulty tests is shown in Figures 13 and 14. It can be clearly seen that the overall brain function scores of the student population on a daily basis show a decreasing trend as the difficulty of the test task increases. In general, as the difficulty increases, especially at difficulty 4 and 5, the overall brain function scores of the left and right hands at different test durations mostly show relatively significant decreases, probably because compared to the test tasks of difficulty 1 to 3, which only require playing four notes at equal intervals, the test tasks of difficulty 4 to 6 require the playing of two combinations of six notes of the first four and the last eight at unequal and shorter intervals, requiring a more variable intensity, and therefore requiring the playing of two combinations of six notes of the first four and the last eight, requiring a more variable intensity, and therefore requiring a more variable intensity. They require faster changes in strength, so they require faster reaction speeds and stronger body control, and most of the student population has no piano playing experience, and their finger dexterity and sensitivity to rhythm are insufficient, so it is more stressful for the student population.

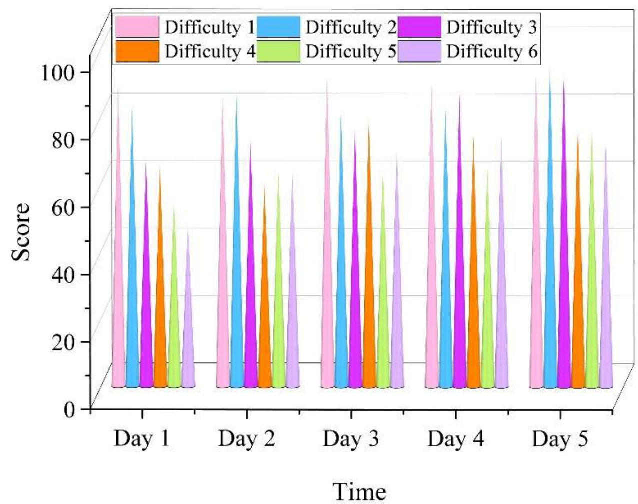


Fig. 13. The overall change of brain function of the left brain

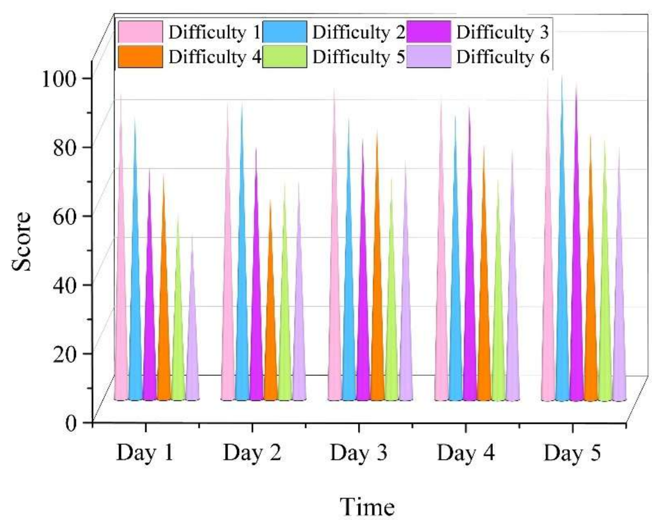


Fig. 14. The overall change of the right brain function scores

When analyzing the results of the overall brain function scores above, it can be seen from Figures 11 and 12 that the overall trend of the left-handed brain function scores under the prolonged test shows a more stable increase compared to the right-handed brain function scores; and from Figures 13 and 14, it can be seen that the overall trend of the left-handed brain function scores under the tests of different levels of difficulty shows a more stable decrease compared to the right-handed brain function scores. The overall trend of the left-handed brain function scores under different difficulty tests also shows a more stable downward trend compared to the right-handed brain function scores. As can be seen from the comparison of Figures 11 and 12, and the comparison of Figures 13 and 14, the overall brain function scores of the right hand are higher than those of the left hand, which is in line with the fact that the majority of the student population is right-handed.

The overall brain function scores of three randomly selected students at different test difficulties are shown in Table 5, from which it can be seen that the brain function scores of individuals in the student population vary, but most of them have higher scores in the right hand than in the left hand, and with the increase in difficulty, the brain function scores of the right and left hands are both on a decreasing trend, especially at difficulty 4 and 5, where the decrease is obvious, following the student population's overall trend. There were a few students who were able to achieve higher scores at higher levels of difficulty, and the brain function scores slowly declined with increasing difficulty.

Table 5. The overall score of the brain function was tested by different students

	Left hand						Right hand					
Student	Difficulty 1	Difficulty 2	Difficulty 3	Difficulty 4	Difficulty 5	Difficulty 6	Difficulty 1	Difficulty 2	Difficulty 3	Difficulty 4	Difficulty 5	Difficulty 6
A	93	90	93	81	74	68	96	95	92	80	73	69
B	85	85	81	70	60	61	92	86	87	76	65	62
C	88	82	86	68	62	57	95	92	84	72	63	63

In summary, the quantitative scoring rules for piano skill level established in this study can better respond to the change trends of piano brain function scores in the student population that gradually increase with time and decrease with difficulty.

4. Conclusion

This paper carries out the research on the evaluation method of students' piano ability based on fuzzy neural network in the established evaluation index system of students' piano ability. By calculating the weight coefficient of each index, it is concluded that among the indicators of students' piano ability, the highest weight of creative skills is 0.471. Then the data of students' skills are analyzed, and the results show that the combination model of this paper is practical, effective and feasible. Finally, by analyzing the change trend of students' brain function scores, it can be seen that the quantitative scoring rules of piano skill level established in this study can better respond to the change trend of the brain function scores of the student population that gradually increase with the growth of time, as well as the change trend of gradually decreasing with the growth of difficulty.

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