Research on Improving Piano Performance Evaluation Method in Piano Assisted Online Education

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***Abstract*—With the continuous progress of science and technology and the popularization of the Internet, online piano education has gradually emerged. This educational model provides piano learning resources and communication platforms through the network platform, so that students can learn piano at home anytime and anywhere. However, there are still some problems in the evaluation method of piano assisted online education, which hinders the development of piano assisted online education. Aiming at the problem that piano assisted online education is difficult to evaluate correctly, this paper proposes to integrate the bidirectional long and short memory network into the instrument digital interface piano performance evaluation model, and to integrate the attention mechanism into the bidirectional long and short memory network, hoping to improve the evaluation accuracy of the model. In the comparison experiment of the evaluation model based on the bidirectional long term memory network, it is found that the accuracy of the bidirectional long term memory network model is 0.91, which is significantly higher than the comparison model. In addition, through the empirical analysis of the model, it is found that the piano online education course integrated with the model can improve students' performance level scores and promote their participation enthusiasm. The above results indicate that the digital interface piano performance evaluation model can not only be used to evaluate digital interface piano performance more accurately, but also to promote the development of online piano education.**

Keywords—Short-term memory network; attention mechanism; musical instrument digital interface; online education; piano performance evaluation model

I. Introduction

Piano performance is a subject full of artistry and technique that places high demands on the performer's musical understanding, skill and expression. In the process of piano learning, effective performance evaluation is crucial for the progress of students [1]. However, traditional methods of evaluating piano performance are often limited by subjective factors, which tend to produce inaccurate and unfair evaluation results [2]. With the continuous progress of science and technology and the popularity of the Internet, piano-assisted online education has gradually emerged [3]. This education model provides piano learning resources and communication platforms through the network platform, so that students can learn at home anytime and anywhere [4]. However, in piano assisted online education, there are still some problems in the evaluation method, such as unclear evaluation standards and inaccurate evaluation results, which limit students' progress in the learning process [5]. Therefore, the aim of this study is to improve the midi piano performance evaluation method so that it can be better applied in piano assisted online education. Specifically, we will use BiLSTM to analyse the musical characteristics and technical requirements of piano performance, and establish a scientific and objective evaluation system. By analyzing the midi data of students' performances, the accuracy, sound quality, expressiveness and other aspects of performance can be accurately evaluated. This research innovatively introduces the two-way LSTM model into the piano performance evaluation model, so as to realize the automatic evaluation and feedback of students' performance, help students find and correct problems in time, and improve the learning effect. At the same time, the improved evaluation method can also serve as a reference for piano teachers, assist them in teaching and guiding students, and promote the sustainable and healthy development of the piano education industry. This research is mainly divided into five parts. The first part analyzes the status quo of the evaluation model and the LSTM algorithm. The second part describes the construction process of the improved piano performance evaluation model based on LSTM. The third part is the comparative analysis of the performance of the improved algorithm and the evaluation model based on the improved algorithm. The fourth part is the discussion of the results of this study; the fifth part is the summary of the full text.

II. Literature Review

With the boom of computer technology, there are several new methods applied to the evaluation model. Ju's team proposed an evaluation model with the cuckoo algorithm to evaluate the permeability of natural fractures more accurately and found the evaluation model could improve the accuracy of the evaluation of the permeability of natural fractures [6]. Chao et al. proposed a wheat yield evaluation model based on a simple algorithm to improve the accuracy of the winter wheat yield estimation model and used the model for empirical analysis, which was found to be of great relevance in estimating not only the yield of wheat accurately, but also the biomass and yield future sensing data [7]. Lai's team has improved the reliability evaluation model for public transportation routes and proposed an information entropy based reliability evaluation model for public transportation routes, which has been empirically analyzed. The experimental results found that the overall reliability of this model is higher than that of traditional evaluation models [8]. Li and Sun proposed a cloud computing-based English-speaking quality evaluation model to improve the precision of the English teaching quality evaluation model, and the model for comparative experimental analysis, and the results showed this method can evaluate the teaching quality of spoken English with accurate evaluation results [9]. Ding et al. proposed a model for evaluating the timeliness of online instruction with intelligent learning to accurately assess the quality of online instruction, and this study used statistical feature analysis methods to statistically analyze and robustness test the model, and the results showed this model has high credibility in evaluating the timeliness of online teaching, which can increase the precision of online teaching quality assessment [10].

With the wide application of neural network technology, LSTM neural network has been applied in many fields. Guo's team proposed an LSTM-based path planning algorithm for mobile robots and conducted simulation experiments to show that the algorithm not only improves the computational speed compared with similar algorithms but also can adapt to an environment with many obstacles [11]. Li et al. designed a hybrid model with LSTM neural network for the prediction of monthly runoff to resolve low precision of water utilization prediction models. The model was empirically analyzed and found the prediction model was more accurate than similar models and provided a reliable basis for the full utilization of water resources [12]. Geng proposed a deep learning architecture based on LSTM neural networks to grasp the nature of patents more quickly and intuitively, used the architecture to accurately simplify the patent text, and found the architecture can increase the efficiency of researchers in mastering patents [13]. Yao's team proposed a reinforcement learning network with an LSTM network to predict the tool life to increase the machining quality of tools and the productivity of the tool automation system, and the empirical analysis of the proposed network showed that the accuracy of the network in predicting the tool life was is greater than that of traditional prediction methods, which is important for improving the machining quality of tools [14]. Altuve and Hernandez proposed a heart rhythm identification model based on the bidirectional LSTM technique for the problem of insufficient measures for early cardiovascular disease detection, and the proposed model was subjected to empirical analysis, and the results showed that the model can accurately identify heart rhythm identification and to discriminate, providing technical support for early detection of cardiovascular diseases and prompt action to protect people's health [15].

Through the above research, it can be found that the current application range of LSTM neural networks is wide, and there are many methods applied to evaluation models. Through the specific analysis of the above studies, it is found that there is little research that combines LSTM neural network with piano performance evaluation model at present. In this study, the bidirectional LSTM neural network is applied to the MIDI piano performance evaluation model, which is quite different from previous research. It is expected to improve the accuracy of MIDI piano performance evaluation model with LSTM neural network, and to provide technical basis for piano assisted network education.

III. Construction of Improved Piano Performance Evaluation Model Based on Long-Term Memory Network

A. *Long-term Memory Network Based on Recurrent Neural Network*

Traditional RNNs are prone to the problem of gradient disappearance, and the analysis is not accurate when encountering long sequence-type data [16]. The LSTM, as a special recurrent NN, can resolve the question well by improving the hidden layer structure [17]. Some special "gate" structures are added to the neurons of each layer of the LSTM neural network. The purpose of this is to make the error not all attributed to the current neuron in the propagation process, but some of it directly through the "gate" structure, only in this way can the error be well directed to the next layer to avoid the phenomenon of disappearing gradient. This also leads to better convergence [18].

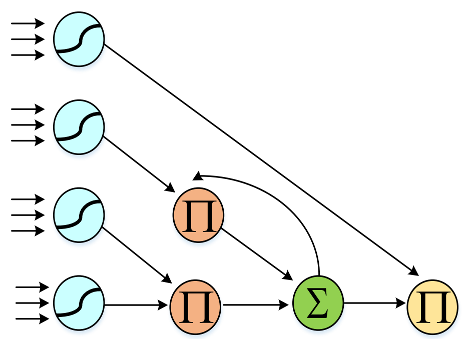

Fig. 1. Memory structure of the LSTM model.

Fig. 1 shows the structure of the LSTM neural network. Compared with the RNN NN, LSTM NN improves the performance by changing the structure so that it can handle long-time series data. This is demonstrated by the introduction of three gating structures, namely, forgetting gates, input gates and output gates. The expression of the forgetting gate f_t is shown in equation (1).

$$f_t = \sigma(W_f h_{t-1} + U_f x_t + b_f) \qquad (1)$$

In equation (1), f_t represents the calculation rule of the forgetting gate at the moment of t, W_f and U_f are the parameter matrices, b_f represents the bias term and σ represents the Sigmoid activation function. equation (2) is an expression for the Sigmoid function.

$$\delta(x) = \frac{1}{1+e^{-x}} \qquad (2)$$

From equation (2), it can be seen that the Sigmoid function makes the output value of the forgetting gate lie between [0,1], which can make the data better aggregated in the transmission process of the network. So, the Sigmoid activation function is also chosen for the calculation in the output and input gates. The function of the input gate of the gating structure is a one-time filtering of the current input information to determine what percentage of the current information is added to the current cell state, and the input gate i_t is calculated as shown in equation (3).

$$i_t = \sigma(W_i h_{t-1} + U_i x_t + b_i) \quad (3)$$

In equation (3), i_t represents the calculation rule of the input gate at the moment of t, σ represents the Sigmoid function, W_i and U_i are the parameter matrices, and b_i represents the bias term. When the current new information is received, some information from the previous moment is superimposed with a certain probability to form the new input information. The expression of the new memory $\tilde{C}_t$ is shown in equation (4).

$$\tilde{C}_t = \tanh(W_C h_{t-1} + U_C x_t + b_C) \quad (4)$$

In equation (4), x_t represents the input information at the time of t, h_{t-1} represents the hidden state at the time of $t-1$, W_C and U_C are the parameter matrices, and b_C represents the bias term. tanh function is an activation function, also called hyperbolic tangent function, which is mainly used in neuron state and output calculation, and its calculation equation is shown in equation (5).

$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (5)$$

From equation (5), the output of the tanh activation function lies between [-1,1] and, in particular, when the input value is 0, the output of the function is also 0. Using the tanh activation function is equivalent to adjusting the mean of the input values to 0, which facilitates subsequent processing. When a new message is received, the cell state is updated by multiplying x_t and $\tilde{C}_t$ to the new cell state, the forgetting gate and the input gate change the current cell state C_t by probabilistically selecting the previous moment and the current message, the cell state is updated from the original C_{t-1} to the current C_t process, and the final memory C_t is specified in equation (6).

$$C_t = C_{t-1} \odot f_t + i_t \odot \tilde{C}_t \quad (6)$$

In equation (6), denotes the cell state at the moment of C_{t-1} $t-1$, f_t denotes the state of the forgetting gate at the moment of t. i_t represents the input gate state at time t. The final memory of the current cell state is obtained by adding the information passed by the old cell plus the filtered content of the new information C_t. The output gate extracts information from the current cell state, and the output gate o_t expression is given in equation (7).

$$o_t = \sigma(W_o h_{t-1} + U_o x_t + b_o) \quad (7)$$

In equation (7), o_t represents the computation rule of the output gate at the time of t, x_t represents the input information at the time of t, h_{t-1} represents the hidden state at the time of $t-1$, W_o and U_o are the parameter matrices, and b_o represents the bias term. The extracted information is used to generate the hidden state h_t and the expression of the hidden state at the time of t is shown in equation (8).

$$h_t = o_t \odot \tanh(C_t) \quad (8)$$

In equation (8), the final memory state of the cell at time t, denoted as C_t is input into the hyperbolic tangent function for calculation. Subsequently, the output gate, denoted as o_t, is combined with it through an operation represented as $\odot$ resulting in the extraction of the information component h_t. The equation (9) can be obtained by associating equations (4), (6) and (8).

$$h_t = o_t \odot \tanh\left(C_{t-1} \odot f_t + i_t \odot \tanh\left(W_C h_{t-1} + U_C x_t + b_C\right)\right) \quad (9)$$

From equation (9), h_t is the size of the hidden state at the moment of t. W_C is the main cause of the gradient disappearance inside the traditional recurrent NN, while here, when the forgetting gate f_t is opened, the gradient of C_t can be effectively passed to the cell state C_{t-1} at the previous moment; so by adding the gating structure on top of the traditional recurrent NN.

B. *Bidirectional Long and Short Time Memory Network and Improvement Method*

LSTM can effectively improve the gradient disappearance and gradient explosion problems though. However, it can only process data in one direction in the time series problem, which often ignores future information [19-20]. In contrast, bidirectional LSTM networks can propagate not only forward but also backwards, and this combination of combining past information with future information is similar to the human appreciation of music [21-22]. Using this approach to train the MIDI piano playing evaluation model, more reliable parameters can be obtained and the piano performance evaluation accuracy can be improved. Fig. 2 shows the structure of a bidirectional recurrent NN.

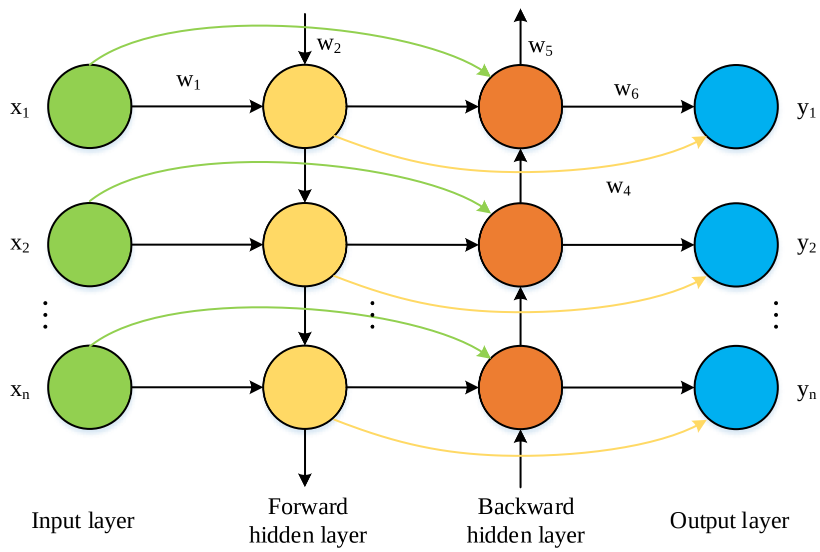

Fig. 2. Structure of bidirectional recurrent neural network.

In Fig. 2, the bidirectional recurrent NN consists of two recurrent neural networks connected backwards and use the tanh function as the activation function, and the output layer receives information not only from forward propagation, but also from backward propagation, and there is information exchange between the forward hidden layer and the backward hidden layer. In Fig. 2, w_1 -w_6 are six different ways of information transfer, which have the same weights in the information transfer process. It is difficult to establish the dependency between the current information and the remote information in the bidirectional recurrent neural network because of the gradient descent. Therefore, the neuron module in the hidden layer of the bidirectional recurrent NN is replaced with the LSTM network module to become a bidirectional LSTM model. The bidirectional LSTM model can not only effectively reduce the probability of gradient explosion, but also maintain the dependency relationship between the current value and the remote value. This way of processing both past and future information is consistent with the traditional music evaluation method, and can better judge the expression and coherence of music so that the MIDI piano performance can be accurately evaluated. To better apply the bidirectional LSTM network to the MIDI piano playing evaluation model, the study combines the attention mechanism and the Softmax function, which is mainly to resolve the difficulty of remote information dependence, and its expression is shown in equation (10).

$$\alpha = \frac{\exp(e_{t,i})}{\sum_{j=1}^{N}\exp(e_{t,j})} \quad (10)$$

In equation (10), $\exp(e_{t,i})$ denotes the output value of the bidirectional LSTM model. After the input music information is passed through the attention mechanism layer, it is then classified using the Softmax function, which is normalized to obtain the probability of which category the MIDI music belongs to. The Softmax function is a nonlinear function that maps the output of multiple neurons to a vector of real numbers in the interval (0,1), and the sum of all elements in the real vector is 1. Its expression is shown in equation (11) is shown.

$$S(x_j) = \frac{e^{x}\ j}{\sum_{k=1}^{k} e^{x}\ k}, j = 1, 2, \cdots, K \quad (11)$$

In equation (11), $S(x_j)$ denotes the value of the i-th dimension of the feature vector and k denotes the number of categories. Equation (12) is the equation for the MIDI piano playing classification label.

$$\widehat{m} = \arg\max S(x_j) \quad (12)$$

There is a very simple functional relationship between the gradient of the cross-entropy function and the output value of Softmax, which can save a lot of time in the gradient calculation and make the calculation faster and more stable. Therefore, the loss function for the training of the MIDI music evaluation prediction model is chosen as the categorical cross-entropy function, whose functional expression is shown in equation (13).

$$L = -\sum_{j=1}^{T} y_j \log s_j \quad (13)$$

In equation (13), s_j denotes the estimated probability of each category in the classification, and T is the number of categories in the classification. The study improves the precision of MIDI piano playing evaluation by incorporating the attention mechanism and Softmax function in the bidirectional LSTM network, and better provides technical support for the development of piano online education.

C. Design of Piano Performance Evaluation Model Based on Two-way Long and Short Time Memory Network

To perform accurate evaluation of MIDI piano performance, the study proposes to implement a bidirectional LSTM neural network model with an attention mechanism on the framework of Spark and Deeplearning4J to evaluate MIDI piano performance with this model. The model mainly consists of a data acquisition module, data pre-processing module and music evaluation classification module, and its specific framework diagram is shown in Fig. 3.

From Fig. 3, the MIDI piano playing evaluation model is mainly divided into three modules: data acquisition, data pre-processing and music evaluation classification. The data pre-processing module mainly filters the original data that are not suitable for model training or transforms them into a matrix suitable for model training, and divides the data into a training set, validation set, and test set; the data acquisition module uses the acquisition tool to migrate data to the storage system; the model is primarily trained on pre-processed data in the classification module. The parameters of the model are then adjusted in real-time in response to the training results to obtain model parameters with better evaluation effects. The test set data are then trained to obtain the rating prediction results for the purpose of classification by the model after the parameters have been adjusted. In the evaluation of MIDI, piano performance is usually evaluated for multiple MIDI music, and the evaluation results are divided into five grades: excellent, good, moderate, poor, and bad. The study uses the bidirectional LSTM NN and attention mechanism layer in deep learning to classify by softmax function to evaluate MIDI piano performance more accurately.

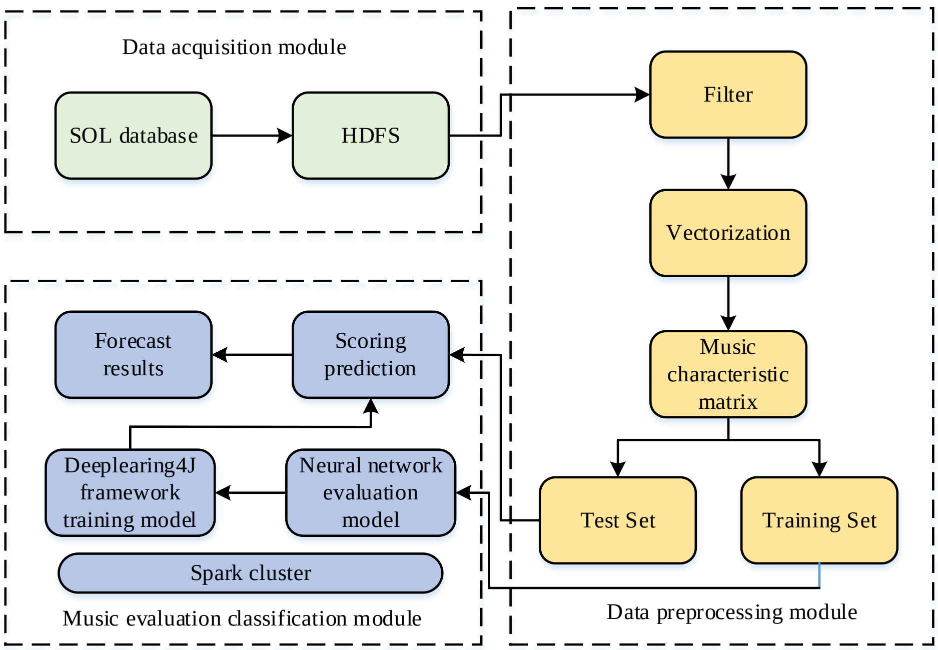

Fig. 3. MIDI-Piano Evaluation Model Framework.

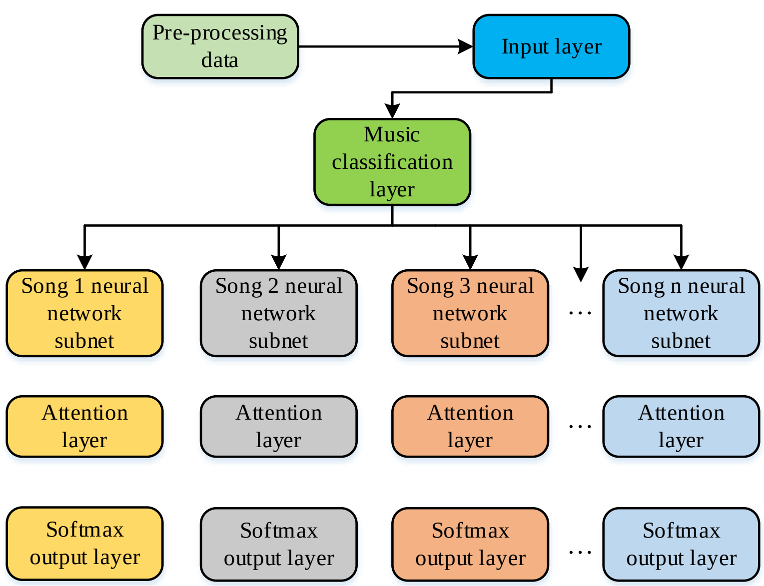

Fig. 4. Bidirectional LSTM neural network evaluation model.

Fig. 4 shows the structure of the bidirectional LSTM NN evaluation model, in which several subnet models are included, and each subnet model needs to be trained separately to ensure that each subnet model is evaluated for a specific piano repertoire, thus realizing the function of evaluating multiple piano repertoires. In the evaluation process of the subnet models, the differences in the training level of each track are used to obtain the feature matrix, and they are classified into one of five categories: excellent, good, moderate, poor, and bad according to the classification algorithm. In each subnet model mainly consists of an input layer, a bidirectional LSTM layer, an attention mechanism layer, and an output layer. The role of the input layer is to receive the difference sample tracks, obtain the input feature matrix through data preprocessing, and then input to the bidirectional LSTM hidden layer, and after the attention mechanism layer, finally, the evaluation is derived by the softmax function in the output layer. In this way, the evaluation results of MIDI piano performance are obtained and used to promote the development of piano online education and achieve the healthy development of piano online education.

IV. Comparative Analysis of Model Performance and Empirical Effect Analysis

A. *Experimental Results Analysis of Model Performance Comparison*

To verify the function of the MIDI piano playing evaluation with the bi-directional LSTM model proposed in the study, the BP, RNN, LSTM, and bi-directional LSTM models with a single hidden layer were compared in the experiments, and the model accuracy, precision, recall, and F1 values were compared as the comparison indexes. Accuracy refers to the percentage of the number of samples correctly classified by the classifier to the total number of samples, reflecting the situation where the classifier correctly identifies each sample. The calculation equation is shown in Equation (14).

$$Accurcy = \frac{TP + TN}{TP + TN + FP + FN} \qquad (14)$$

In equation (14), TP represents true positive; TN represents true negative, FP and FN represent false positive and false negative. Accuracy refers to the number of true cases in the sample where the prediction result is positive, and the calculation equation is shown in Equation (15).

$$\Pr ecision = \frac{TP}{TP + FP} \qquad (15)$$

Recall refers to the percentage of positive predictions, with the equation shown in Equation (16).

$$\operatorname{Re} call = \frac{TP}{TP + FN} \qquad (16)$$

In order to better evaluate the performance of the classifier, the precision and the recall rate are called the measure, and the calculation equation is shown in Equation (17).

$$F_{\alpha} = \frac{(1+\alpha^2) * \Pr ecision * \operatorname{Re} call}{\alpha^2 * \Pr ecision * \operatorname{Re} call} \qquad (17)$$

In equation (17), α is a non-negative real number. When α is 1, it is F1, which is the harmonic mean of precision and recall.

The Google Open Image dataset is used as a test set to compare the accuracy of the four models. The Google Open Image dataset contains 1.9 million images, 600 species and 15.4 million bounding box annotations. It is currently the largest dataset with object location annotation information. The results of the accuracy comparison of the four algorithms are shown in Fig. 5.

Fig. 5 shows the accuracy curves of the four different models compared with epochs, from which the accuracy curves of the bidirectional LSTM model are higher than those of the other three models, and the accuracy curves show an increasing trend with the increase of the number of iterations. The accuracy curve of the two-way LSTM model has a maximum value of 0.91, which is higher than the LSTM model (0.73), the BP model (0.46) and the RNN model (0.38), and the performance of the two-way LSTM model is better than the three comparison models in terms of accuracy dimension. The Google Open Image dataset was used as the training and test set to perform two comparison experiments on the four models, and the results of the four models in five different classification categories were compared. The accuracy rate curves of the four models in the two comparison experiments are shown in Fig. 6.

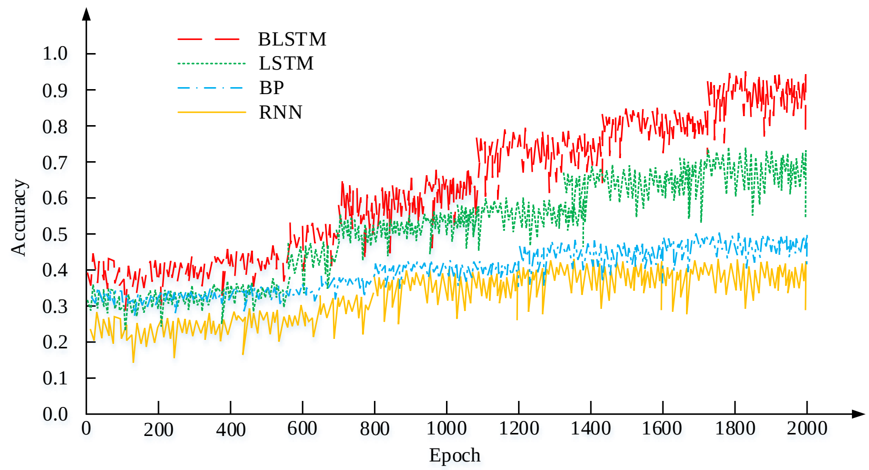

Fig. 5. Comparison of accuracy of different models.

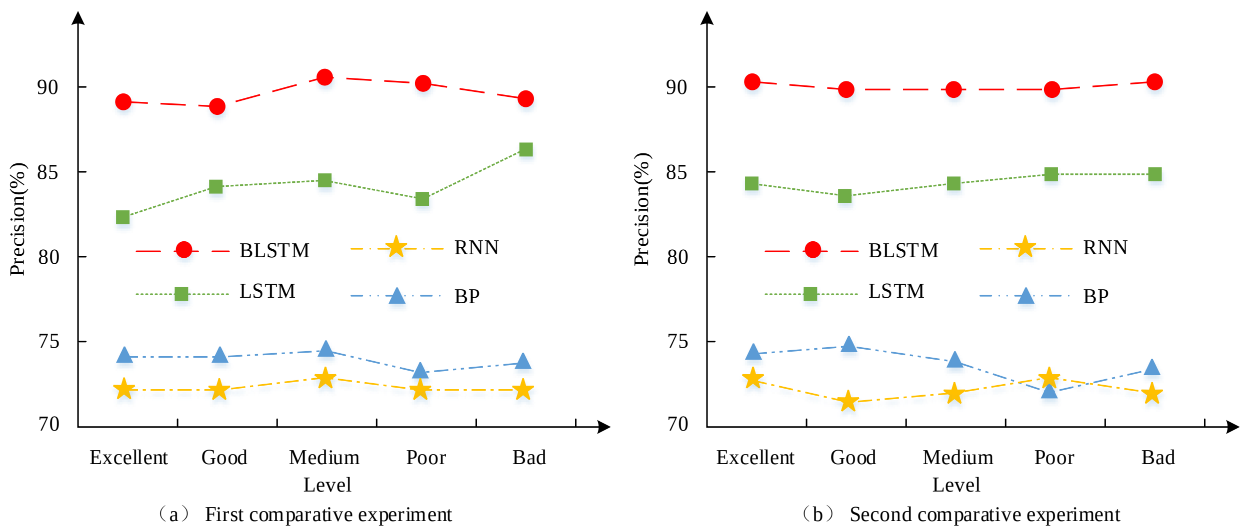

Fig. 6. Accuracy curve of two comparative experiments.

Fig. 6 shows the precision rate curves of the four models in the five classification categories. Fig. 6(a) shows the results of the first comparison experiment. From Fig. 6(a), the precision curves of the bidirectional LSTM model are higher than those of the other three models, and its average precision rate is 88.7 % in the datasets of the five different categories, which is higher than that of the LSTM (83.8%), the BP (73.9%) and RNN (72.6%). Fig. 6(b) shows the results of the second comparison experiment. From Fig. 6(b), the precision curve of the bidirectional LSTM model is higher than the other three models, and its average precision rate in the dataset of five different categories is 89.3%, which is higher than 84.1% of the LSTM model, 73.8% of the BP model, and 72.9% of the RNN model. The above results indicate that the two-way LSTM model has the best performance in terms of the dimension of precision rate. Fig. 7 shows the recall curves of the four models.

Fig. 7 shows the recall curves of the four models in the five classification categories. Fig. 7 (a) shows the results of the first comparison experiment, from which the recall curve of the bidirectional LSTM is higher than the other three models, and its average recall rate in the five different categories 88.8% is higher than that of LSTM (79.5%), BP (68.4%) and the RNN model (63.4%). Fig. 7(b) shows the results of the second comparison experiment. From Fig. 7(b), the recall curve of the bidirectional LSTM model is higher than the other three models, and its average recall rate in the dataset of five different categories is 89.2%, which is higher than LSTM (79.8%), BP (68.8%), and RNN (63.6%). The above results indicate that the two-way LSTM model has the best performance in terms of the dimension of recall rate. Fig. 8 shows the F1 value curves of the four models.

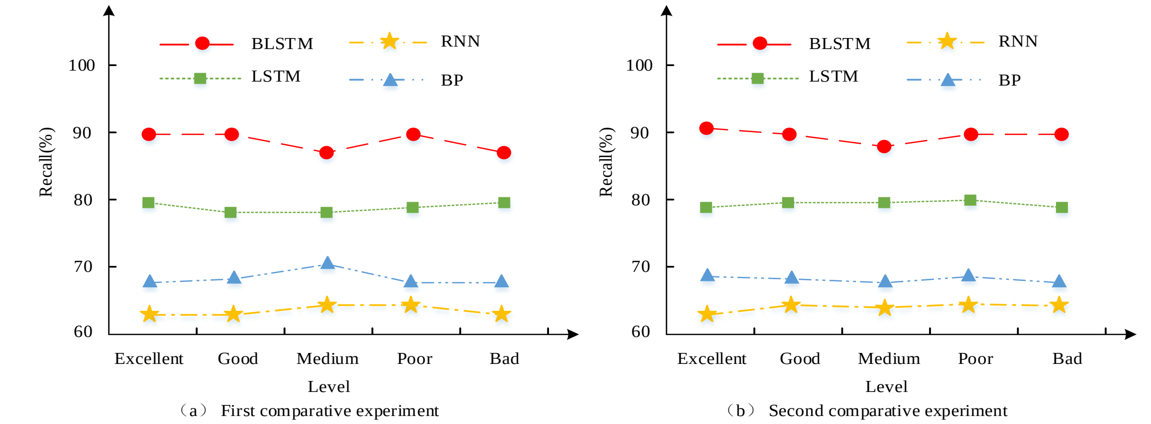

Fig. 7. Recall rate curve of two comparative experiments.

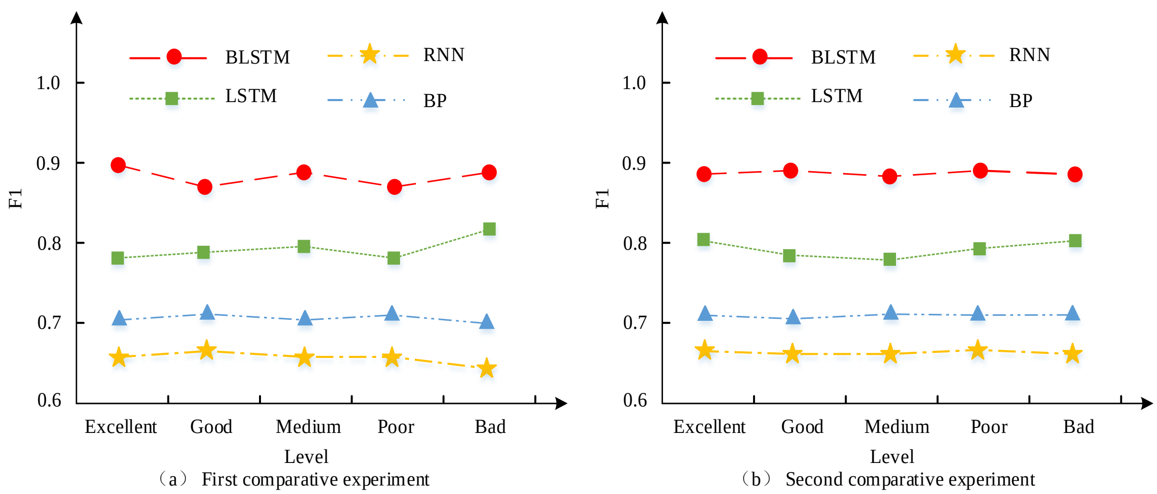

Fig. 8. F1 value curve of two comparative experiments.

Fig. 8 shows the F1 value curves of the four models in the five classification categories. Fig. 8(a) shows the results of the first comparison experiment, from which the F1 value curve of the two-way LSTM is higher than the other three models, and its average F1 value in the five different categories is 0.88, which is higher than LSTM (0.79), BP (0.70) and RNN (0.65). The above results show that the bidirectional LSTM model has a higher F1 value curve than the other three models, and its average F1 value is 0.89 in the data set of five different categories, which is higher than LSTM (0.78), BP (0.71) and RNN (0.66). In conclusion, the overall performance of the bidirectional LSTM model is better than that of the LSTM model, BP model and RNN model, and using this model to evaluate MIDI piano playing can improve the accuracy of the evaluation model.

B. Effect Analysis of Evaluation Model Based on Bidirectional Long Term Memory Network in Piano Online Education

In addition to testing the function of the proposed model, the study also analyzed the actual teaching effects of its integration into piano online education. Students with the same basic information were divided into two groups, and the experimental group was taught with the piano online education course integrated with the model, while the control group was taught with the regular piano online education course. The results of students' performance level score and willingness to participate in the course for both groups are shown in Fig. 9. Both evaluation indexes have a full score of 10.

As can be seen in Fig. 9(a), the performance score of the experimental group was higher than control group in all five groups, and the average performance level score of the experimental group was 8.9, much higher than control group, which was 7.3. As can be seen in Fig. 9(b), the willingness to participate in lessons was higher than control group in all five groups, and the average willingness to participate in lessons of the experimental group was 8.7, much higher than control group, which was 7.5. The average willingness score of the experimental group is 8.7, which is much higher than the 7.5 score of the control group. These results indicate that the LSTM-based MIDI piano performance evaluation model can effectively improve academic piano performance and willingness to participate in lessons. In addition, Table I shows the results of the questionnaire on students' subjective emotional experiences.

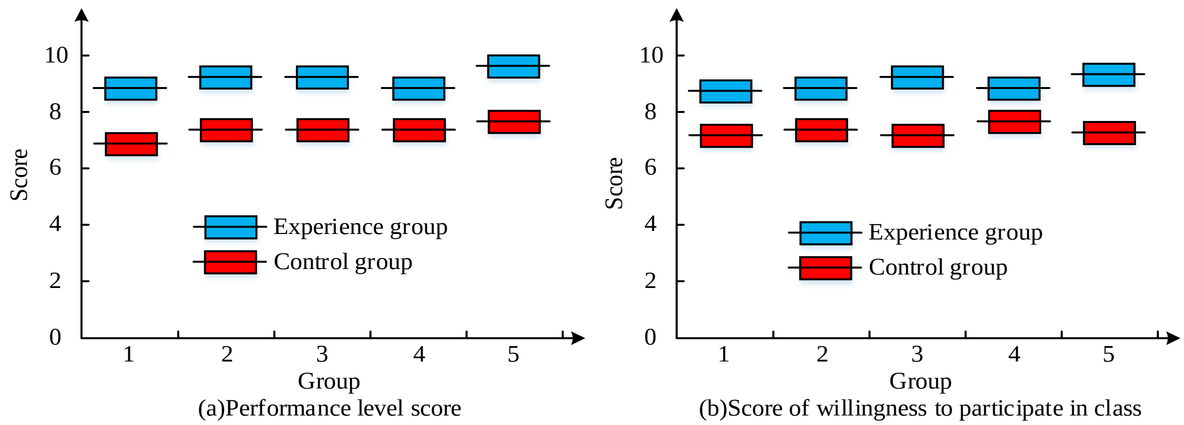

Fig. 9. Performance score and willingness to participate.

TABLE I. SUBJECTIVE MOOD SURVEY RESULTS

/	Experimental class	Control class	T	*P*
Happiness	8.63±0.92	7.56±0.71	1.12	<0.0001
Psychological annoyance	6.57±0.57	7.33±0.69	-0.56	<0.0001
Feeling of fatigue	7.25±0.74	8.13±0.81	-0.47	<0.0001
Initiative	9.17±0.93	7.58±0.83	0.62	<0.0001
Sense of gain	8.85±0.85	7.32±0.76	0.73	<0.0001
Self-confidence	8.98±0.94	7.62±0.82	0.51	<0.0001
Fulfilment	9.08±1.02	8.03±0.79	0.66	<0.0001

Table I demonstrates that the experimental group students' happiness, motivation, acquisition, self-confidence, and achievement scores were higher than those of the control group students, demonstrating that the piano performance evaluation model proposed in the study can effectively improve students' performance in piano online education courses the positive subjective emotional experience. Additionally, Table I demonstrates that the piano performance evaluation model can lessen students' negative subjective emotional experiences. In conclusion, the piano performance evaluation model applied to the piano online education course can improve the overall teaching quality of the physical education course, promote students' positive emotions in class, and can improve students' piano performance level.

V. DISCUSSION

With the continuous improvement of people's material living standards, their awareness of spiritual needs is also deepening, which promotes the second rapid development of piano education. Whether it is entering art schools for collective learning or seeking individual learning opportunities for piano lessons, the demands on piano education professionals are increasing, and the number of traditional piano teachers in China is seriously insufficient, making the contradiction between supply and demand difficult to solve in the short term. In addition, due to the lack of formal teaching and training institutions and teachers, many piano students acquire piano knowledge and skills through self-study or entrust others with their practice. In the field of piano education, the commission received by traditional teachers is generally high, and the price of wooden pianos is also very high, which makes it difficult for ordinary families to afford them, and the high cost has become an important obstacle to the development of piano education. In addition, due to the large population in our country, parents and children are the only children, which leads to the outdated concept of family education, the lack of scientific and systematic guidance, so that piano education has been in the "low age" stage for a long time. Therefore, in the process of promoting piano education, reducing the cost of learning has become an essential trend. MIDI is a protocol proposed in the early 1980s to solve the communication between electroacoustic instruments. With the development trend of "network + education", MIDI piano has gradually become an indispensable tool in piano education.

In this study, the MIDI piano performance evaluation model based on bidirectional LSTM was compared with BP, RNN and LSTM models. From the perspective of the accuracy dimension, the accuracy of the bidirectional LSTM model is higher than 0.73 of the LSTM model, 0.46 of the BP model and 0.38 of the RNN model. Compared to the three comparison models, the bidirectional LSTM model has a better performance. Similar results were found in the study by Dandil's team [23]. From the accuracy dimension, in the first comparison experiment, the accuracy of the bidirectional LSTM model is higher than 83.8% of the LSTM model,73.9% of the BP model and 72.7% of the RNN model. In the second comparison experiment, the accuracy of the bidirectional LSTM model is higher than 84.1% of the LSTM model,73.8% of the BP model and 72.9% of the RNN model, and the performance of the bidirectional LSTM model is the best compared to the three comparison models. This is similar to the conclusion obtained by Xie et al. [24]. From the dimension of recall rate, in the first comparison experiment, the recall rate of the bidirectional LSTM model is higher than 79.5% of the LSTM model, 68.4% of the BP model and 63.4% of the RNN model. In the second comparison experiment, the recall rate of the bidirectional LSTM model is higher than 79.8% of the LSTM model, 68.8% of the BP model and 63.6% of the RNN model, and the performance of the bidirectional LSTM model is the best compared to the three comparison models. Tao's team also found similar results [25]. From the perspective of F1 value dimension, in the first comparison experiment, F1 value of the bidirectional LSTM model among the four models was higher than 0.79 of the LSTM model, 0.70 of the BP model and 0.65 of the RNN model. In the second comparison experiment, the F1 value of the bidirectional LSTM model is higher than 0.78 of the LSTM model, 0.71 of the BP model and 0.66 of the RNN model. The performance of the bidirectional LSTM model is the best among the three comparison models. This is in line with the conclusion of Jian et al [26].

In addition to testing the performance of the proposed evaluation model, this study also analyzes the actual teaching effect of integrating it into online piano education. The experimental group took the piano online education course integrated with the model for teaching, and the control group took the conventional piano online education course for teaching, and the score of piano playing level and students' subjective experience were used as evaluation indicators for comparative analysis. Among the five groups, the score of the performance level of the experimental group was 8.9 points higher than that of the control group, and the score of the experimental group's willingness to participate in the class was 8.7 points higher than that of the control group. It can be seen that the MIDI piano performance evaluation model based on LSTM can effectively improve the academic piano performance level and the willingness to participate in the class. This result is consistent with the research findings of Bao's team [27]. In addition, by conducting a questionnaire on students' subjective emotional experience, the scores of happiness, initiative, sense of gain, self-confidence and achievement of students in the experimental group were all higher than those of students in the control group, indicating that the piano performance evaluation model proposed in this study can effectively improve students' positive subjective emotional experience in online piano education courses.

VI. CONCLUSION

In this study, performance comparison experiments were conducted on the proposed two-way LSTM performance evaluation model, and the results showed that the accuracy rate, accuracy rate, recall rate and F1 value of the model were 0.91, 88.7%, 88.8% and 0.88, respectively, which were higher than the other three comparison models. In addition, in the empirical analysis of the model, it is found that the model can not only improve the performance level and enthusiasm of the students, but also promote the positive subjective emotions of the students. In conclusion, the improved MIDI piano performance evaluation model based on two-way LSTM is not only accurate, but can also promote the development of online piano education. This research innovatively integrates the two-way LSTM network model into the piano performance evaluation model, which not only improves the evaluation accuracy of the piano performance evaluation model, but also improves the integration degree of deep learning and piano education, making up for the lack of integration between the current piano education and deep learning. However, there are still shortcomings in the process of this study, such as crude evaluation and classification methods and unreasonable selection of data sets. In the future, it is necessary to find effective evaluation and classification methods, and to obtain more closely related data sets through self-preprocessing for comparison experiments in order to obtain more accurate results.

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