Research Article

Evaluation Strategy of the Piano Performance by the Deep Learning Long Short-Term Memory Network

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With the development of society and the progress of technology, the piano education industry has a large market. In view of the problem of high payment fees in the piano education industry, the scientific and automatic nature of piano performance evaluation has attracted people’s attention. However, since most of the piano performance evaluation schemes are based on rules, the continuity of the piano music and the accuracy of playing are ignored. Therefore, the purpose is to design a scientific piano performance evaluation scheme that can play a certain role in the sustainable development of the piano education industry. Firstly, long short-term memory in deep learning is explored. Secondly, the musical characteristics of piano performance are analyzed according to the musical instrument digital interface. The piano music features are extracted, and a long short-term memory-based musical instrument digital interface piano performance evaluation model is constructed. Finally, it analyzes the number of hidden layers implemented in the long short-term memory model for piano performance evaluation. The accuracy of piano performance evaluation under different models is analyzed. Under the bidirectional long short-term memory network model, different piano performance levels are evaluated to realize the study of piano performance evaluation strategies. Compared with the accuracy of the recurrent neural network and the long short-term memory model with different hidden layers, the bidirectional long short-term memory model has the highest test accuracy, with an average of 69.78%. When the hidden layer of the bidirectional long short-term memory model is 3, the loss function $L$ value is the smallest, which is 0.11. Different levels of piano skills are evaluated, and the results of the systematic evaluation are consistent with the performance of different levels. This shows that the BLSM model is feasible for the piano performance evaluation strategy system. This study not only conducts an in-depth analysis of the deep learning long short-term memory model but also proposes a long short-term memory-based musical instrument digital interface piano performance evaluation model. Additionally, the flaws such as the incomplete consideration of musical continuity and expressiveness when evaluating piano performance pieces have been compensated. Finally, through different model validations, the bidirectional long short-term memory model is concluded with good accuracy in piano performance evaluation. These conclusions provide theoretical research and practical significance for the accuracy of piano performance evaluation.

1. Introduction

People improve their personal cultivation in different ways and turn their attention to spiritual pursuits [1]. Music is “the refuge of the human soul,” and the piano is known as the “king of musical instruments” [2]. Nowadays, with the rapid development of China’s cultural and economic undertakings, many piano learners have emerged among people of different age groups and many piano training institutions have emerged as the time requires. However, there are differences in piano training, the music literacy level of teaching workers, and teaching level. It is a difficult problem to find a piano teacher who matches the piano player in the process of piano learning and practice [3–5]. Additionally, there is a lot of economic pressure in the process of learning the piano. Hiring a piano teacher to learn the piano is often expensive. There are piano hardware maintenance costs in the process of learning the piano. These often result in the need to spend a lot of financial resources in the process of learning the piano, which makes piano learners bear greater economic
pressure [6, 7]. However, the learning of the piano mainly depends on the learner’s usual practice. During this period, the piano teacher needs to evaluate the performance level of the learners and help the players to have a clear understanding of their own technical level. The individual practice process will lead to the assumption of one’s own performance level, and there is no good judgment of one’s own performance, and whether the piano performance is contagious or not and whether the music played is complete [8, 9]. Therefore, piano performance evaluation can not only help players have a clearer understanding of their own playing skills, increase the fun of playing, and improve players’ enthusiasm for playing the piano but also assist piano teaching to a certain extent [10].

In the early 1960s, Taba et al. proposed an evaluation method for hall sound quality. This opens the door to the research on the combination of technical theory and music, but the evaluation effect is not very good. This is because there is a problem in the mapping relationship between the subjective evaluation index and the physical evaluation index [11]. Bilder et al. gave important definitions and suggestions for the factors involved in the process of musical instrument sound quality evaluation, such as evaluation terms and evaluation methods. In order to improve the process and precautions of musical instrument sound quality evaluation, the objectivity and scientific nature of its sound quality evaluation have received extensive attention [12].

Hu et al. proposed a two-stage decay theory, which proved that the time-domain characteristics of the piano playing sound were closely related to the piano itself, the player’s playing strength, and other factors, providing a more effective basis for the identification of piano performance [13]. Bragagnolo and Guigue proposed a certain degree of relationship between the timbre and spectral amplitude components of piano performance, which contributed to recognizing complex multipart piano music by auditory computer systems [14]. Luizard et al. studied the application of subjective criteria of timbre to the objective evaluation system in the process of vocal performance, using neural networks to process the signal characteristics of music, and discussed in detail the relationship between subjective evaluation indicators and objective evaluation systems. They made the results obtained using an objective evaluation system consistent with subjective criteria [15]. The main contribution of Sharafati et al. was the construction of a fuzzy expert system capable of multifaceted recognition of violin music [16]. The main contribution of López et al. was to use fuzzy mathematical theory to describe the pitch, tonality, chord, dynamics, etc., of musical features to improve the efficiency of music identification [17]. However, according to the research direction, the evaluation of deep learning mainly focuses on the evaluation of learning results and the learning process. Shi evaluated teachers’ teaching methods and students’ learning outcomes based on the structure of the observed learning outcome (SOLO) classification theory, proving that the SOLO classification theory can reflect the quality of learning [18]. Nieminen and Tuohilampi divided evaluation into two categories: orientation process and orientation result, according to the different orientations of evaluation. They pointed out that when teachers evaluate students, different methods can be combined for evaluation [19].

This study provides an in-depth exploration of deep learning toward long- and short-term memory networks. According to the musical instrument digital interface (MIDI) analysis of the musical features in the piano performance, the piano musical features are extracted. The novelty lies in constructing an LSTM-based MIDI piano performance evaluation model. Based on the BLSTM model, the evaluation results of different piano playing levels are analyzed to realize the research on the evaluation strategy of piano performance.

Section 1 conducts a literature study on the current state of piano usage and deep learning evaluation. Section 2 proposes a piano performance evaluation scheme based on a long short-term memory network. Section 3 analyzes the data of the deep learning evaluation results. The conclusion section summarizes the research methods and results and makes a future outlook.

2. The Scheme of Piano Performance Evaluation Based on LSTM

2.1. The Exploration Process of Deep Learning to LSTM. The information processing of the human visual system is hierarchical. The working process of nerve-center-brain is a process of continuous iteration and continuous abstraction. At present, the idea of solving problems through machine learning is shown in Figure 1.

In Figure 1, features are the raw material for learning. If the data are well represented as features, usually, linear models can achieve satisfactory accuracy. The characterization of the problem requires consideration of the granularity of the feature representation, the primary (shallow) feature representation, the structural feature representation, and the amount of data needed to feature. The essence of deep learning is to learn more useful features by building a machine learning model with many hidden layers and massive training data and ultimately improve the accuracy of classification or prediction [20]. Therefore, the “deep model” is only a means and the goal is to perform “feature learning.” Computer scientists adapted deep learning models using the way that the brain processes time-series data to come up with circular networks. The recurrent neural network unrolled by time is shown in Figure 2.

In Figure 2, the state at each moment is regarded as a layer of the FNN. A recurrent neural network (RNN) can be regarded as a neural network with shared weights in the time dimension, where $x_t$ is the input of the network at time $t$, $h_t$ is the state of the hidden layer, and $h_{t-1}$ is not only related to the current input $x_t$, but also related to the previous one. The hidden layer state $h_{t-1}$ at the moment is related. $y_t$ is the output value. Due to the problem of gradient explosion and gradient disappearance, a simple RNN has a long-range dependency problem. The most effective method is to add a gating mechanism to solve this problem, such as an LSTM network. All recurrent neural networks consist of repeated chain modules, and the repeated modules of the
standard RNN contain only one tan \( h \). The repetition module of LSTM contains three sigmoid layers and a tan \( h \) [21, 22]. The structure of LSTM is shown in Figure 3.

In Figure 3, the memory unit of LSTM consists of upper and lower lines. Each line represents the transfer of a vector. The upper line represents the cell state \( C_t \) (cell state) in the hidden state, like a conveyor belt, which is passed directly across the chain with only a few linear interactions. The flow of the abovementioned information remains unchanged. The line below is the gated structure calculation. Gate is a method of selectively letting information through, adding, or subtracting information about the state of a cell. There are mainly three-gate structures in LSTM to control the cell state. The input gate determines how much of the input \( X_t \) at the current moment is saved to the cell state \( C_t \) to avoid the current irrelevant content from entering the memory. It is divided into two steps generating a temporary new state and updating the old state. The sigmoid layer decides which values need to be updated. The tan \( h \) layer creates a new candidate vector \( \tilde{C}_t \) in preparation for the state update. Firstly, the forget gate decides what kind of information is discarded from the cell state and how much of the cell state \( C_{t-1} \) at the previous moment is retained to the current moment \( C_t \), which can save the information from a long time ago. \( \sigma \) is the sigmoid layer. The output result of the sigmoid layer is 0 or 1, indicating the proportion of information passing through the threshold. 0 means do not let any information through. One means to let all information through [23]. The calculation of the forget gate is shown in equations (1) as follows:

\[
F_t = \sigma(X_tW_{xf} + H_{t-1}W_{hf} + b_f). \tag{1}
\]

In equation (1), \( X_t \) is the input at the current moment. \( H_{t-1} \) is the value of the hidden state of the previous layer. \( W_{xf} \) and \( W_{hf} \) are the connection weight matrix between the input at the current moment and the hidden state of the previous layer, respectively. \( b_f \) is the bias. The forget gate accepts the value from the input \( X_t \) and the hidden state \( H_{t-1} \) of the previous layer for weighted calculation processing. If a value in \( F_t \) is 0 or close to 0, the corresponding information of the previous unit \( C_{t-1} \) will be discarded. Conversely, if the value of \( F_t \) is 1, the corresponding information
will be retained. Then, the update gate needs to determine what information can be stored in the cell state. The calculation of the candidate value and the update gate is shown in equation (2) as follows:

\[
I_t = \sigma(X_t W_{xi} + H_{t-1} W_{hi} + b_i), \quad \tilde{C}_t = \tanh(X_t W_{xf} + H_{t-1} W_{hf} + b_f),
\]

\[
F_t = \sigma(X_t W_{xi} + H_{t-1} W_{hi} + b_i), \quad \tilde{C}_t = \tanh(X_t W_{xf} + H_{t-1} W_{hf} + b_f) \quad (2)
\]

\[
C_t = F_t \odot C_{t-1} + I_t \odot \tilde{C}_t. \quad (3)
\]

Finally, the output gate can get the output value \(O_t\) of the current unit and the hidden state value \(H_t\) passed to the next unit, as shown in equation (4) as follows:

\[
O_t = \sigma(X_t W_{xo} + H_{t-1} W_{ho} + b_o), \quad H_t = O_t \odot \tanh(C_t). \quad (4)
\]

The sigmoid layer decides to output the cell state and puts the cell state into tanh. Finally, the result is multiplied by the output of the \(\sigma\) gate and the part that needs to be output is obtained.

2.2. Feature Extraction of Piano Performance. Many people assess a pianist’s skill by the difficulty of the pianist’s repertoire. Even many professional musicians use this as a standard. Accuracy refers to the degree of overpressing and missing-pressing by playing the keys compared to the standard keys. Fluency indicates whether the spacing between adjacent keys is proportional to the standard key spacing. Velocity indicates whether the force with which the key is pressed is proportional to the force of the standard key.

Piano performance evaluation involves various audio processing technologies, such as audio acquisition, speech decoding, music synthesis, speech recognition and understanding, audio data transmission, audio-video synchronization, audio effects, and editing. Voice synthesis technology is used to achieve computer voice output. It can be used for speech synthesis and music synthesis. The musical instrument digital interface (MIDI) is used to analyze the musical characteristics of piano performances. It generally refers to an international standard for digital music, describing the instructions for the process of music performance. MIDI files require the least amount of storage to play music [24]. The MIDI system is shown in Figure 4.

In Figure 4, the MIDI input port receives messages from the device. It is used to send the generated raw MIDI messages. MIDI file records are a standard file format for storing information. A MIDI file contains note, timing, and channel selection instructions. Notes include keywords (keys of musical notes), channel numbers, pitch (low, middle, and high), duration (beat), volume, speed, and instrument configuration. A score consists of a sequence of notes, timing, and instrumental definitions of synth sounds. When a set of MIDI messages is played through a music synthesis chip, the synthesizer interprets the characters and produces music. The MIDI keyboard itself does not emit sound but touches the keys on the keyboard, sends out key messages, and generates MIDI music messages, which are recorded by the sequencer to generate MIDI files. Frequency modulation (FM) is used for synthesis and wavetable synthesis to turn these commands into music. The principle of FM music synthesis is shown in Figure 5.

In Figure 5, the synthesis method of FM is generated by the combination of waveforms. The digital-analog converter
(DAC) converts the digital input quantity into an analog quantity through a resistor network according to the weight. It then converts it into an analog quantity proportional to the digital quantity through an addition circuit. The waveform table synthesis structure is shown in Figure 6.

In Figure 6, firstly, the piano sound played by the piano is recorded and stored in a digital signal processing (DSP) chip. Pulse code modulation (PCM) is encoded to store the sound of the piano as digital signal samples in read-only memory (ROM). The compact disc-read-only memory (CD-ROM) interface is connected to the bus. So, when the interface makes a piano sound, the wavemeter makes a real piano sound. The feature extraction process of piano music is shown in Figure 7.

In Figure 7, firstly, high-definition audio extraction is performed during the piano performance. MIDI is used to
capture piano music signals. The piano player’s strength, duration control, and keystroke accuracy are analyzed for piano playing sound effects [25]. The rhythm of the piano score is good or bad, as shown in equation (5) as follows:

\[ f(x) = \sum ads(S_i - B_i)Q_i + abs(E_i - D_i)Q_i. \]  

In equation (5), the piano score is divided into measures. \( i \) is the note number in the measure. \( S \) is the key time of the piano playing. \( B \) is the standard time. \( E \) is the key release time of the piano performance. \( D \) is the standard key release time. \( Q \) is the weight corresponding to different notes. The calculation of good or bad beats of piano scores is shown in equation (6) as follows:

\[ f(x) = \sum ads(A_i - C_i)Q_i. \]  

\( A \) is the volume of the keys played by the piano, and \( C \) is the standard volume.

2.3. Construction of the Piano Performance Evaluation Model. Ode to Joy is a repertoire evaluated as piano performance. The construction of the piano performance evaluation model is analyzed through Ode to Joy. This piece provides an efficient and accurate evaluation of the MIDI piano performance evaluation scheme. The construction of the MIDI piano performance evaluation model is shown in Figure 8.

In Figure 8, the data collection can be distributed through the structured query language (SQL) database for data collection and storage. The data preprocessing stage is not suitable for training data filtering. Raw data is
transformed into input for deep learning training. The data-
set is divided into a training set and a test. The training set is
used for model training. The test set is used for piano perfor-
mance evaluation. The classification label calculation for
MIDI piano music evaluation prediction [26] is shown in
equation (7) as follows:
\[ \hat{m} = \arg\max S(x_j). \]  
(7)

\( S(x_j) \) is the value of the \( j \)th dimension of the feature
vector. \( \hat{m} \) is the predicted value of piano performance eval-
uation. The model training loss function is shown in equation
(8) as follows:
\[ L = -\sum_{j=1}^{T} y_j \log s_j. \]  
(8)

In equation (8), \( s_j \) is the estimated probability of each
class. \( T \) is the number of categorical categories. \( y_j \) is a \( 1 \times T \) vector with 0s except the \( j \)th element which is 1.

3. Results and Discussion

3.1. Implementation of LSTM Model Evaluation. Ode to Joy
piano pieces in 4/4 time is used to analyze the evaluation
model. The relationship between the number of nodes in
the LSTM hidden layer and the \( L \) value is shown in Figure 9.

In Figure 9, the single- and double-layer LSTM models
have smaller \( L \) values as the number of nodes increases.
The \( L \) value of the three-layer and four-layer LSTM models
does not change significantly with the increase of the num-ber of nodes. The reduction of the number of nodes can
optimize the model structure with the change of the decreas-
ing range of the \( L \) value at different inflection points. A
LSTM model with three hidden layers is chosen. The num-
ber of hidden layer nodes in the first layer is 352, the second
layer is 176, and the third layer is 88.

3.2. Analysis of the Results of the Piano Performance
Evaluation Model. The number of iterations of the piano
performance evaluation model is set to 2000 times. The
number of input layer nodes is 88. The number of nodes
in the output layer is 5, and the learning rate is 0.001. In
order to compare the accuracy of piano performance eval-
uation under different models, RNN, LSTM, and bidirectional
LSTM (BLSTM) models are used for comparative analysis.
The accuracy of different models is shown in Figure 10.

In Figure 10, the accuracy of model training increases
with the number of iterations. At 1000 iterations, the accu-
\r
ra\c{c}y of the RNN model is 47.52%. The accuracy of the LSTM
model is 67.65%. The accuracy of the BLSTM model is
76.80%. When iterating 2000 times, the accuracy of the
RNN model did not change significantly. The accuracy of
the LSTM model is 69.91%. The accuracy of the BLSTM
model is 83.86%. Therefore, the BLSTM model has the high-
est test accuracy. The performance of the piano performance
evaluation model is tested by the music of Ode to Joy. For
piano 10, 6, and 5, different levels of piano proficiency are evaluated. The evaluation results of different piano playing levels are shown in Figure 11.

In Figure 11, the performance evaluation results of piano grade 10 are significantly higher than the performance results of piano grade 6 and piano grade 5. The results of the systematic review are consistent with different levels of playing effects. Among them, the overall evaluation of piano grade 10 is 0.91, the expressiveness is 0.83, and the rhythm is 0.83. The playing effect of piano grades 6 and 5 is also in line with the playing level of this grade. The data show that the model is feasible when used in a piano performance evaluation strategy system.

Wang et al. proposed an end-to-end piano performance scoring system based on a convolutional neural network and attention mechanism. It inputs two sequences of acoustic features and directly predicts a performance score. This is consistent with the results obtained in this study. Deep learning models can improve the efficiency of piano performance evaluation [27]. Luo and Ning used a neural network model to evaluate piano performance and simulated teachers to guide students to practice. The abovementioned results are consistent with the results of this study, which all indicate that the use of deep learning techniques can improve the efficiency of piano performance evaluation [28].

4. Conclusions

The research analyses the number of hidden layers realized by the LSTM model in the piano performance evaluation, the accuracy of the piano performance evaluation under different models, and the different piano performance levels
under the BLSTM model. The research results show that the $L$ value of the single-layer and double-layer LSTM models becomes smaller as the number of nodes increases. The $L$ value of the three-layer and four-layer LSTM models does not change significantly with the increase in the number of nodes. The reduction of the number of nodes can optimize the model structure with the change of the decreasing range of the $L$ value at different inflection points. A LSTM model with three hidden layers is used. The training accuracy of different models increases with the number of iterations, and the BLSTM model has the highest accuracy of 83.86%. The overall rating of piano grade 10 is 0.91, the expressiveness is 0.83, and the rhythm is 0.83. The performance evaluation result of piano grade 10 is significantly higher than that of piano grade 6 and piano grade 5. The results of the systematic review are consistent with different levels of playing effects. The data show that the SM model is feasible when used in a piano performance evaluation strategy system. This study not only conducts an in-depth analysis of the deep learning LSTM model but also proposes a MIDI piano performance evaluation scheme based on LSTM, which makes up for the defects of incomplete consideration of the continuity and presentation of music when evaluating piano performances. Finally, through different model validations, the BLSTM model is concluded with good accuracy in piano performance evaluation. These conclusions provide theoretical research and practical significance for the accuracy of piano performance evaluation. However, the evaluation of piano performance is only carried out from the three indicators of overall evaluation, rhythm, and expressiveness and there is no comprehensive research on the emotional expression and performance atmosphere of piano performance. The later research can evaluate and explore the piano performance from the emotional aspect. The evaluation of the piano performance is scientific and close to the emotional expression of the piano repertoire.

Data Availability

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

Conflicts of Interest

The authors declare no conflicts of interest.

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