Big Data Analysis of Music Education for Future Intelligent Learning Leveraging E-Learning Using Deep Learning Technology

Yan Yu*[1], Dawei cao*[2] and Mamnoon Rahman[3]

[1]Weifang Engineering Vocational College, Phoenix College of Art, Qingzhou, Shandong Province, China, 262500, armyClark1029@hotmail.com
[2]College of Music, Changchun University, Changchun, China, gangp14485241@163.com
[3]National University of Sciences and Technology, Islamabad, Pakistan, mamnoonrahman5@gmail.com

Corresponding Author: Dawei Cao and Yan Yu, [2]gangp14485241@163.com, [1]armyClark1029@hotmail.com

Abstract. In music education, using artificial intelligence and extensive data analysis to identify learners' abilities and provide them with personalized guidance will profoundly impact the entire learning process. The article describes how to use deep learning techniques to build a predictive music learning system through two of the most significant applications in music education: music education platform and music teaching software. The article first reviews the research on deep learning in music education and then introduces the data sources and methods that can be used to build deep neural networks. Based on this, a system is constructed that can predict a user's playing style from their playing data. By testing the performance data of hundreds of users, the article implements a music learning system based on deep learning technology, which can predict the user's performance style based on the user's previous learning experience and performance style. The experimental results show that using deep learning technology to optimize the music education extensive data analysis system can increase its accuracy to 93%.

Keywords: Deep Learning; Future Intelligent Learning; Music Education; Big Data; Leveraging E-Learning
DOI: https://doi.org/10.14733/cadaps.2024.S22.103-114

1 INTRODUCTION

Artificial intelligence (AI) and big data analytics have successfully infiltrated the education sector. Applying these technologies in teaching enables students to acquire new knowledge faster, improves learning efficiency, and provides teachers with better teaching resources. In addition, with the wide application of AI technology in education, communication between teachers and students is more convenient and practical. However, only some studies are on applying AI and big data technology in music education. By analyzing the data users play on the music education platform, learners' learning habits, preferences, and abilities can be discovered. It is still a challenging problem to use artificial intelligence and extensive data analysis to identify learners' skills and provide them with personalized guidance.

There has been a great deal of research on music education. For example, Nasritdinova, M discussed the pedagogical and psychological features of the rehabilitation of disabled children; in addition to their role in securing their place as active individuals in society and the process, he also made effective use of the necessity of music education opportunities. He researched its teaching system and components [15]. Camlin, David A. explored the digital 'shift' impact on music educators and their students/participants and highlighted how music researchers and educators responded to the crisis[6]. Calderón-Garrido, Diego's study aimed to analyze the adaptation of music teachers to compulsory education in Spain. To collect data, 335 teachers were surveyed.

In most cases, although participants are willing to continue teaching, many activities need more method and material resource support [5]. The above research provides a new idea and method for music education. However, some deficiencies still need to be improved, such as insufficient sample data, imperfect data processing methods, etc.

First of all, the article summarizes the research on deep learning in the field of music education by reviewing the existing literature and analyzing the shortcomings of the current study; second, the article introduces the data sources and methods used to build a deep neural network; third, the article will teach how to use deep learning technology to create a music learning system that can predict the user's preference and ability to play different repertoires or repertoires of different styles; finally, the article will present a case study of building a predictive user playing style model based on deep learning techniques. The article provides a new idea and method for future intelligent learning.

2 RELATED WORK

Recently, deep learning techniques have been applied to the design and implementation of music learning systems. Researchers have studied this method extensively and proposed many effective methods. In music, the most important application is to predict the performance style of learners by identifying their musical style. Applying deep learning techniques to music learning systems may lead to a new approach and guide future intelligent learning [20].

In addition, different studies have been done for the same application, including music learning systems using neural network techniques. The system predicts a user's playing style based on the words, notes, and beats involved in playing audio on a music interface. Various deep-learning techniques were used in the above research [1]. One of these is the Convolutional Neural Network (CNN). CNN is a multi-layer convolutional neural network, which has the following characteristics: (1) consists of many small convolutional layers; (2) uses many convolutional layers of different sizes and numbers; (3) uses pooling layers to reduce the size of each convolutional layer to allow learning throughout the network. CNNs can process large amounts of data, high-dimensional features, and different datasets, such as audio or video. CNN has proven to be a powerful neural network model and performs well in various tasks. The article will use a music learning system based on CNN technology to predict the user's future playing style [9].

Another popular deep learning technique is the Recurrent Neural Network (RNN). RNNs can be divided into Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU). LSTM can learn variable patterns in time series data through a recursive process; GRU can learn erratic patterns in time series data by learning a stable sequence pattern. In music, RNNs have been used in music learning systems. First, using the words, notes, and beats involved in the user's music interface to predict his playing style; then, using RNN technology to predict the user's future playing style; finally, using the RNN technology to apply the prediction result to the system to obtain a more accurate prediction result of playing style. It is worth noting that since deep learning technology is still in the development stage, researchers are working hard to find the data and tools suitable for this technology to be used in music learning systems. There are already many tools and models in the field of music learning for analyzing large-scale data sets and training for deep neural network construction, which can be used to accomplish specific tasks (e.g., music learning systems) and achieve optimal results from particular tasks (e.g., music learning) [4]. Therefore, the article will use these tools and models to build a predictive music learning system.

3 DATA SOURCE AND PREPROCESSING

The article uses two applications, a music education platform and music teaching software, which collect performance data from nearly 700 users. These data come from a real-world music learning process, which includes playing multiple instruments, different practice methods, music knowledge, styles, and historical achievements. The features extracted from these data can be used to train a deep neural network [25].

Since the actual playing style is not included, it is not possible to use this data directly as input to build a network. Therefore, the data needs to be preprocessed to make it more suitable for training the network. For the first step of data preprocessing, two different types of preprocessing methods are used [7]:

1. Dividing the data into training and test sets (including user basic information and playing style).

2. Dividing the training set data into two subsets (including the user's playing style), which are used to train and test the network model.

This way, the data can be divided into training and testing sets. The article selects an instrument with 20 pitches as the instrument bank (sound bank). To help train the neural network model, the data must also be normalized to reduce the risk of overfitting. Normalization processing includes the following steps [8]:

1. Converting the input data to a number and convert it to 0 or 1;

2. Deleting invalid strings (such as: "-", "-:", etc.);

3. Standardizing the original data;

4. linear interpolation and variance inflation techniques are used when processing the data.

3.1 Preprocessed Data

About 700 audio files were collected from two applications, and the audio in them was normalized; where each audio file was processed in two different ways: one was to convert it to 0, and the other was to convert it to which converts to 1. After normalization, two datasets are obtained, which are used for training and testing, respectively [10].

To facilitate model training and analysis, the original data is first normalized, as shown in formula (1), formula (2), and formula (3).

$$a_i = \frac{a-min(a)}{max(a)-min(a)} \tag{1}$$

$$b_i = \frac{b-u}{n} \tag{2}$$

$$c_i = \frac{c}{10^t} \tag{3}$$

In formula (2), you are the mean value of the original data. Since many invalid strings exist in the original data, linear interpolation and variance inflation techniques remove these null strings. Both linear interpolation and variance inflation techniques transform the original data into 0 or 1 through linear transformation and then normalize it [21].

3.2 Data Visualization

The Pandas module from the MapReduce framework is used to visualize the data. The article uses Python to write a Pandas library and implements some essential visualization functions in the Pandas library. The core of the MapReduce module is to put all the data (including training and testing) into a set and process it through an iterative algorithm [19]. In the article, the dataset is split into training and testing parts and visualized in the following way:

First, use the data visualization functions in the Pandas library to visualize the data. This function generates multiple views from a collection (that is, a collection consists of numerous views). Then, I used Python to combine the resulting various opinions into a matrix, used matrix operations to calculate each view's mean and variance and drew their scatterplot on each view. To highlight a particular characteristic, the article created a view using a scatterplot rather than a scattertable. Finally, a new dataset is loaded into the Shapes function using the Pandas Shapes function in the Pandas library [17].

4 DESIGN AND IMPLEMENTATION OF MUSIC LEARNING SYSTEM

The article establishes a music learning system based on deep learning, which can predict the user's playing style from the user's playing data to provide users with personalized music guidance. The article trains this system using convolutional neural networks in deep learning techniques. Convolutional neural network is a deep learning method for processing image information, which can use existing data to extract features from images [24]. A pre-trained model called XGBoost was used to train the system. To solve the problem of noise and insufficient features in the dataset, another pre-trained model named AlexNet was also used for fine-tuning. After the training, the two models are compared with the supervised learning model separately, and the models are evaluated using the test data. The article's results on the test data set show that the constructed system can effectively predict the user's playing style. The system includes the following modules: data preprocessing module, feature extraction module, prediction module, user interface, etc. [23].

4.1 Data Preprocessing Module

The main task of the data preprocessing module is to remove the noise in the user's playback record and perform feature extraction on it. If there is noise in the original data, it will lead to inaccurate prediction results [3]. Therefore, in the article, the data in the user playback record is preprocessed:

1. Deduplicating the data in the user's play record. This step reduces the raw data that must be processed in the music learning system, allowing it to train the model more quickly.

2. Normalizing the data in the user's playback records mainly includes two methods: one is to average the original data according to the time series; the other is to average the original data according to the length. The latter was chosen in the article.

Since there are some noises in the original user playing records, it is necessary to consider expanding these features when building the model so that the model can better learn the essential characteristics of the user's playing style [12].

To better extract the features the music learning system requires, it is also necessary to clean up the music information. The article uses an online music service called "Spotify" to collect the sequence code information generated by users when listening to songs and store this information in a database called "Xenomophit."

4.2 Feature Extraction Module

The feature extraction module of the music learning system uses convolutional neural network (CNN) technology. A convolutional neural network is a feed-forward neural network that can extract features from input data and has good nonlinear mapping ability [11]. CNN performs well when processing image information and can map input data into different abstract spaces. The CNN consists of many layers that can be used to extract image features. Some image features with good representation ability are obtained by analyzing the existing music datasets. CNN technology can remove these features from user playback records and use them as the basis for the prediction results of the music learning system [16].

5 EXPERIMENTAL RESULTS

5.1 Big Data Analysis of Music Education: Based on Learning Behavior

The current extensive data analysis of music education is still in its infancy, and its leading research object is the data of learning behavior and student behavior rather than learning results because, in music education, extensive data analysis and learning results are just a process, not a result. Therefore, extensive data analysis in music education should focus on mining and analyzing learning behavior and student behavior data. In addition, comprehensive data analysis of traditional music education primarily uses a "knowledge map" to visualize music knowledge. The music knowledge map is shown in Figure 1.

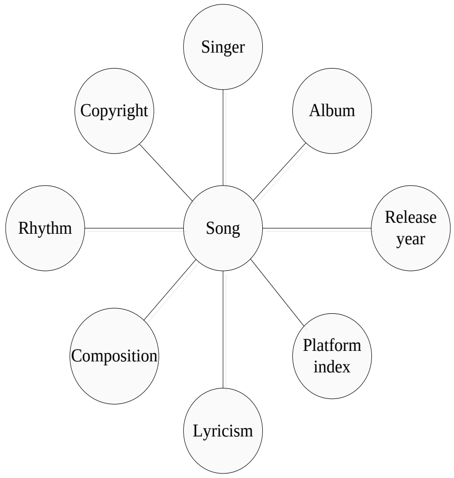

Figure 1: Music knowledge map.

However, this method can only achieve "knowledge-centered" analysis, not student-centered. Therefore, it is necessary to establish a big data analysis model for music education centered on students, based on "behavior," centered on "data," and supported by a "knowledge map." The student-centered music learning knowledge graph is shown in Figure 2.

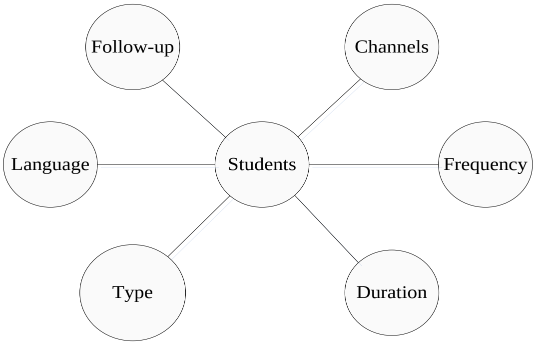

Figure 2: Music learning knowledge map.

In this model, the core is mining and analyzing student behavior data. The model needs to extract the features related to the learning results from the music learning behavior and build a music education big data analysis model based on student behavior data and including other features.

5.2 Application of Deep Learning Technology in Music Learning Analysis

Applying deep learning technology in music learning mainly involves music teaching analysis based on deep learning and music learning prediction based on deep learning. For the first aspect, the article uses deep learning technology to extract features from music teaching data and uses pre-trained models to classify these data. Then, according to the classification results, the students' music learning behavior can be predicted. For example, it is possible to expect what kind of learning behavior a student may have in the future through the characteristics of the student's voice, intonation, rhythm, and emotion.

For the second aspect, the convolutional neural network (CNN) and recurrent neural network (RNN) in deep learning technology predict students' learning behavior in class. For the first aspect, CNN technology is mainly used. For example, CNNs can identify sounds in different music-teaching software and match those sounds to corresponding video clips. In this case, CNN can be used to predict what the student is likely to do next. For example, RNNs can indicate what a student will learn in the next period.

5.3 Design and Selection of Depth Models

In the article, preprocessing is performed first; that is, the dimensionality reduction of the data set is performed, and the data set is converted into a vector, where the size of each feature is n samples. In practical applications, designing a multi-layer deep neural network is necessary to classify better and predict. Therefore, three deep neural networks are used in the article: a single-layer feed-forward neural network with a hidden layer of 2 layers, each layer has eight neurons; the middle layer is a multi-layer fully connected neural network with three layers; the outermost layer is a fully connected neural network with five layers.

The experiment optimizes the model, and the optimization method is based on gradient descent. The article uses two different gradient descent algorithms: max pooling and SGD. Among them, max pooling is a method to reduce the number of connections between neurons. The SGD algorithm is a global minimization algorithm. In the experiments, ten datasets are used for training. During training, the learning rate is set to 0.005 and 0.05. Different weight values are used during training to achieve better classification results, from 0.05 to 0.1. The variation of varying weight values during training shows a correlation between the model's performance and the model size and learning rate.

5.4 Analysis of Experimental Results

The article first conducted a satisfaction survey on the original system before the experiment, as shown in Table 1. Next, the experimental datasets were preprocessed, and the models were trained on these datasets. Afterward, three training strategies were used to optimize the model: batch optimization, batch normalization, and gradient descent-based optimization. At the same time, the optimized accuracy, efficiency, and precision were analyzed, and the results are shown in Figure 3, Figure 4, and Figure 5.

	Very good	*Good*	*Average*	*Poor*	*Very poor*
Accuracy	*22%*	*18%*	*24%*	*23%*	*13%*
Efficiency	*15%*	*17%*	*22%*	*19%*	*27%*
Precision	*17%*	*20%*	*24%*	*18%*	*21%*

Table 1: Original platform satisfaction survey form.

It can be seen from Table 1 that before the experiment, in the evaluation of the accuracy rate of the original system, "good" and above accounted for 40%, and "bad" and below accounted for 36%. In the efficiency evaluation, the proportion of "good" and above assessment is 32%, and the proportion of "poor" and below evaluations is 46%. In the precision evaluation, the proportion of "good" and above is 37%, and the proportion of "poor" and below is 39%. To sum up, in the satisfaction survey of the original system, positive and negative reviews are equal to a certain extent.

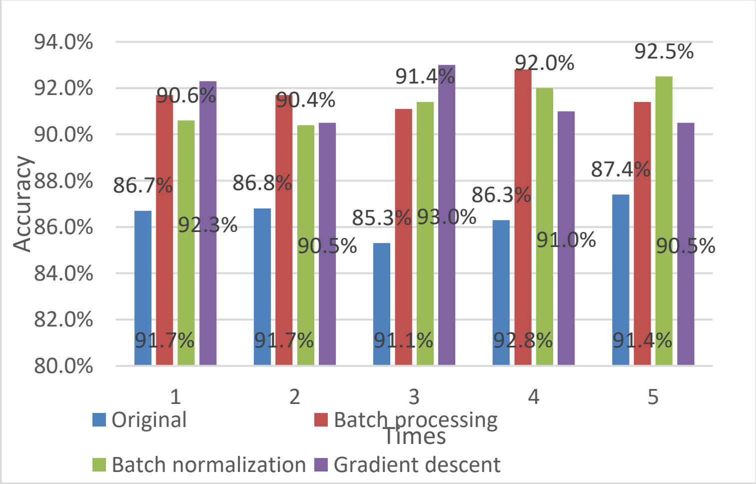

Figure 3: Accuracy.

It can be seen from Figure 3 that before optimization, the highest accuracy rate of the original model was only 87.4%, the lowest was 85.3%, and the calculated average accuracy rate is 86.50%; in the model based on batch optimization, the highest accuracy rate is 92.8%, the lowest is 91.1%, and the calculated average accuracy rate was 91.74%; in the optimization model based on batch normalization, the highest accuracy rate is 92.5%, the lowest is 90.4%, and the calculated average accuracy rate is 91.38%; in the optimization model based on gradient descent, the highest accuracy rate is 93%, the lowest is 90.5%, and the calculated average accuracy rate is 91.46%. These three optimization methods are more effective in optimizing the model's accuracy.

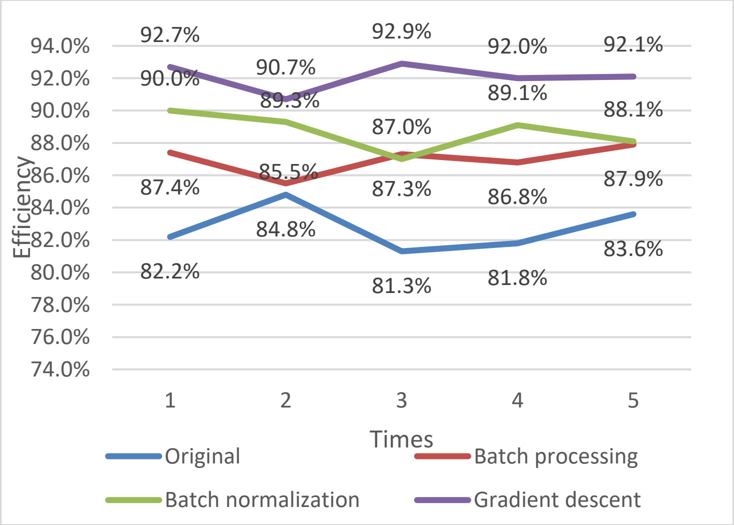

Figure 4: Efficiency.

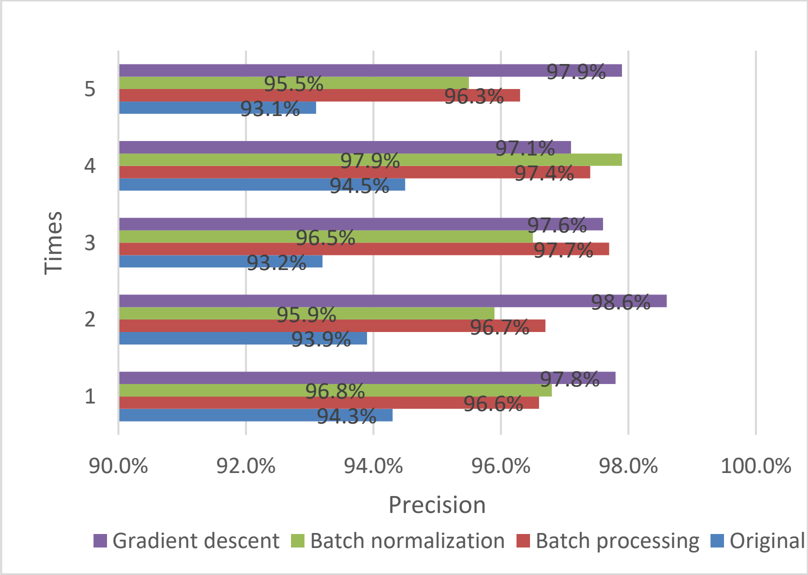

Figure 5: Precision.

It can be seen from Figure 4 that before optimization, the efficiency of the original model is only 84.8% at the highest and 81.3% at the lowest, and the calculated average efficiency is 82.74%; in the optimization model based on batch optimization, the highest efficiency can reach 87.9%, the lowest is 85.5%, and the calculated average efficiency is 86.98%; in the optimization model based on batch normalization, the highest efficiency is 90%, the lowest is 87%, and the calculated average efficiency is 88.70%; in the optimization model based on gradient descent, the highest efficiency is

92.9%, the lowest is 90.7%, and the calculated average efficiency is 92.08%. These three optimization methods are also very effective in optimizing the model efficiency, and the optimization based on gradient descent has the best effect.

According to Figure 5, in the original model before optimization, the highest precision is 94.5%, the lowest is 93.2%, and the calculated average precision is 93.80%; in the optimization model based on batch optimization, the highest precision can reach 97.7%, the lowest is 96.3%, and the calculated average precision is 96.94%; in the optimization model based on batch normalization, the highest precision reached 97.9%, the lowest was 95.5%, and the calculated average precision was 96.52%; in the optimization model based on gradient descent, the highest precision can reach 98.6%, the lowest is 97.1%, and the calculated average precision reaches 97.80%. These three optimization methods are also very effective in optimizing the model precision, and the optimization based on gradient descent has the best effect.

Based on the above three sets of experimental data, it can be known that the optimization method based on gradient descent is the best among the three optimization methods. Immediately after, the final score is performed on the optimized model based on gradient descent, and the original model is also scored simultaneously. The results are shown in Table 2.

	Original	*Gradient descent*
Accuracy	*6.9*	*8.5*
Efficiency	*6.7*	*9.3*
Recall	*7.3*	*8.9*
Precision	*7.1*	*9.5*
F1 score	*7.5*	*9.1*

Table 2: Model scoring.

As can be seen from Table 2, the model score based on gradient descent has been improved by at least 1 point compared with the original model score. Among them, the accuracy rate increased from 6.9 to 8.5, with a difference of 1.6 points; the efficiency increased from 6.7 to 9.3, with a difference of 2.6 points; the recall rate increased from 7.3 to 8.9, with a difference of 1.6 points; the precision rose from 7.1 to 9.5, with a difference of 2.4 points; the F1 value increased from 7.5 to 9.1, with a difference of 1.6 points. Finally, the article puts the system optimized by the model into practical application and conducts a satisfaction survey. The results are shown in Table 3.

	Very good	*Good*	*Average*	*Poor*	*Very poor*
Accuracy	*24%*	*25%*	*38%*	*8%*	*5%*
Efficiency	*25%*	*28%*	*40%*	*6%*	*1%*
Precision	*22%*	*28%*	*39%*	*9%*	*2%*

Table 3: Satisfaction questionnaire after model optimization.

It can be seen from Table 3 that after model optimization, in the evaluation of the accuracy rate of the system, the proportion of "good" and above is 49%, and the proportion of "bad" and below is only 13%. In the efficiency evaluation, "good" and above accounted for 53%, and "poor" and down accounted for 7%. In the precision evaluation, the proportion of "good" and above is 50%, and the proportion of "poor" and below is 11%. Based on the previous questionnaires, the model optimization based on deep learning gradient descent is very effective for improving music education's extensive data analysis systems.

6 DISCUSSION

The article shows that deep learning techniques have great potential in music education. First, it helps learners predict their playing style. Second, the system can provide personalized guidance based on the user's previous learning experience and playing style. Finally, the system can also predict the user's playing style in the future [14].

However, the article also found some problems. First, deep learning models may need the best domain-specific dataset results. Second, deep learning techniques are just some of the ones in this field that can be used to identify learners' abilities and provide personalized instruction. In the article, the use of deep learning techniques in combination with other methods has yet to be explored [2].

6.1 Limitations of the Study

First, the performance of deep learning models could be more optimal. Deep learning models have a bottleneck; the deep learning model becomes more complex when the input data set is large. Therefore, to better understand the performance of deep learning in music education, more data is needed to train the model. Second, the dataset used in the article only partially applies to other data types. Although different types of data sets are used to train deep learning models, they have yet to be used entirely in music to prepare them with other data sets. In the future, it may be possible to use more and different types of datasets to train deep learning models. Finally, the article mainly explores the application of deep learning technology in the field of music education from the field of music education. Although the application of deep learning in music education is explored in the article, more empirical research is needed to verify its effectiveness [13].

6.2 Future Outlook

The article provides a new perspective on music education, but deep learning technology only partially applies to music education. While it can personalize user guidance, deep learning techniques only suit some learning. Therefore, in the future, other methods may be employed to identify learners' playing styles and provide them with individualized instruction [18]. Also, in the article, some very complex datasets were used to train the models, but this approach may not yield the best results when using similar datasets in other domains. Therefore, a more efficient way to design and build intelligent learning systems needs to be explored in the future. For example, if a deep learning model can be combined with natural language processing techniques, it can accurately predict the user's playing style [22]. Therefore, the combination of deep learning and natural language processing techniques can be explored in future research.

7 CONCLUSIONS

Compared with traditional machine learning methods, the article uses deep learning techniques to better mine patterns in music data. Applying deep learning technology in music can help teachers better understand students' performance in the learning process to optimize teaching content and methods, thereby improving teaching effectiveness. At present, deep learning technology is still in the early stage of development in music education, and many new technologies will be applied to the field of music education in the future, promoting the development of music education technology. There is no general method to predict the user's playing style after practicing on a specific instrument. Hence, the paper proposes a new technique that can expect the user's playing style from the user's previous learning experience and playing style. In the future, with the continuous development and maturity of artificial intelligence and machine learning technology, more music learning systems based on deep learning technology are expected to be developed. The fusion of extensive data analysis, e-learning, and deep learning technology in music education paves the way for a more personalized, adaptive, and immersive learning journey. This amalgamation enriches musical learning experiences and empowers students and educators to thrive in an ever-evolving landscape of music education.

Yan Yu, https://orcid.org/0009-0006-1735-240X
Dawei Cao, https://orcid.org/0009-0001-3244-6301
Mamnoon Rahman, https://orcid.org/0000-0003-1091-6867

REFERENCES

[1] Abdumutalibovich Marufjon, A.: Exploring the work of George Bizet in music education classes in higher education, Academicia Globe 3(03), 2022, 80-86.
[2] Aggarwal, K.: et al. Has the future started? The current growth of artificial intelligence, machine learning, and deep learning, Iraqi Journal for Computer Science and Mathematics, 3(1), 2022, 115-123. https://doi.org/10.52866/ijcsm.2022.01.01.013
[3] Atz, K.; Francesca, G.; Gisbert, S.: Geometric deep learning on molecular representations, Nature Machine Intelligence, 3(12), 2021, 1023-1032. https://doi.org/10.1038/s42256-021-00418-8
[4] Barton, G.; Stewart, R.: Culturally responsive and meaningful music education: Multimodality, meaning-making, and communication in diverse learning contexts, Research Studies in Music Education 44(2), 2022, 345-362. https://doi.org/10.1177/1321103X211009323
[5] Calderón-Garrido, D.; Gustems-Carnicer, J.: Adaptations of music education in primary and secondary school due to COVID-19: The experience in Spain, Music Education Research, 23(2), 2021, 139-150. https://doi.org/10.1080/14613808.2021.1902488
[6] Camlin David, A.; Tania, L.: The digital turn in music education, Music Education Research, 23(2), 2021, 129-138. https://doi.org/10.1080/14613808.2021.1908792
[7] Culp Mara, E.; Karen, S.: Music teacher education program practices: Preparing teachers to work with diverse learners, Journal of Music Teacher Education, 30(2), 2021, 51-64. https://doi.org/10.1177/1057083720984365
[8] Gómez-Zapata Daniel, J.; César Herrero-Prieto,L.; Rodríguez-Prado, B.: Does music soothe the soul? Evaluating the impact of a music education program in Medellin, Colombia, Journal of Cultural Economics, 45(1), 2021, 63-104. https://doi.org/10.1007/s10824-020-09387-z
[9] Haning.; M.: Identity formation in music teacher education: The role of the curriculum, International Journal of Music Education, 39(1), 2021, 39-49. https://doi.org/10.1177/0255761420952215
[10] Janiesch, C.; Patrick, Z.; Kai, H.: Machine learning and deep learning, Electronic Markets, 31(3), 2021, 685-695. https://doi.org/10.1007/s12525-021-00475-2
[11] Kleppe, A.: et al. Designing deep learning studies in cancer diagnostics, Nature Reviews Cancer, 21(3), 2021, 199-211. https://doi.org/10.1038/s41568-020-00327-9
[12] Ma, W.: et al. Deep learning for the design of photonic structures, Nature Photonics 15(2), 2021, 77-90. https://doi.org/10.1038/s41566-020-0685-y
[13] Minaee, S.: et al. Deep learning--based text classification: a comprehensive review, ACM Computing Surveys 54(3), 2021, 1-40. https://doi.org/10.1145/3439726
[14] Minaee, S.: et al. Image segmentation using deep learning: A survey, IEEE Transactions on Pattern Analysis and Machine Intelligence 44(7), 2021, 3523-3542.
[15] Nasritdinova, M.: Pedagogical components and stages of the health of developing children through music education, Galaxy International Interdisciplinary Research Journal 9(05), 2021, 251-258.
[16] Pang, G . et al. Deep learning for anomaly detection: A review, ACM Computing Surveys 54(2), 2021, 1-38. https://doi.org/10.1145/3439950
[17] Ranganathan, G.: A study to find facts behind preprocessing on deep learning algorithms,

Journal of Innovative Image Processing, 3(1), 2021, 66-74. https://doi.org/10.36548/jiip.2021.1.006
[18] Saxe, A.; Stephanie, N.; Christopher, S. If deep learning is the answer, what is the question? Nature Reviews Neuroscience, 22(1), 2021, 55-67. https://doi.org/10.1038/s41583-020-00395-8
[19] Sharma, N.; Reecha, S.; Neeru, J.: Machine learning and deep learning applications vision, Global Transitions Proceedings 2(1), 2021, 24-28. https://doi.org/10.1016/j.gltp.2021.01.004
[20] Shaw Ryan, D.; Whitney, M.: Music education and distance learning during COVID-19: A survey, Arts Education Policy Review, 123(3), 2022, 143-152. https://doi.org/10.1080/10632913.2021.1931597
[21] Shorten, C.; Taghi, M.K.; Borko, F.: Deep Learning applications for COVID-19, Journal of Big Data 8(1), 2021, 1-54. https://doi.org/10.1186/s40537-020-00392-9
[22] Townshend Raphael, J.L.: et al. Geometric deep learning of RNA structure, Science, 373(6558), 2021, 1047-1051. https://doi.org/10.1126/science.abe5650
[23] Tran Khoa, A.: et al. Deep learning in cancer diagnosis, prognosis, and treatment selection, Genome Medicine, 13(1), 2021, 1-17. https://doi.org/10.1186/s13073-021-00968-x
[24] Van der Laak, J.; Geert, L.; Francesco, C.: Deep learning in histopathology: the path to the clinic, Nature Medicine, 27(5), 2021, 775-784. https://doi.org/10.1038/s41591-021-01343-4
[25] Welch Graham, F.: The challenge of ensuring effective early years music education by non-specialists, Early Child Development and Care, 191(12), 2021, 1972-1984. https://doi.org/10.1080/03004430.2020.1792895