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RESEARCH ARTICLE

The Analysis of Chinese and Japanese Traditional Opera Tunes With Artificial Intelligence Technology Based on Deep Learning

MIN YAO[1] AND JINGCHUN LIU[2]
[1]School of Music, Chengdu Normal University, Chengdu, Sichuan 611130, China
[2]College of Physics and Electromechanical Engineering, Jishou University, Jishou, Hunan 416000, China

Corresponding author: Min Yao (111052@cdnu.edu.cn)

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ABSTRACT This study aims to propose a comparison model of Chinese and Japanese traditional opera tunes based on deep learning (DL) and artificial intelligence technology, which can be used to effectively analyze and classify the tune characteristics of Chinese and Japanese traditional opera. To achieve this aim, a multi-layered DL model, including Convolutional Neural Network, Long Short-Term Memory, Recurrent Neural Network, and Gated Recurrent Unit, is constructed based on the tune characteristics of Chinese and Japanese traditional opera. In the extensive experimental verification, the proposed model has achieved remarkable results in the task of classifying Chinese and Japanese traditional opera tunes. Specifically, the proposed model achieves an accuracy of 89% and 88%, recall of 88% and 87%, and F1-score of 88% and 87% in the tune classification task of the Chinese and Japanese traditional opera, respectively. Compared with similar models, the proposed model performs better in classification.

INDEX TERMS Chinese and Japanese traditional opera tunes, deep learning, artificial intelligence, tune classification, convolutional neural network.

I. INTRODUCTION

A. RESEARCH BACKGROUND AND MOTIVATIONS

With the development of globalization and the swift growth of science and technology, as an important cultural heritage of China and Japan, traditional opera's protection, inheritance, and innovation have attracted more and more attention [1], [2], [3]. However, due to the differences between China and Japan in language, culture, history, and other aspects, the inheritance and development of Chinese and Japanese traditional operas face many challenges [4], [5]. Among them, how to dig deeply and compare the tune characteristics of Chinese and Japanese traditional operas has become a topic worthy of study [6], [7], [8]. The tune is a vital part of traditional opera, which not only represents the opera's musical style and singing characteristics but also contains rich cultural connotations and artistic values [9], [10]. The comparative analysis of Chinese and Japanese traditional opera tunes allows the similarities and differences between their traditional opera art to be better understood, thus providing references for the cross-cultural communication and inheritance of the two countries' traditional opera [11], [12], [13]. However, the comparative studies on Chinese and Japanese traditional opera tunes are relatively few and lack systematism and depth [14].

Furthermore, China and Japan have deep historical and cultural origins, and there are many similarities in the traditional opera art between the two countries [15], [16], [17]. However, due to differences in language, region, and other aspects, there are also obvious differences between Chinese and Japanese traditional operas regarding tunes, performance, and costumes [18]. This difference is reflected in the form of performance on the surface, cultural connotation, and artistic value [19], [20], [21]. A comparative study of Chinese and Japanese traditional opera tunes can help to better understand the differences and similarities between the two countries' opera art, and offer references for the cross-cultural communication and inheritance of their traditional opera [22].

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At the same time, with the rapid development of artificial intelligence (AI) and deep learning (DL) technologies, these technologies are increasingly widely used in the field of music [23]. DL technology can automatically extract features from audio data and process a large amount of data, which makes it possible to extract and analyze the tune features of Chinese and Japanese traditional operas through these technologies [24], [25], [26].

Consequently, this study aims to construct a comparative model of Chinese and Japanese traditional opera tunes based on DL and AI technologies. This study further reveals the similarities and differences between the two tunes by extracting and analyzing the characteristics of Chinese and Japanese traditional opera tunes. It provides new ideas and methods for protecting, inheriting, and innovating Chinese and Japanese traditional opera. This study can promote the cross-cultural communication between China and Japan and the inheritance and development of traditional culture, and provide new ideas and methods for related research in the field of music.

B. RESEARCH OBJECTIVES

The goal of this study is to implement a comparative model of Chinese and Japanese traditional opera tunes by the DL and AI technologies. This model extracts and analyzes the Chinese and Japanese traditional operas' tune characteristics, and then realizes the comparison and analysis of traditional opera tunes of the two countries. Specifically, the methods of this study are as follows. (1) The audio data of Chinese and Japanese traditional operas are collected and sorted out, and the corresponding data set is established; (2) Using sound signal processing technology and DL algorithm, the tune characteristics of Chinese and Japanese traditional opera are extracted; (3) Effective learning and classification of the tune characteristics of Chinese and Japanese traditional opera can be realized by training DL model; (4) The trained model is evaluated and optimized to improve the accuracy and generalization ability of the model. This study is expected to provide new ideas and methods for the Chinese and Japanese traditional operas' protection, inheritance, and innovation, and promote the cross-cultural communication between China and Japan and the inheritance and development of traditional culture.

II. LITERATURE REVIEW

Chinese and Japanese traditional operas are an essential part of world cultural heritages [27], [28], [29]. Studying these traditional operas involves many fields, such as musicology, dramatics, and literature [30]. For example, Zhang et al. [18] conducted on-site measurements and simulations of Jiayin Hall Theater in Shenyang Palace Museum to determine the basic parameters of the sound field of traditional courtyard theater. Wu et al. [31] believed that the academic exchanges between China and Japan re-evaluated the once-neglected drama appreciation texts. Gao [32] studied that Mei Lanfang Troupe created a "pure" dramatic Chinese character by "purifying" the stage presentation system of Peking Opera.

Regarding the definition and understanding of Chinese music, Zhang et al. [33] pointed out that in recent years, Chinese music has been considered as an independent music school. However, the definition of Chinese music was still an abstract and subjective concept. Previous research in musicology explored how elements such as melody and instruments shape specific music genres, including Chinese music. Nevertheless, these findings cannot be directly applied to relevant Music Information Retrieval (MIR) tasks for large-scale users and real-world issues. The study devised a process involving perceptual investigations to explore how different musical elements influence people's perception of "Chinese-style" music. The results hold practical value for MIR tasks, such as understanding, representing, and recommending Chinese music. By delving into the impact of musical elements on people's perception of "Chinese-style" music, this research provided crucial insights for leveraging AI technology in the field of Chinese music for information retrieval. Chen et al. [34] established a scientific and standardized audio database of Cantonese opera. They proposed a classification method for Cantonese opera singing genres based on the genre classification network model in view of the similarity of rhythmic characteristics of different genres of Cantonese opera singing. Odefunso et al. [35] proposed a new framework to apply data science algorithms to the field of cultural conservation by applying various DL techniques to identify, classify, and model traditional African dances in video. Summary of research in related fields: Previous studies on traditional Chinese and Japanese operas are exhibited in Table 1:

In the existing studies, the comparative analysis of the Chinese and Japanese traditional opera tunes mainly focuses on the performance art and music style. It lacks the in-depth exploration and analysis of tune characteristics. This study is expected to fill the gaps in the existing research and provide new ideas and approaches for the protection, innovation, and inheritance of Chinese and Japanese traditional opera. By providing high-quality audio data of Chinese and Japanese traditional opera, and standardizing and normalizing it, the quality and reliability of data can be improved. Meanwhile, a comparison model of Chinese and Japanese traditional opera tunes based on DL and AI technology is developed to extract and analyze their tune characteristics efficiently. From the interdisciplinary perspective, combining the research methods and technical means of musicology, linguistics, computer science, and other fields, this study makes a comprehensive and in-depth comparative analysis of Chinese and Japanese traditional opera tunes.

III. RESEARCH METHODOLOGY

A. THE DL MODEL FOR EXTRACTING TUNE CHARACTERISTICS OF OPERA

In the field of audio processing today, DL models, particularly the Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN), have achieved remarkable success [36], [37], [38]. CNN is mainly used to process data with

TABLE 1. Summary of research in related fields: previous studies on traditional chinese and japanese operas.

Research	Methods and models	Accuracy/Results	Database
Zhang et al. (2023) [18]	On-site measurement and simulation	The mid-frequency sound intensity in the main hall and hallway decreased by 1.6 and 2.6 dB, respectively.	Jiayin Hall Theater in Shenyang Palace Museum
Wu et al. (2021) [31]	Dialectics, practice, and reflection	N/A	Chinese Drama in the 1930s
Gao (2022) [32]	Dialectics, practice, and reflection	N/A	Mei Lanfang Troupe's Peking Opera stage presentation system
Zhang et al. (2022) [33]	Statistical analysis and comparison	The contribution of music content is greater than that of instruments	MIR
Chen et al. (2022) [34]	Genre classification network model	95.69%	Cantonese opera singing genres
Odefunso et al. (2022) [35]	Various DL techniques	93%~98%	Traditional African dances in video

the grid structure, and it can extract local features in input data through convolution operation [39]. In sound processing, CNN can effectively capture various frequency features in the sound spectrogram. In contrast, an RNN is a network structure suitable for processing sequence data [40]. Traditional RNNs encounter the problem of vanishing or exploding gradients when dealing with long sequences, and variants of RNNs, such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), have been designed to solve this problem. The RNN can better capture the timing characteristics of sound data [41], [42], [43].

In traditional opera tunes, the fundamental frequency refers to the basic frequency of the sound, which is the primary determinant of the pitch of the sound [44]. A spectrogram is a representation of sound frequencies in time, which shows the distribution of sound at different frequencies [45]. These features represent the basic properties of sound and are an essential basis for sound synthesis and recognition [46]. These features are chosen as inputs to the model because they effectively express the basic properties of sound. To convert the sound signal into a digital representation, the audio data is divided into small time windows, and the sound waveform within each window is converted into a spectrogram using the Fourier transform (FT).

The DL model designed here includes input, convolutional, RNN, and output layers. The structure is presented in Figure 1.

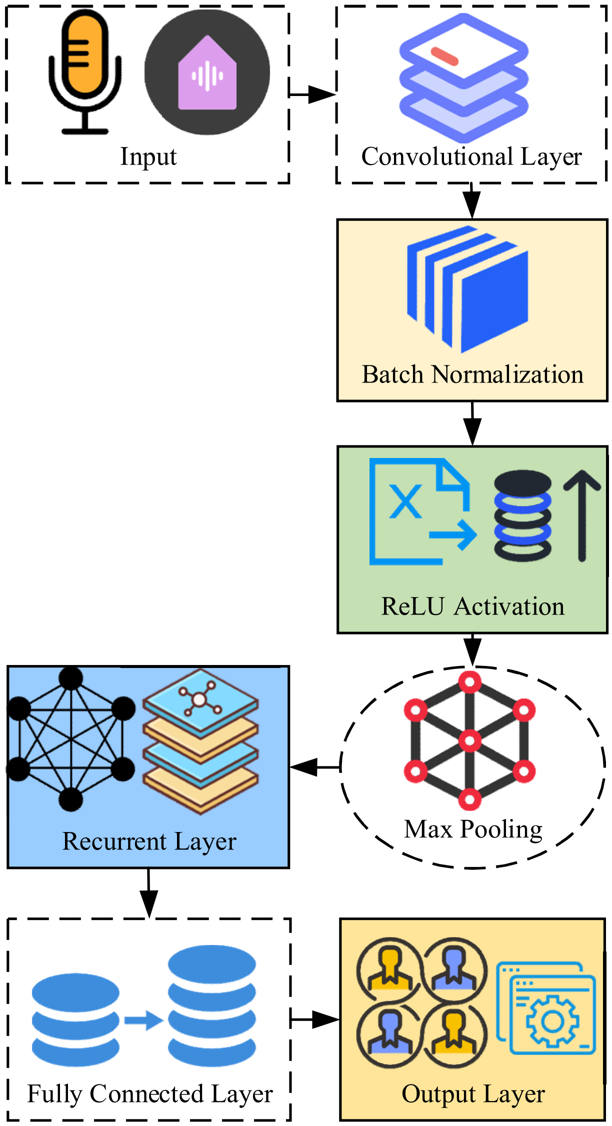

FIGURE 1. The DL model for extracting opera tune characteristics.

In Figure 1, the input layer receives the audio data and converts it into a format that the network can process. The convolutional layer scans the input data through a series of convolution kernels to extract features of various frequencies. Convolution operation can be regarded as a feature extraction process of a sliding window on input data. Then, there is the RNN layer, which can process time series data and capture timing changes in audio. It can be expressed by equation (1):

$$C_i = relu(sum\left(W_j * X_{i+j}\right) + b) \tag{1}$$

C_i refers to the i-th output of the convolutional layer; W_j signifies the weight of the convolutional kernel; X_{i+j} indicates the i+jth element of input data; b means the bias term; *relu* represents the correction of linear unit functions to ensure non-negative output.

The batch normalization layer is to normalize the output of the convolutional layer to accelerate the network training process and improve the stability of the model. After that, the ReLU activation function is applied to introduce nonlinear properties so that the network can learn nonlinear relationships. The maximum pooling layer maximizes the convolutional layer's output, reduces the data dimension, retains the main features, and reduces the computational complexity. When processing the data of each time step, the RNN introduces a hidden state, which is employed to remember the information of the previous time step. The fully connected (FC) layer connects the output of the RNN layer to the FC layer for learning higher-level feature representations. Finally, the output layer is responsible for mapping the features learned by the network to the final tune characteristics. To preserve the nonlinear characteristics, modified linear units (RELUs) are adopted at each level as activation functions, which import the nonlinear capabilities of the network.

B. DATA PREPROCESSING AND TRAINING PROCESS

After a deep understanding of the architecture and characteristics of the DL model, the data preprocessing and training processes should be focused on, as these two steps play a crucial role in model training. In the data preprocessing stage, it is necessary to deeply comprehend the audio samples of traditional opera tunes. The processing process is displayed in Figure 2:

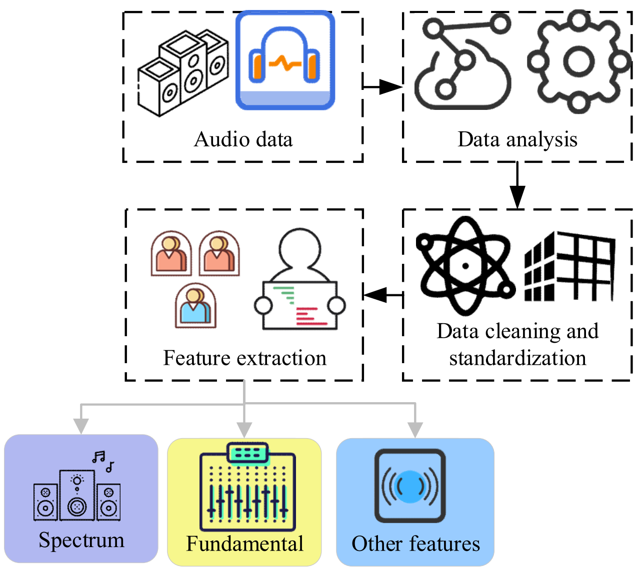

FIGURE 2. The preprocessing process of the opera tune data.

Through the analysis of audio data in Figure 2, information such as sampling rate and channel number can be obtained, which offers a basis for subsequent processing. Subsequently, data cleaning and standardization help eliminate noise, truncate silent segments and give audio signals a uniform range in amplitude. Feature extraction is a key part of data preprocessing, which uses FT, short-time FT, and Maier frequency cepstrum coefficient technology to convert audio signals into spectral graphs or other time-frequency features to provide the model with data that can be used for learning.

In the model training process (Figure 3), the data set is first classified into a training set and a test set to evaluate the model performance. Next, the model is initialized, then the loss function and optimizer are selected, and the model is iteratively trained. In each training iteration, the model's parameters are adjusted according to the feedback information of the loss function to minimize the loss function. In the training process, the model's hyper-parameters must be tuned to ensure that the model can achieve the best performance on the test set. Ultimately, through model evaluation and tuning, it can ensure that the trained DL model has the ability to accurately model the traditional opera tune.

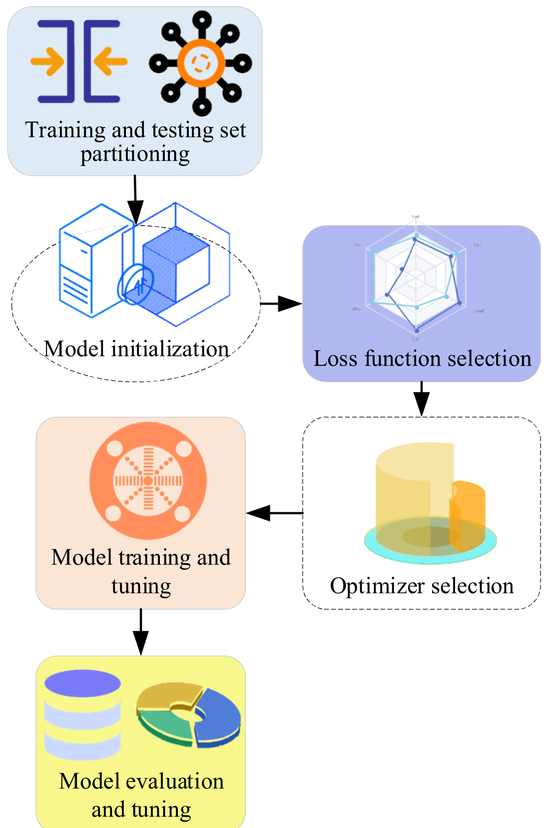

FIGURE 3. The training process of the opera tune model.

C. INTEGRATION OF AI TECHNOLOGY

Based on the DL model, AI technology is further integrated to better simulate and inherit Chinese and Japanese traditional opera tunes. Text-to-speech Synthesis (TTS) technology converts the input text information into natural speech and provides the basis for the automatic generation of tune in traditional opera [47]. Hence, the TTS system is utilized to convert opera text into sound signals and realize the automatic generation of tune, making traditional opera's performance more diverse and plastic. Specifically, the TTS system is embedded in the DL model as part of the model. When the traditional opera tune is generated, the model first generates text and then converts the text into a sound signal through the TTS system to complete the automatic generation of the tune.

Furthermore, the emotion speech recognition technology is used to analyze the emotional information contained in the sound, such as happiness, sorrow, and joy, to give the traditional opera tune richer emotional expression. Emotional speech recognition technology is applied to capture the emotional features of traditional opera tunes and make the generated tune more emotional. To be specific, an emotional speech recognition module is added to the DL model. The module receives the sound signal as input, analyzes the emotional information therein, and then fuses the emotional features into the tune generation model, so that the generated tune has a more accurate and rich emotional expression. Finally, when the DL model is deployed, the model is accelerated with a hardware accelerator, such as a graphics processor. At the same time, the model quantization technology is employed to reduce the model's parameters and calculation amount, improve its reasoning speed, and ensure the real-time generation of tune.

Through the above integration methods (the integrated model is plotted in Figure 4), the transformation of text to speech, the capture of emotional features, and the optimization of real-time performance are realized. It makes the DL model better simulate and inherit the traditional opera tune, providing greater creative space for artistic performance.

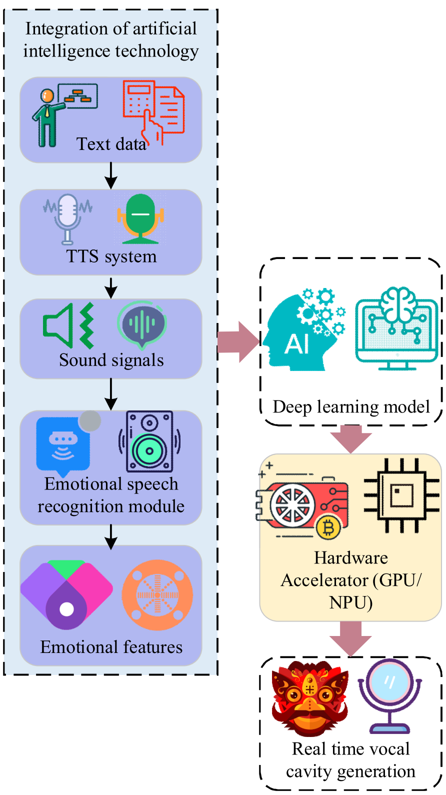

FIGURE 4. The opera tune extraction generation model after integrating AI.

IV. EXPERIMENTAL DESIGN AND PERFORMANCE EVALUATION

A. DATASETS COLLECTION

The self-collected data is used to construct the traditional opera tune multimodal data set, which contains performance recordings, text scripts, and emotional annotations of Chinese and Japanese traditional operas, covering various traditional opera performance styles and recording samples of different roles. The recording data record the performance tune of different characters in different plays, covering 5 traditional Chinese opera characters and 5 traditional Japanese opera characters, in 20 different plays, a total of 100 hours of performance tune. The multimodal nature of the data set allows it to be used both for tune generation tasks and for the study of tasks such as emotional speech recognition. The distribution and usage of the dataset are outlined in Table 2:

TABLE 2. The distribution and usage of the dataset.

Dataset	Usage	Training data volume	Test data volume	Verify data volume
Overall dataset	-	80 hours	10 hours	10 hours
Tune Generation	Training to generate melodies	60 hours	10 hours	10 hours
Emotional speech recognition	Training emotional speech recognition	40 hours	30 hours	30 hours

B. EXPERIMENTAL ENVIRONMENT

The experiments are conducted on a high-performance server equipped with an NVIDIA RTX 3090 graphics processor, with powerful parallel computing capabilities, suitable for training and reasoning for DL tasks. In the software environment, mainstream DL frameworks such as TensorFlow and PyTorch are employed to implement and train the model. In the experiment, TTS engines such as Google Text-to-Speech API are adopted. These engines have highly natural speech synthesis capabilities that convert text into fluent speech signals. In addition to the DL framework and TTS engine, various data processing tools and scientific computing libraries, such as NumPy and Pandas, are used. These tools and libraries facilitate data preprocessing and analysis of experimental results.

C. PARAMETERS SETTING

The key components, such as the DL model and TTS engine, are set in detail in the experiment. The details are exhibited in Table 3:

D. PERFORMANCE EVALUATION

Accuracy, recall, and F1-score are used to evaluate the performance of the proposed model on the traditional opera tune

TABLE 3. Parameter setting.

Parameter	Setting value
Model type	Deep neural network
Activation function	ReLU
Optimizer	Adam
Learning rate	0.001
Loss function	Mean square error loss
Batch size	32
Number of training iterations	1000
Convolutional kernel size	(3, 3)
Number of convolutional layers	64
Number of RNN layers	2
Number of RNN hidden units	128
TTS engine	Google Text-to-Speech API
Text preprocessing	Word segmentation and punctuation processing
Speech synthesis speed	Medium speed
Tone settings	Natural tone

classification task. The calculation equations are as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{4}$$

TP represents a true positive; TN indicates a true negative; FP is a false positive; FN means a false negative. At the same time, the contrast of acoustic features is utilized to show the difference between Chinese and Japanese traditional opera tunes, encompassing fundamental frequency, harmonic richness, and formant frequency. The comparison results of tune characteristics of Chinese and Japanese traditional operas are outlined in Table 4:

TABLE 4. Comparison of tune characteristics in Chinese and Japanese traditional operas.

Characteristic parameter	Traditional Chinese opera tune	Tune parameters of traditional Japanese opera
Fundamental frequency (F0)	120 Hz	200 Hz
Formant frequency	500 Hz, 1200 Hz, 2500 Hz	400 Hz, 800 Hz, 1500 Hz
Harmonic richness	High	Medium

The classification results of Chinese and Japanese traditional opera tunes are revealed in Figures 5 and 6:

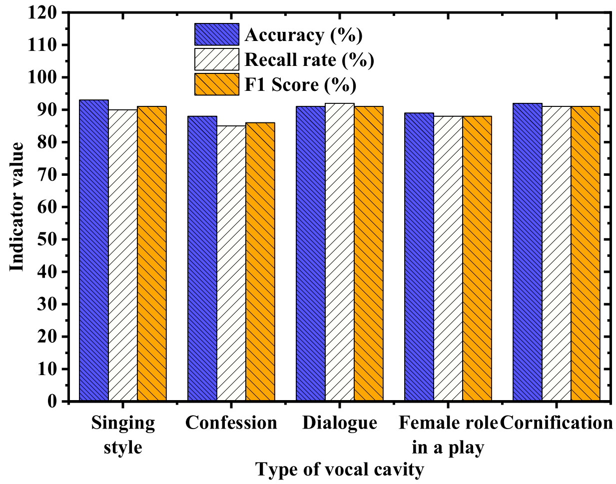

FIGURE 5. Classification results of Chinese traditional opera tunes.

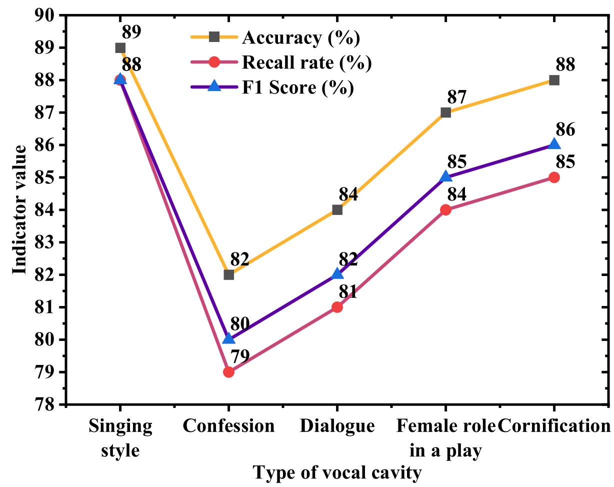

FIGURE 6. The classification results of Japanese traditional opera tunes.

Figure 5 suggests that the proposed model has the highest classification accuracy of 91% and 92%, respectively, which shows that the model also has good classification ability in complex tune types. The classification performance of singing, dialogue, and female roles is also quite excellent, indicating that the model has good discrimination ability for different tunes. The model also performs well on various tune types in the traditional Japanese opera tune classification (Figure 6). Especially in classifying the two tune types, dialogue, and male role, the model achieves quite high accuracy and recall of 90% and 91%, respectively. The classification performance of dialogue, singing, and female roles is also relatively good, again verifying the model's generalization ability in diverse opera traditions.

The comparison of classification performance with other similar models is depicted in Figure 7:

Figure 7 portrays that the accuracy of the proposed model is 89%, which is significantly higher than 82% of the CNN model, 84% of the RNN model, 87% of the LSTM model,

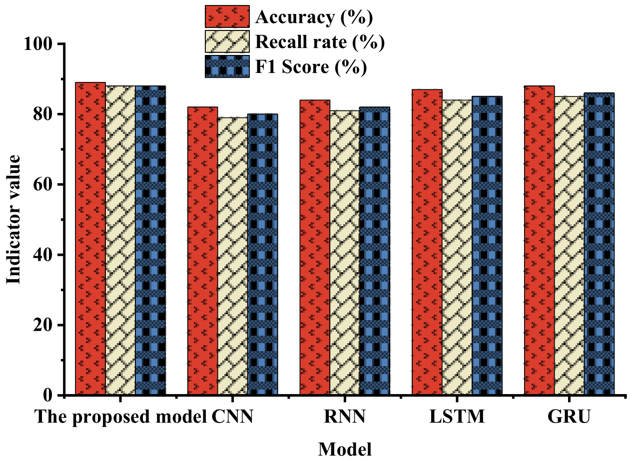

FIGURE 7. Performance comparison of different DL models.

and 88% of the GRU model. This means that the proposed model can more accurately identify different types of Chinese and Japanese traditional opera tunes in the classification task. In terms of recall rate, the proposed model performs equally well, at 88%, outperforming the other models, indicating that the proposed model is better able to find all positives in the real category. The F1 score, which considers accuracy and recall, is a more comprehensive performance indicator. The F1 score of the proposed model can reach 88%, which illustrates that this model has a good balance between accuracy and recall, and has better overall performance.

E. DISCUSSION

The above research demonstrates that the proposed comparison model has excellent performance in classification recall, accuracy, F1-score, and other performance indicators, exceeding other similar models. This confirms the proposed model's validity and indicates that DL and AI techniques have broad application prospects in Chinese and Japanese traditional opera tunes analysis. Moreover, it provides an efficient tune analysis tool and promotes the exchange and research of Chinese and Japanese traditional culture. This is similar to the conclusions of Bai [48] and Wang [49]. In addition, the model performs well on different types of tunes, which illustrates that the model has a strong generalization ability. It is also analogous to the conclusion of Wang [50], which has important implications for actual opera performance and tune analysis, as opera often involves several different types of tune.

V. CONCLUSION

A. RESEARCH CONTRIBUTION

This study proposes and successfully applies a comparison model of Chinese and Japanese traditional opera tunes based on DL and AI technology. It realizes the efficient analysis and classification of the two countries' traditional opera tunes. The proposed model performs well in the Chinese and Japanese traditional opera tune classification tasks through extensive experimental verification, achieving high accuracy, recall, and F1-score, surpassing similar models. It not only realizes the classification of tune but also carries on the in-depth analysis of tune characteristics, reveals the subtle difference between Chinese and Japanese traditional opera tunes, and provides a deeper understanding for studying tune in opera.

B. FUTURE WORKS AND RESEARCH LIMITATIONS

Although the model performs well in the current task, some directions are still worth further research. For instance, more complex methods for extracting tune characteristics can be explored, or TTS technology can be combined to achieve perfect tube generation. In future studies, the expansion of more samples and more data sets of tune types can be considered to improve the generalization and robustness of the model. At the same time, the phonetic features of Chinese and Japanese traditional opera tunes are further analyzed, and more fine features are extracted by integrating acoustic theory to increase the model's performance.

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