

Retraction

Retracted: Research on Music Classification Technology Based on Deep Learning

Security and Communication Networks

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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- [1] F. Zhang, "Research on Music Classification Technology Based on Deep Learning," *Security and Communication Networks*, vol. 2021, Article ID 7182143, 8 pages, 2021.

Research Article

Research on Music Classification Technology Based on Deep Learning

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With the advent of the digital music era, digital audio sources have exploded. Music classification (MC) is the basis of managing massive music resources. In this paper, we propose a MC method based on deep learning to improve feature extraction and classifier design based on MIDI (musical instrument digital interface) MC task. Considering that the existing classification technology is limited by the shallow structure, it is difficult for the classifier to learn the time sequence and semantic information of music; this paper proposes a MIDIMC method based on deep learning. In the experiment, we use the MC method proposed in this paper to achieve 90.1% classification accuracy, which is better than the existing classification method based on BP neural network, and verify the music with its classification accuracy. The key point is that the music division method used in this paper has correct MC efficiency. However, due to the limited ability and time involved in the interdisciplinary field, the methodology of this paper has certain limitations, which still needs further research and improvement.

1. Introduction

Song can improve attention, relieve people's pressure in work and study, and benefit their physical and mental health. Song can bring people pleasure of hearing and enjoyment of spirit, help to get rid of bad emotions such as sorrow, loneliness, and sadness, and purify the soul. Song can inspire people to forge ahead, make people full of energy and passion, make people quiet and concentrate their thoughts, and improve the efficiency of study and work. Song can also be used as an auxiliary therapy, which often has the effect that medicine cannot achieve, and also has the function of health care. With the rapid development of the Internet, people begin to have access to different songs around the world and enjoy the pleasure brought by song [1]. In different countries and places, although there are some differences in the way of song, music can always express people's thoughts and convey people's thoughts, and music fully expresses its value in human life [2]. Since the 1990s, with the rapid development of network technology and multimedia technology, the amount of network load information has become increasingly huge, including a large number of video, music,

pictures, flash, and other multimedia information. Therefore, it is a hot research topic to establish an efficient information classification and retrieval system to effectively manage the expanding network information [3].

Since ancient times, music has always played an important role in people's lives. Especially with the development of Internet at home and abroad in recent years, the spread of data is more and more rapid and extensive. Many Internet companies at home and abroad provide online digital music services, such as Netease Cloud Music, Xiami Music, and LastFM. This online digital music makes it easier for people to get music, which makes music more closely related to people's daily life [4]. In order to facilitate users' choice, almost all online music platforms provide MC services, which classify music in different ways, such as language, style, scene, emotion, and theme [5]. As machine learning and deep learning are gradually widely used in face recognition, speech recognition, image recognition, etc., scholars are also getting more and more in-depth research on them. People are gradually trying to apply machine learning and deep learning to the field of music generation. Because deep learning is more powerful than machine

learning in storing and processing large amounts of data, more and more deep neural networks are used in music analysis and processing, especially RNN and long short-term memory network [6]. RNN was first used in MC, but the classification effect is not very satisfactory. Due to the large relevance of music before and after, when using ordinary RNN, data from the previous moment or earlier cannot be obtained so that the effect of classification or the characteristics of music such as pitch, timbre, loudness, and rhythm is not accurate [7]. According to these methods mentioned above, the classification accuracy of the existing algorithms is not enough, and the algorithm overhead is relatively large.

According to the existing classification technology, it is difficult for the classifier to learn the time sequence and semantic information of music. So, our motivation of this paper is to propose a new method which can realize music classification. According to the deep learning method, it can automatically learn the method of pattern features and integrate feature learning into the process of building the model, thereby it can reduce the incompleteness caused by human design features. In order to solve the problem of the connection between data that needs to be recorded for a long time, RNN has been improved, and the forgetting gate has been added on the original basis to enable RNN to record the related data information before, which successfully overcomes the long time series problem [8]. More and more people are now using short and long memory networks for emotional analysis and processing, as well as some intelligent recommendation systems [9]. At present, with the wide application of deep learning, especially for music style classification or generation, it gradually becomes popular. As one of the networks often used in deep learning, the short-term memory network is rarely used for music style generation and use [10]. With the emergence of deep learning, MC technology has entered a new era of development. Deep learning is used in various fields such as image processing and speech recognition and has demonstrated performance beyond existing machine learning in many tasks. In order to improve the effectiveness of MC, it is necessary to continue the MC technology based on deep learning [11]. This paper proposes an MC method based on deep learning and verifies the effectiveness of this method in experiments and obtains relatively ideal results. According to the proposed method, it analysis RNN and attention mechanism, according to the characteristic sequence of the input MIDI music segment, the MIDI classification network model is designed using Bi-GRU and attention mechanism, and MC is performed. Bi-GRU is good at processing sequence data. Adding attention mechanism can give different attention weights to the features learned by Bi-GRU so that the final music features can better represent the music.

The contributions of this paper can be concluded as follows:

- (1) This article focuses on music classification technology, which is very interesting; therefore, the article has certain practical significance

- (2) This paper uses deep learning to deal with the problem of music classification, which has a better performance

The structure of this paper is as follows. Section 1 is the introduction which gives the background of this paper. Section 2 is the related work which can give the related research work. Section 3 is MC which means music frequency and classification. Research on MC technology based on deep learning is given in Section 4. Section 5 is the experiments and result analysis. The last section is conclusion.

2. Related Work

The rapid development of music provides great convenience for users to obtain music. Music is usually categorized for user selection. In recent years, with the development of in-depth learning research, the paper [12] proposed the use of neural network algorithm, through the training and learning of the computer itself, which provides a new way of thinking for music genre classification, but it has the drawbacks of slow convergence and falling into local optimum. Literature [13] shows that music emotion cognition itself is subjective, which is based on various influences, such as cultural background, age, gender, personality, and related education level. Because of these subjective differences, it is a very difficult task for different users to achieve a consistent cognition of emotion classification, but in fact it is also an unrealistic task. This requires emotional MC to consider these factors and automatically generate specific classification results according to different individuals.

Literature [14] shows that so far, most of the research on automatic classification of music is based on audio sources. The traditional MIDIMC method analyzes the content of the entire piece of music according to the classification task, specifically designs and extracts strong and distinguishable music features, designs and trains a machine learning classifier with good performance, and inputs the music features into the classification. Document [15] indicates that in MC experiments, bass lines are extracted from MIDI, interval difference statistical histogram is extracted from bass lines as input feature, perceptual weighted Euclidean distance is proposed, and a nearest neighbor classifier is designed. Literature [16] presents a two-layer neural network using manifold learning technology for music genre classification and concludes that when data are represented by a rich feature space, the classification effect of the neural network can be comparable to that of the classical machine learning model. Literature [17] shows that deep learning can automatically learn deeper features from shallow features and can reflect the local correlation of input data.

3. MC

3.1. Music Frequency and Classification. According to music characteristics, music can be divided into many genres, each of which has its own representative works with distinctive characteristics. Through these representative works, we can

fully feel the differences between different genres of music. In the early days, the classification of music genres mainly depended on manual work. Now, with the development of computer technology, supervised learning in machine learning has been used to classify music genres and analyze music through known music genres [18].

Music genre is a unique music category formed under the mutual influence of the market and artists over a long period of time. Each genre has different characteristics. Some music genres have a dull style, and some are more cheerful. These characteristics show the differences in the personalities of different musicians or songwriters [19]. However, there are similarities and differences between music genres. In order to make the style of music genre more accurate, the widely used category structure, which mainly includes GTZANGenre and ISMIR2004GenRe, is used in this paper. GTZANGenre mainly classifies music genres into 10 categories, including Blues, Country, Hiphop, Jazz, Pop, Disco, Classical, Rock, Reggae, and Metal. ISMIR2004Genre mainly divides music genres into five categories, which are Classical, Electronic, Jazz/Blues, Metal/Punk, and Rock/Pop. Each different genre often contains its own representative musical instruments [20]. For example, piano and orchestral instruments often appear in Classical music, while piano and quartet often appear in Jazz production. The classification structure of music genre is shown in Figure 1.

3.2. Music Feature Selection. Music characteristics are the essential attributes of music. In order to distinguish different styles and genres of music, it is very important to extract the characteristics of music. There are many methods for feature extraction, and there are also many feature selections. If the appropriate features can be selected, the experimental results can be made more accurate [21].

Feature extraction, as an important work in the classification system, has been the focus of research in various classification fields. In the task of music genre classification, it is possible to improve the accuracy of the classification system only if the music characteristics that can fully characterize music works are extracted as shown in Figure 2.

At present, there are usually two methods to divide music features. One is based on human sensory characteristics. According to human auditory feelings, music features are mainly divided into Note, Pitch, and Velocity. The other is that music features are divided into short-term features and long-term features according to the length of features by Weihscl et al. [22].

Tone color refers to the characteristic attributes that can distinguish two identical tones. Different musical instruments will have different sound quality. Through the difference in sound quality, people can easily distinguish different musical instruments. Loudness is also a very important musical feature in music. Loudness represents the amount of velocity that needs to be used when playing a certain note at a certain moment. Tone is another characteristic that people can feel [23].

The three music features mentioned above are short-term because they can be represented by specific numerical features. Other time-domain features that cannot be expressed in specific numbers are as follows:

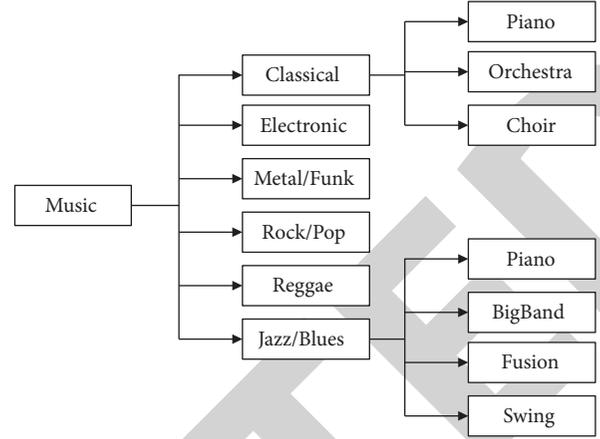


FIGURE 1: Classification structure of music genres.

- (1) Short-term energy represents the magnitude of the music signal at a given time, and the calculation method is as follows:

$$E_n = \sum_{m=-\infty}^{\infty} [x(m)w(n-m)]^2 \quad (1)$$

$$= \sum_{m=n-(N-1)}^n [x(m)w(n-m)]^2,$$

in which n represents the n th sampling point, $w(n-m)$ represents the window function, and n is the window length.

- (2) Short-time average zero-crossing rate is an important index to measure the high-frequency components of signals. When analyzing waveforms, the more high-frequency components, the more times they pass through zero points. The calculation formula of this feature is as follows:

$$Zn = \frac{1}{2N} \sum_{m=n-(N-1)}^n \text{sgn}[x(m)] - \text{sgn}[x(m-1)]w(n-m), \quad (2)$$

$x(m)$ represents the signal value of the m -th sampling point and sgn represents the sign function, which can be expressed as follows:

$$\text{sgn} = \begin{cases} 1, & x(n) \geq 0, \\ 0, & x(n) < 0. \end{cases} \quad (3)$$

In addition, the analysis can be performed using the frequency domain characteristics, which usually contain the spectral centroid and the spectral energy. These two music eigenvectors are often used in music signal processing analysis, and the formula for calculating the spectral energy is as follows:

$$SE = \sqrt{\frac{1}{h_0 - l_0} \sum_{w=l_0}^{h_0} |F(w)|^2}. \quad (4)$$

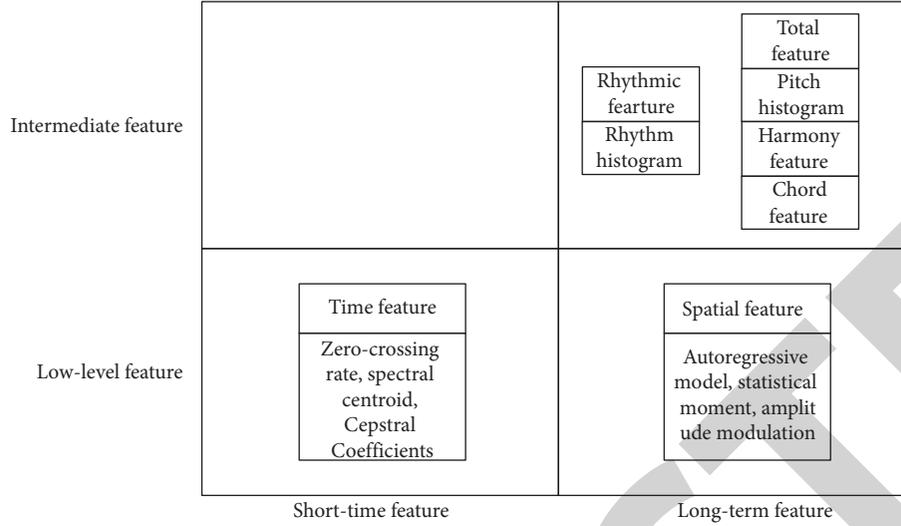


FIGURE 2: Classification of music signal features.

In the formula, the value of w is between l_0 and h_0 , the minimum value of frequency is expressed by l_0 , and the maximum value of frequency is expressed by h_0 . The formula for calculating the frequency spectrum centroid is shown as follows:

$$SC = \frac{\sum_{w=l_0}^{h_0} w|F(w)|^2}{\sum_{w=l_0}^{h_0} |F(w)|^2}. \quad (5)$$

3.3. Introduction to MIDI. MIDI (musical instrument digital interface) is an important digital music format, widely used in music creation and education. MIDI is a general format standard. It was proposed in the 1880s to solve the incompatibility problem of electronic music equipment produced by various music manufacturers. Since then, there is no longer a “language barrier” between electronic musical instruments [24].

A standard MIDI has 16 channels, of which Channel 10 is specially designed for percussion. Understanding the MIDI file format is of great help to the analysis and processing of sequential MIDI data. Figure 3 shows the file structure of a standard MIDI. MIDI files consist of multiple data blocks, including a MIDI file header block and several track blocks. Each track block contains events independently, and the data portion of the track block records the “instruction stream” that controls music play.

4. Research on MC Technology Based on Deep Learning

At present, the MC method based on deep learning is mainly used in audio classification task of storing waveforms, while the MIDIMC method still mainly uses traditional machine learning classifier based on BP neural network. Because of the limitation of shallow structure, it is difficult for classifiers to express music time series and semantic information in a deeper level, which affects the classification performance.

Therefore, in this paper, we propose a MIDIMC method based on deep learning. We decided to study the circulating neural network (RNN) and attention mechanism according to the characteristic sequence of the input MIDI music, design the classification network of this paper by using Bi-GRU and attention mechanism, and then carry out MC. Bi-GRU is good at processing sequence data, automatically learning music context meaning and advanced functions from the functional sequence of music segments, and adding attention mechanism to automatically give different attention weights to different segments in MIDI classification, so that some segments get more attention, highlight key information, and finally learn music features to represent music more effectively, thus improving the classification accuracy.

4.1. RNN. The main purpose of RNN is to process and predict sequence data. Its structure has memory characteristics, has deep expression ability of temporal and semantic information in mining sequence data, and is widely used in the field of natural language processing [25].

RNN is a kind of neural network specially dealing with time series, and its basic network structure is shown in Figure 4.

The left side of Figure 4 shows the structure diagram of RNN. The module A represents the hidden node in the network, x_t is the value of the input sequence x at the t -th time, o_t is the output of the hidden node at the t -th time, h_t is the hidden state of the hidden node at the t -th time, and u , v , and w are the parameter matrices in the network. It can be seen that, at the t -th time, the input of module A is from x_t but also the hidden state h_{t-1} of the previous time provided by the edge of a loop. At each moment, after the hidden node A reads x_t and h_{t-1} , it generates a new hidden state h_t and generates the output o_t at the current moment.

The forward propagation of RNN can be described by the following formula:

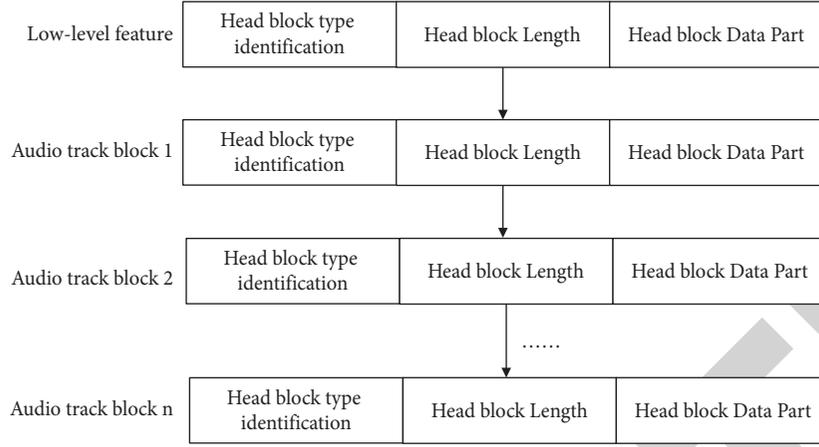


FIGURE 3: Standard MIDI file format.

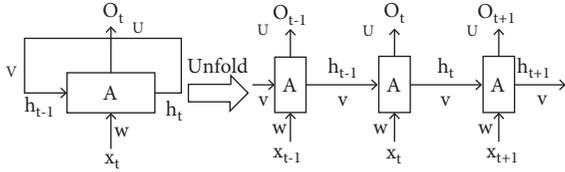


FIGURE 4: Schematic diagram of the basic structure of the recurrent neural network.

$$\begin{aligned}
 z_t &= Wx_t + Vh_{t-1} + b, \\
 h_t &= H(z_t), \\
 s_t &= Uh_t + c, \\
 o_t &= F(s_t),
 \end{aligned} \tag{6}$$

where B and C represent offsets for the hidden layer and the output layer, respectively, $H(\cdot)$ is the activation function for the hidden layer to compute the hidden state, usually the tanh function, and $F(\cdot)$ is the activation function for the output layer to compute the hidden state.

The loop edge of the hidden node A is expanded along the time axis, and the chain structure shown on the right side of Figure 4 can be obtained. RNN shares parameters at different moments and positions. The benefits of doing so are twofold. On the one hand, the parameter space can be reduced, the scale of the neural network can be reduced, and the generalization ability can be guaranteed. On the other hand, RNN is given the memory and learning ability, and the useful information is stored in the parameter matrix U , V , and W . It can be seen that the hidden state and output of all time positions are calculated using shared weights. The hidden state at each moment is determined by the input at the current moment and the hidden state at the previous moment. The structural characteristics of RNN show that it is best at solving problems related to time series.

4.2. Classifier Design Based on Bi-GRU and Attention Mechanism. Based on the input segment feature sequence, using two-way RNN can effectively learn the deep

expression of music about time series information and semantic information. The structure of GRU (Gate-RecurrentUnit) is simpler than that of LSTM (long short-term memory) network in memory cell selection of BRNN. It has fewer computations and faster convergence. Therefore, this paper takes GRU as the memory unit of BRNN. In music, different passages express different emotions and themes due to different playing and performance techniques and play different roles on MC. In order to pay attention to important music segments and highlight local important information, attention mechanism is added on the basis of BRNN. Attention mechanism can automatically give different probability weights to the features acquired by BRNN from different segments so that some segments can get more attention, learn more significant music features, and better characterize music characteristics, thus improving the classification performance.

Figure 5 is a network model structure diagram of MC. According to different functions, it can be divided into three parts: input layer, hidden layer, and output layer.

In the attention mechanism, the attention score corresponding to each feature vector is calculated by the formula as follows:

$$e_t = \tan h(WH_t + b). \tag{7}$$

Among them, e_i represents the attention score of feature vector H_t at time t in H .

Then, the calculated attention score is irradiated between 0 and 1 by softmax function, and the attention probability distribution of each feature vector is obtained:

$$\begin{aligned}
 a_i &= \text{softmax}(e_i) \\
 &= \frac{\exp(e_i)}{\sum_{k=1}^L \exp(e_k)}.
 \end{aligned} \tag{8}$$

The calculated attention probability distribution and each feature vector of the feature representation H are weighted and summed to obtain the feature vector representation of the music file as follows:

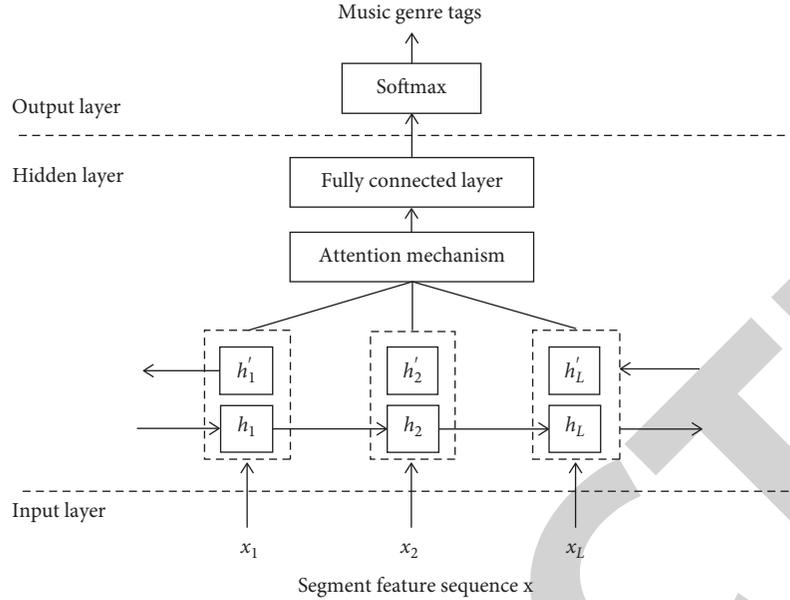


FIGURE 5: Music genre classification network model structure.

TABLE 1: Comparison of MC results.

Experiment number	Accuracy	Macro precision rate	Macro recall rate	Macro F1
1	0.7637	0.7338	0.7478	0.7329
2	0.8757	0.8671	0.8667	0.8669
3	0.8939	0.8889	0.8915	0.8912
4	0.9121	0.9116	0.9112	0.9114
5	0.8835	0.8754	0.8763	0.8759
6	0.8991	0.8963	0.8966	0.8965

$$v = \sum_{i=1}^L a_i H_i. \quad (9)$$

5. Experiments and Result Analysis

Based on the MIDIMC task, this paper carries out related experiments on the dataset, analyzes and compares the experimental results, and draws conclusions.

The marked MIDI music files are downloaded from websites dedicated to sharing MIDI music on the Internet, and a real dataset is constructed, with a total of 1920 MIDI music files collected. There are five datasets, including classical, country, dance music, folk, and metal. In this paper, *Python* language is used to program, and Keras is used to call Tensorflow background for MIDIMC experiment. In the experiment, 80% of MIDI files of each music are extracted as the training set and the remaining 20% as the verification set. The training set and verification set are independent and have no intersection.

In the experiment, the experimental results with the highest accuracy rate obtained in the verification set during the training process are selected for analysis, and the accuracy rate is the main point for performance comparison. The experimental results are shown in Table 1.

Comparing experiment 3 and experiment 4, the classification network model in experiment 4 introduces attention mechanism on the basis of Bi-GRU and assigns different attention weights to the features learned by Bi-GRU from different segments, so that some segments get more attention, which is conducive to highlighting the key information of music, learning more prominent features, and making the final music features better describe the genre characteristics of music, thus further improving the accuracy of MC. In experiment 4, using the MC method in this paper, the accuracy rate is 90.1%, and the classification effect is the best, which verifies the effectiveness of this method.

Figures 6 and 7 show the accuracy and loss function changes during the training of the experiment 4 network model. It can be seen from the figure that in the first and mid-stage of training, as the number of training rounds increases, the accuracy of the training set and the validation set gradually increases, and the corresponding loss function continues to decrease, indicating that the network model is being optimized. In the later stage of training, the accuracy of the validation set no longer improves, and the loss function tends to stabilize, indicating that the network model parameters have converged and the training is over. The predicted results are expressed by the confusion matrix, as shown in Table 2.

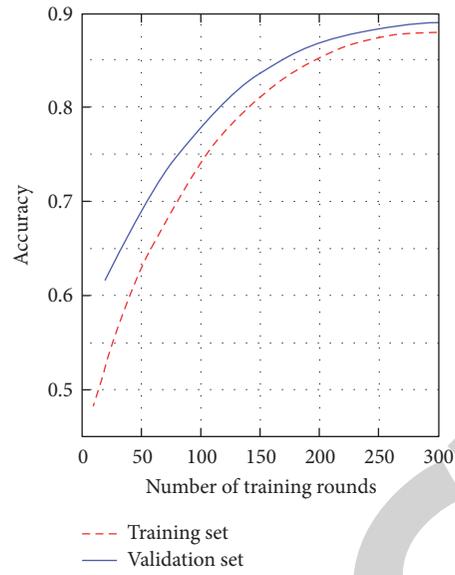


FIGURE 6: Accuracy change process of training set and validation set.

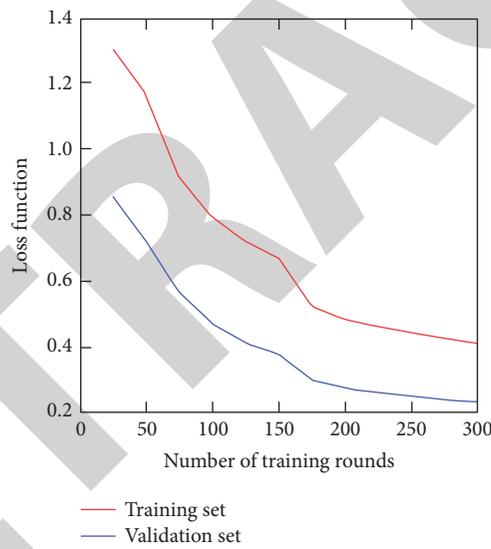


FIGURE 7: The change process of the loss function of the training set and the validation set.

TABLE 2: Confusion matrix (%).

		Forecast				
		Dance music	Metal	Rural	Classical	Folk
Real	Dance music	85.18	6.08	9.07	0	0
	Metal	3.91	95.05	0	0	1.38
	Rural	15.49	0	82.16	0	2.67
	Classical	2.61	1.36	2.61	92.61	2.36
	Folk	1.36	0	0	3.86	95.11

Generally speaking, the method proposed in this paper can effectively classify the above five genres of MIDI music, and the accuracy can basically meet the use requirements.

6. Conclusions

The amount of digital music on the Internet is growing rapidly, and how to manage these massive music resources is a thorny issue faced by major music media platforms. This paper conducts in-depth research on MC based on deep learning. Aiming at the limitations of the traditional MIDIMC method for extracting features and the limitation of the shallow structure of the classifier, a MIDIMC method based on deep learning is proposed, and the effectiveness of the method in this paper is verified in experiments, and relatively ideal results are obtained. Through the analysis of RNN and attention mechanism, according to the characteristic sequence of the input MIDI music segment, the MIDI classification network model is designed using Bi-GRU and attention mechanism, and MC is performed. Bi-GRU is good at processing sequence data. Adding attention mechanism can give different attention weights to the features learned by Bi-GRU, so that the final music features can better represent the music. In this paper, the feature extraction and classifier design are improved, and good classification results have been achieved in the task of MIDI music genre classification. However, due to the limited ability and time, involving interdisciplinary, the method of this article has certain limitations, and further research and improvement are still needed.

Data Availability

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

Conflicts of Interest

The author declares that there are no conflicts of interest.

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