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The Current Status and Challenges of Chinese Folk Music Preservation and Transmission

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Abstract Chinese folk music, originating from real life and grassroots communities, often features rich forms and humorous content, possessing invaluable historical, cultural, and artistic value. This study aims to promote the inheritance and development of Chinese folk music by designing a user needs survey questionnaire for a digital learning resource repository of Chinese folk music, summarizing its current development status and the challenges it faces. Given the diversity and irregularity of Chinese folk music entities, a music named entity recognition model is constructed with a main structure comprising a representation layer, a TDCNN encoding layer, a recurrent network layer, and a prediction layer, specifically for entity recognition in the field of Chinese folk music. Additionally, a link prediction model based on feature mapping and bidirectional convolution is established to achieve mapping conversion between entities and relationships, thereby uncovering their subtle connections. By integrating the two models, a folk music relationship extraction model is proposed to provide technical support for the establishment of a Chinese folk digital learning resource repository. In comparative experiments with various similar models, this model demonstrated the highest accuracy rate (99.08%) and F1 score (97.17%), showing high compatibility with the requirements of Chinese folk music relationship extraction tasks.

Index Terms folk music, music named entity recognition, digital learning resource repository, link prediction model, relationship extraction

I. Introduction

Chinese folk music is a cultural product that has been cultivated over time through the daily lives and activities of each ethnic group. China has 56 ethnic groups, each with its own unique folk music, which are rich in diversity and charm. These musical traditions are not only treasures of Chinese culture but also hold significant positions in the development of global music culture [1]-[3]. Over the course of history, Chinese folk music has intertwined with regional culture, customs, religious beliefs, ethnic traditions, historical events, and lifestyles, giving rise to various forms of ethnic music, such as the Yao ethnic group's Butterfly Song, Suzhou Pingtan, mountain songs, small tunes, erhu music, and Peking Opera music, among others. These have collectively formed a rich Chinese folk music system, collectively showcasing China's culture and spirit [4]-[8].

From a value perspective, folk music plays a role in the inheritance of world culture and the development of personal physical and mental health. Compared to the widely circulated popular music of today, folk music has deeper cultural connotations and greater stability in the long-term development of society [9]-[11]. From the perspective of its role in music development, Chinese folk music has a unique musical system, which is also adopted by the Han ethnic group and the majority of China's minority ethnic groups [12], [13]. In the process of inheritance and appreciation, the requirements for conforming to Chinese cultural traditions and aesthetic concepts are becoming increasingly stringent. To firmly establish ethnic folk music on the world music stage, it is essential to focus on inheriting local music, promoting ethnic culture, and strengthening the international status of Chinese folk music. This is also an important path for the creation and development of Chinese music [14]-[17].

However, with the acceleration of modernisation and globalisation, many traditional musical forms have gradually been marginalised, related folk music activities have decreased, and some music is even on the brink of extinction [18], [19]. Additionally, the rapid development of the global economy has intensified the trends of cultural integration and diversification. China's cultural market has been strongly impacted by foreign and modern cultures, with traditional Chinese culture facing even greater challenges. Folk music has not been spared in this impact [20]. Against this backdrop, how to protect and inherit ethnic music, enabling it to thrive anew in the contemporary era, has become a focal point of attention in academic and cultural circles.

Bian and Pikulsri [21] noted that the protection and inheritance of Hakka mountain songs have been affected by multicultural impacts and social and environmental changes, resulting in a lack of audiences and inheritors, as well as insufficient innovation. They suggested that the state should establish relevant inheritance mechanisms, build brands, innovate in creation, and integrate education. Zhang [22] pointed out that Liaozhai folk songs, as vernacular songs in a dialect, have declined over the course of three centuries. Musicians and the government have organised the songs, innovated repertoires, and cultivated professional inheritors to protect Liaozhai folk songs. Wang and Thotham [23] analysed the dissemination and transmission of folk songs in southern Shaanxi Province, which have been influenced by economic pressures, traditional environments, and folk song techniques. They suggested relying on technology, community participation, and policy implementation to create conditions for the transmission of folk songs. Zhuan et al. [24] reported that Jiangzhou folk drum music in China has faced challenges due to urbanisation and the intrusion of foreign cultures, including the destruction of the original environment suitable for drum music, as well as issues such as incorrect transmission, insufficient participation, and a lack of diversity in transmission and protection methods. They suggested strengthening the training of relevant inheritors and introducing digital technology for effective transmission and protection. Fan and Chuangprakhon [25] revealed the educational protection and inheritance mechanisms for folk songs in Youyang, China, including the design of folk song courses, rural community folk song activities, government legislation and financial support, and publication and distribution of books. Guocheng et al. [26] conducted an in-depth study on the inheritance and protection of folk songs in Xinxiang, Henan Province, China, focusing on three main areas: creating a suitable ecological environment for folk songs, leveraging the influence of new media communication technologies, and developing intangible cultural heritage (ICH) courses. Liu et al. [27] explored the inheritance and protection of Ba County music, a local intangible cultural heritage in Guangxi, China. In the context of modernisation and evolving cultural values, over-reliance on oral transmission, generational differences, and economic constraints pose challenges to its inheritance and protection. Qingtang et al. [28] utilised knowledge graph technology to construct an intelligent application service system for ethnic instrumental music culture. This system encompasses four modules: knowledge management, intelligent question-answering, personalised recommendations, and intelligent search, serving as an important digital pathway for the protection and transmission of ethnic instrumental music and its associated culture.

With the development of digital technology, an increasing amount of song feature information can be identified and recorded, providing important support for the protection and inheritance of folk music. For example, Yu et al. [29] used a singing voice conversion model to effectively extract the original audio melody, retaining the low-frequency information in the music, thereby generating audio of acceptable quality for the reconstruction of the endangered Southern Music of China. The preservation and transmission of Chinese folk music vary due to regional and complexity factors, with most efforts supported by education and digital technology. It is therefore necessary to conduct in-depth research into the current state of folk music preservation and transmission in China to provide references for establishing a systematic preservation and transmission mechanism.

This paper first briefly outlines the design rationale behind the user needs survey questionnaire for a digital learning resource repository of Chinese folk music, summarizes the occupational and professional characteristics of the surveyed users, and provides user profiles as a reference for the establishment of the learning resource repository. Second, based on the characteristics of the target users, it separately explains the framework composition of the music named entity recognition model and the architecture and principles of the link prediction model based on feature mapping and bidirectional convolutional neural networks, thereby forming a folk music relationship extraction model. Furthermore, music entity recognition comparison experiments and stability experiments are conducted to evaluate the performance of the proposed model. Finally, the proposed folk music relationship extraction model is applied to folk music department teaching in higher education institutions. Using a controlled variable approach, the feasibility and effectiveness of the model are analyzed from two dimensions: teaching effectiveness evaluation and willingness to continue learning.

II. Current Status of Chinese Folk Music

II. A. Questionnaire Design

This paper focuses on users' information needs, processing needs, integrity, security, and other aspects of China's digital learning resource library for folk music. Through investigating users' needs and analyzing and statistically evaluating the survey results, we have identified the needs of users of the digital learning resource library, including the types of data stored in the resource library, the processing users need to perform on the data, and data classification. To collect as much demand information as possible, we used an online questionnaire to collect and analyze user demand information.

II. B. Data Analysis

A total of 1,000 questionnaires were distributed, with 978 valid responses collected, resulting in a response rate of

97.8%. The occupational structure of the survey participants is shown in Figure 1, consisting of (J1) research institute staff, (J2) university faculty members or research/administrative staff, (J3) primary/secondary school teachers or administrators, (J4) university undergraduates, (J5) university master's/doctoral students, and (J6) other categories. The main categories were (J1) research institute staff, (J2) university faculty members or research and administrative staff, (J4) undergraduate students at universities, and (J5) master's and doctoral students at universities, totaling 863 people, accounting for 86.20% of the total.

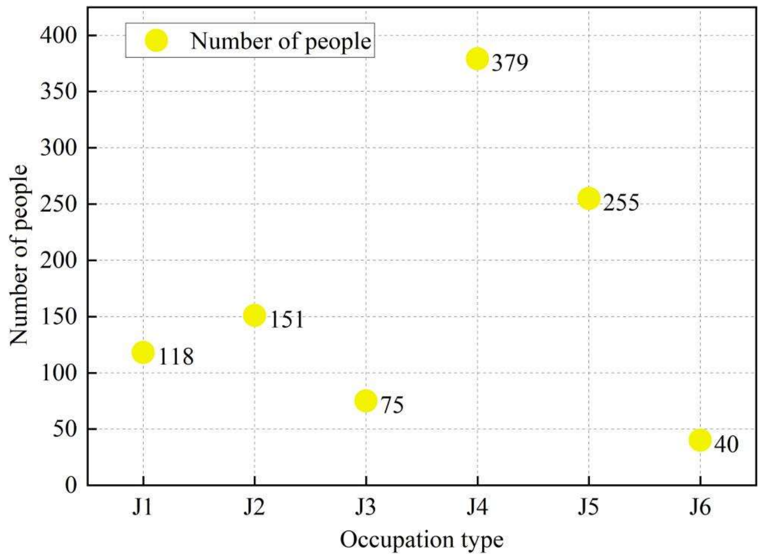

Figure 1: The occupational composition of the participants in the questionnaire survey

The professional composition of the survey participants is shown in Figure 2, which includes (M1) Philosophy, (M2) Economics, (M3) Law, (M4) Education, (M5) Literature, (M6) History, (M7) Science, (M8) Engineering, (M9) Agriculture, (M10) Medicine, (M11) Military Science, (M12) Management, and (M13) Arts. Among these, (M4) Education and (M13) Arts had the highest number of participants, totaling 769 people, accounting for 78.63% of the total.

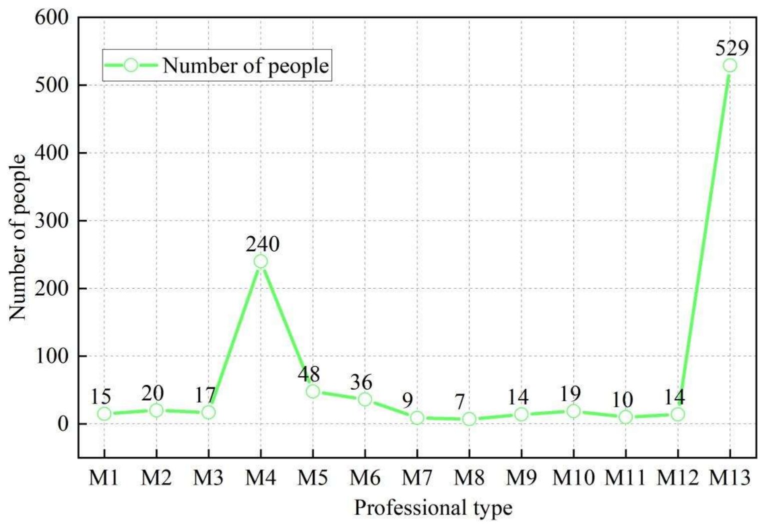

Figure 2: The professional composition of the participants in the questionnaire survey

In summary, the current demand for Chinese folk music comes from learners and researchers in the field of music and the arts. Due to the nature of their studies and research, most of these users are not particularly proficient in relevant information technology. This means that the preservation and transmission of Chinese folk music currently faces significant disciplinary barriers in terms of both content and technology, posing a major challenge to the adaptation of Chinese folk music to contemporary developments.

III. Folk Music Relationship Extraction Model

Based on the challenges of protecting and preserving Chinese folk music mentioned above, this section designs a framework for a music entity recognition model and a relationship link prediction model. After the music entity recognition model extracts the relationships between entity pairs, the relationship link prediction model is used to capture the connections between entities and relationships, thereby proposing a folk music relationship extraction model.

III. A. Music Naming Entity Recognition Model Framework

III. A. 1) Characterization layer

With the introduction of pre-trained models such as BERT, most current approaches involve fine-tuning the BERT model and then applying it to downstream natural language processing tasks, often achieving good performance. Therefore, this paper selects the LERT model as the representation layer. The LERT model is a pre-trained model that enhances semantic information by incorporating three linguistic tasks during the training phase: part-of-speech tagging, named entity recognition, and dependency parsing.

The input to the representation layer is preprocessed natural language text. Assuming the input text sequence is $S=[s_1,s_2,\cdots,s_n]$, the word vector representation obtained after passing through the representation layer is $E=[e_1,e_2,\cdots,e_n]$, where the dimension of e_i is represented as $C\in R^{N\times d_w}$; here, N denotes the maximum sequence length of the text, and d_w denotes the dimension of the word vectors generated by the pre-trained model.

III. A. 2) TDCNN Encoding Layer

Convolutional neural networks are often used to extract local features from text sequences. However, for variable-length sequences, fixed convolution kernel sizes cannot effectively process targets of different sizes. In addition, due to the limitations of the size of the local receptive field, general convolutional neural networks find it difficult to effectively capture sequence context information. To address these issues, this paper proposes a multi-channel, multi-dimensional dilated convolutional network (TDCNN) for character feature extraction. The network framework of TDCNN is shown in Figure 3.

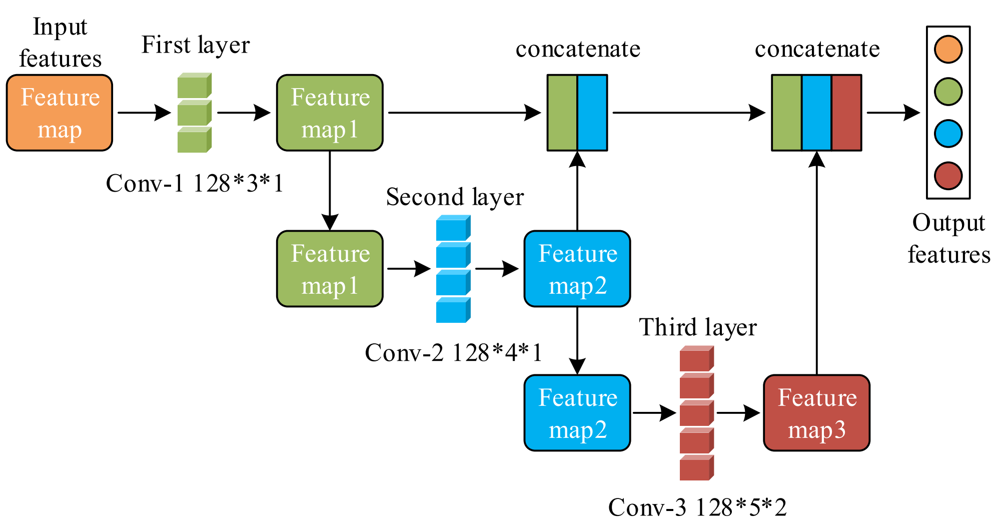

Figure 3: TDCNN framework

TDCNN is composed of four identical convolutional blocks. Each convolutional block contains three different convolutions, namely CNN1, CNN2, and CNN3. The input of CNN2 is CNN1, and the input of CNN3 is CNN2. The output $C1$ of a convolutional block is obtained by concatenating the three convolutions, as shown in Equation (1):

$$C1=CNN1\oplus CNN2\oplus CNN3 \tag{1}$$

In CNN1, the number of filters is 128, the size of the convolution kernel is 3, the stride is 1, and the dilation rate is 1; in CNN2, the number of filters is 128, the size of the convolution kernel is 4, the stride is 1, and the dilation rate is 1; In CNN3, the number of filters is 128, the size of the convolution kernel is 5, the stride is 1, and the dilation rate is 2. That is, for each block, the convolution kernel size is set to [3,4,5], and the dilation rate is set to [1,1,2]. For the word vector matrix output by the feature layer, each block extracts features using convolution kernels of size $3*3$, $4*4$, and $5*5$, respectively, while also increasing the size of the receptive field through dilated convolution to capture a broader range of input information. This is expressed in equation (2):

$$C = C_1 \oplus C_2 \oplus C_3 \oplus C_4 \tag{2}$$

For the input word vector matrix $E=[e_1,e_2,\cdots,e_n]$, after concatenating four identical blocks, the output representation of the TDCNN encoding layer is obtained as $C=[c_1,c_2,\cdots,c_n]$ is obtained by concatenating four identical blocks.

III. A. 3) Recursive Network Layer

The TDCNN encoding layer extracts character-level local features. For text sequences, temporal features are also indispensable. In the recurrent network layer, we choose LSTM to model the long-distance features of the text. Due to the limitation of LSTM in only being able to process unidirectional text information, we use bidirectional LSTM to process feature vectors to ensure that contextual information is not overlooked.

For the vector matrix $C=[c_1,c_2,\cdots,c_n]$ obtained from the TDCNN encoding layer, the hidden state sequence obtained through the forward LSTM is represented as $h=[h_1,h_2,h_3,...,h_n]$, and the hidden state sequence obtained through the backward LSTM is represented as $h'=[h_1,h_2,h_3,...,h_n]$. Concatenating the forward and backward hidden state sequences yields the contextual feature information as shown in Equation (3):

$$H = h \oplus h' = [h_1, h_2, \cdots, h_n] \tag{3}$$

III. A. 4) Prediction Layer

For named entity recognition tasks, CRF is often added to the prediction layer to reduce the output of incorrect label sequences. Given an observed sequence $x=(x_1,x_2,x_3,x_4\cdots x_n)$ and a label sequence $y=(y_1,y_2,y_3,y_4\cdots y_n$, the CRF calculates the score of the entire label sequence by defining the transition probabilities between labels, thereby evaluating its plausibility given the observed sequence, as shown in Equation (4):

$$score(x,y) = \sum_{i=0}^{n}\left(A_{w_i,w_{i+1}} + P_{i,w_i}\right) \tag{4}$$

where A denotes the transition matrix learned by CRF, $A_{i,j}$ denotes the label transition score; P denotes the emission matrix obtained from the network layer; P_{i,w_i} denotes the score of the w_i th label for this character; $score(x, y)$ denotes the comprehensive evaluation score.

The formula for calculating the corresponding probability of the input sequence and the predicted sequence is given by equation (5):

$$P(y \mid x) = \frac{e^{score(x,y)}}{\sum_{y \in Y_x} e^{score(x,y)}} \tag{5}$$

$P(y|x)$ represents the correspondence probability between the input sequence and the predicted sequence; Y_x represents all possible label sequences. By combining the emission score matrix of the recurrent network layer and the transition score matrix learned by CRF, the probability of the input sequence and the corresponding label is obtained. At the same time, the Viterbi algorithm is used for decoding to obtain the output sequence with the maximum score, which is the optimal recognition result.

III. B. Link prediction model based on feature mapping and bidirectional convolution

III. B. 1) Encoding Layer

To obtain the embeddings of entities and relationships, it is necessary to learn the representation of each triplet. This paper uses single-hop triplets $t_{i_s j_s}^{m_s}=(e_{i_s},r_{m_s},e_{j_s})$ and multi-hop triples $t_{i_d j_d k_d}^{m_d n_d}=(e_{i_d},r_{m_d},e_{j_d},r_{n_d},e_{k_d})$ are concatenated to obtain a more comprehensive triplet representation, where t denotes a triplet, s denotes single-hop information, d denotes multi-hop information, and $e_{i_s},e_{j_s},e_{i_d},e_{j_d},e_{k_d}$ denotes entity embedding, r_{m_s},r_{m_d},r_{n_d} represent relation embeddings. First, merge single-hop and multi-hop triples, as detailed in formulas (6)–(8).

$$h_i = concat[e_{i_s}, e_{i_d}] \tag{6}$$

$$h_j = concat[e_{j_s}, e_{k_d}] \tag{7}$$

$$g_k = concat[r_{m_s}, r_{m_d}, r_{n_d}] \tag{8}$$

Then perform a linear transformation as shown in equation (9).

$$c_{ijk} = W_1 \left[h_i \| h_j \| g_k \right] \tag{9}$$

where c_{ijk} is the vector representation after the triple linear transformation. The matrix h_i represents the joint embedding of entities e_{i_s}, e_{i_d}, the matrix h_j represents the joint embedding of entities e_{j_s}, e_{k_d}, the matrix g_k represents the joint embedding of relations $r_{m_s}, r_{m_d}, r_{n_d}$, and W_1 represents the linear transformation matrix.

This paper performs a linear transformation with the weight matrix W_2 as the parameter, then applies the activation function LeakyRelu to obtain the absolute attention b_{ijk} of the triplet, as shown in Equation (10).

$$b_{ijk} = Leaky\,\mathrm{Re}\,LU\left(W_2 c_{ijk}\right) \tag{10}$$

In order to obtain relative attention, the activation function SoftMax is applied to equation (11).

$$\alpha_{ijk} = Soft\max_{jk}\left(b_{ijk}\right) \tag{11}$$

The embedding h_i' of entity e_i is the sum of the attention values between corresponding entities, weighted by each triplet representation, as calculated in equation (12).

$$h_{i'} = \sigma\left(\sum_{j \in N_i} \sum_{k \in R_{ij}} \alpha_{ijk} c_{ijk}\right) \tag{12}$$

Here, N_i denotes the neighborhood of entity e_i, and R_{ij} denotes the set of relationships connecting entity e_i and e_j. The attention mechanism is used to calculate the weighted sum of neighbor entity embeddings and connect them to stabilize the learning process and provide more encapsulated neighbor information. The connection process is described in Equation (13).

$$h_i' = \Big\|_{m=1}^{M} \sigma\left(\sum_{j \in N_i} \alpha_{ijk}^m c_{ijk}^m\right) \tag{13}$$

In the last layer of the model, the multiple head embeddings of the entity are not simply connected, but rather averaged to obtain the final entity embedding vector. The specific calculation method can be seen in Equation (14).

$$h_i' = \sigma\left(\frac{1}{M}\sum_{m=1}^{M}\sum_{j \in N_i}\sum_{k \in R_{ij}} \alpha_{ijk}^m c_{ijk}^m\right) \tag{14}$$

When learning new embeddings, entities lose their initial embedding information. To address this issue, this paper employs a matrix vector W^E to perform a linear transformation on H^i, where H^i represents the input entity embeddings of the current model. Finally, H^f, which represents the initial embedding information of the entities, is added to the final encoding, yielding the result of the linear transformation H^f, as shown in Equation (15).

$$H'' = W^E H^i + H^f \tag{15}$$

The experiments in this paper use hinge loss to train the model, which is given by Equation (16):

$$L(\Omega) = \sum_{t_{ij} \in S} \sum_{t_{ij}' \in S'} \max\left\{d_{t_{ij}'} - d_{t_{ij}} + \gamma, 0\right\} \tag{16}$$

where $\gamma > 0$ is a hyperparameter, S is the set of valid triples, and S' denotes the set of invalid triples. To extend edges to directed paths, this paper introduces an auxiliary relation between two entities and defines it as the sum of all relation embeddings in the path. The model accumulates knowledge iteratively from multi-hop information about entities.

III. B. 2) Mapping Layer

The model in this paper locates the relation-specific translation vector d_r in the relation-specific hyperplane w_r, rather than in the same space as the entity embeddings. For a triplet $t_{ij}^k = (e_i, r_k, e_j)$, the head entity h and tail entity t are first projected onto the relation-specific hyperplane w_r, yielding projection vectors $h_\perp$ and $t_\perp$. If t_{ij}^k is a valid triplet, $h_\perp$ and $t_\perp$ can be connected on the hyperplane via the translation vector d_r, with the projection function defined by equation (17).

$$h_\perp = h - w_r^T h w_r, t_\perp = t - w_r^T t w_r \tag{17}$$

III. B. 3) Decoding Layer

The model used in the experiment employs bidirectional convolution as the decoder, with the purpose of the convolution layer being to analyze the characteristics of global embedding and bidirectional encoding. The scoring function with multiple feature maps is specifically defined by Equations (18)-(19).

$$h_{triple} = concat\left[h_\perp, d_r, t_\perp, t_\perp, d_r, t_\perp, h_\perp\right] \tag{18}$$

$$f\left(t_{ij}^k\right) = \left(\Big\|_{m=1}^{\Omega} \mathrm{Re}\,LU\left(h_{triple} * w^m\right)\right).W \tag{19}$$

In this context, w^m denotes the convolution filter, Ω is the hyperparameter representing the number of filters, * denotes the convolution operation, and W is the linear transformation matrix used to calculate the final score of the triplet. The model employs Equations (20) and (21) as the loss function.

$$L = \sum_{t_{ij}^k \in \{S \cup S'\}} \log\left(1 + \exp\left(l_{t_{ij}^k} \cdot f\left(t_{ij}^k\right)\right)\right) + \frac{\lambda}{2}\|W\|_2^2 \tag{20}$$

$$l_{t_{ij}^k} = \begin{cases} 1 & for\ t_{ij}^k \in S \\ -1 & for\ t_{ij}^k \in S' \end{cases} \tag{21}$$

IV. Effectiveness of folk music relationship extraction models

IV. A. Performance testing

IV. A. 1) Reference experiment

We selected (A1) SVM, (A2) TextCNN, (A3) TextRNN, and (A4) TextBiRNN as comparison models and compared their music entity recognition performance with that of (A5) the model proposed in this paper on the SEAD dataset. The comparison results are shown in Table 1.

Table 1: A comparison of the model in this paper with other models on SEAD

Model	Precision (%)	Recall (%)	F1 (%)
A1	89.73	80.55	87.38
A2	98.45	94.76	96.45
A3	94.04	94.73	94.28
A4	98.55	91.54	94.81
A5	99.08	95.55	97.17

Overall, the music entity recognition model proposed in this paper achieves significantly higher precision (99.08%) and F1 score (97.17%) on the SEAD test set compared to the other four comparison models. Among them, the SVM model, a commonly used entity alignment model, exhibits the lowest precision, recall, and F1 score (all below 90.00%) among the four models. In entity alignment based on this machine learning method, entities can only interact with each other if they share the same attributes. If there is information asymmetry between entities in the data, different attributes cannot interact. In contrast, the model proposed in this paper can combine the overall characteristics and attributes of entities to assess their importance, thereby facilitating effective interaction between different attributes of entities and improving its practical application performance.

IV. A. 2) Stability testing

To validate the stability of the model proposed in this paper (A5), this section conducts experiments using three sets of training data. Three different window combinations are set for comparison: (G1) [2,3,4], (G2) [3,4,5], and (G3) [4,5,6]. The training datasets contain 10,000, 12,000, and 14,000 examples, respectively, while the test dataset shares the same set with 1,500 examples. The changes in the F1 score of the model on the test set are shown in Figure 4. It can be observed that, across all training datasets, the performance of the model proposed in this paper is the best among all window combinations, with its F1 score consistently exceeding 0.92. Only when the training dataset size is 12,000, the window combination of (G1) [2,3,4] shows slightly better performance on the test set than the model in this paper (A5) (0.00025). That is, regardless of the size of the training dataset, the model in this paper (A5) demonstrates good stability and robustness.

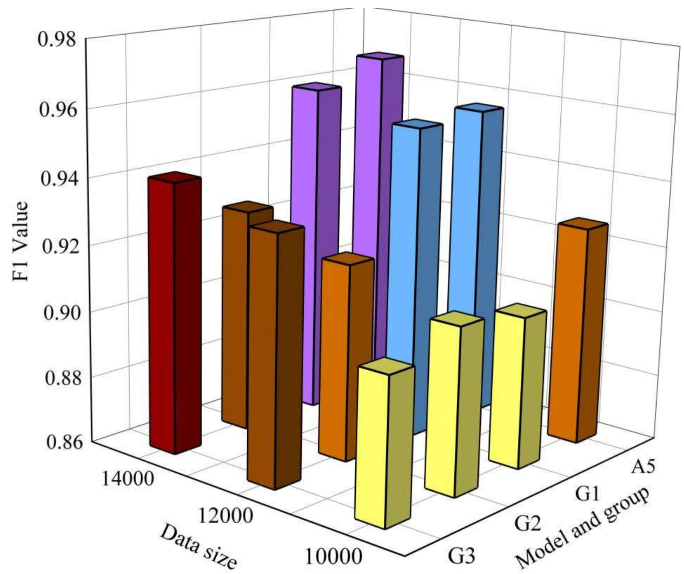

Figure 4: The change of F1 value on the test set

IV. A. 3) Entity Recognition Results

The following entity categories with higher search frequencies in the current Chinese folk music digital learning resource repository were selected: (E1) representative works, (E2) musical modes, (E3) figures, (E4) books, (E5) ethnic groups, (E6) themes, (E7) musical instruments, (E8) music categories, (E9) place names, (E10) intangible cultural heritage names, (E11) Time, (E12) Scenes, (E13) Culture, (E14) Style, (E14) Melody, to conduct a feasibility test of the music entity recognition model designed in this paper. Using accuracy, recall rate, and F1 score as evaluation metrics, the entity recognition performance of this model is shown in Table 2.

Table 2: The entity identification results

Entity category	Evaluation index		
	Precision (%)	Recall rate (%)	F1 Value (%)
E1	100	100	100
E2	100	100	100
E3	92.14	94.91	96.47
E4	91.23	91.23	91.23
E5	86.01	86.01	86.01
E6	88.37	82.56	85.37
E7	83.82	84.05	81.35
E8	73.96	81.23	77.42
E9	77.62	77.09	77.35
E10	71.27	81.42	76
E11	67.9	73.96	70.8
E12	65.67	67.14	66.4
E13	59.56	67.9	63.45
E14	55.52	49.95	52.58
Average	77.44	78.77	78.04

In the identification of 14 commonly used folk music entities, the model demonstrated superior entity recognition performance, with average values for all three evaluation metrics exceeding 77.00%. For the two entities (E1) Representative Works and (E2) Melody Patterns, the model achieved 100.00% recognition accuracy. For the five entities (E3) Characters, (E4) Books, (E5) Ethnic Groups, (E6) Themes, and (E7) Instruments, the recognition accuracy was 80.00% or higher. This indicates that within China's folk music cultural resources, these entities possess distinct characteristics, their boundaries are typically marked by special symbols, and they are relatively evenly distributed.

IV. B. Application Effects

IV. B. 1) Evaluation of Teaching Effectiveness

Two classes from the third year of the Chinese Music Department at H University were selected as the experimental subjects for this study's model application. Each class had 32 students. One class was designated as the experimental group, which used the model designed in this study to assist in learning folk music courses. The other class was designated as the control group, which continued to use the traditional teaching model for learning. After one semester of study, the “Folk Music Course Interest Evaluation Scale” was distributed to the experimental subjects. This scale categorizes interest into the following five levels: (LF1) Very Interesting, (LF2) Fairly Interesting, (LF3) Average, (LF4) Fairly Uninteresting, and (LF5) Very Boring and Tedious. The evaluation results for both groups are summarized in Table 3.

Table 3: Evaluation of Course Interest

Group	Level	Frequency	Percentage	Cumulative percentage
Control Group	LF1	3	9.375	9.375
	LF2	4	12.5	21.875
	LF3	16	50	71.875
	LF4	6	18.75	90.625
	LF5	3	9.375	100
	Total	32	100.00	
Experimental Group	LF1	11	34.375	34.375
	LF2	16	50	84.375
	LF3	4	12.5	96.875
	LF4	1	3.125	100
	LF5	0	0	100
	Total	32	100.00	

Students in the control group primarily rated the traditional teaching model as (LF3) average, (LF4) somewhat uninteresting, or (LF5) very boring and tedious. Among these, the (LF3) average rating occurred 16 times, accounting for 50.00% of the total number of evaluators. Only 21.875% of students found the folk music course (LF1) very interesting or (LF2) somewhat interesting. In contrast, students who learned using the model designed in this study primarily rated the folk music course as (LF1) very interesting or (LF2) somewhat interesting, accounting for 84.375% of the total number of evaluators. Only one student rated the folk music course as (LF4) somewhat uninteresting, and no students rated it as (LF5) very boring and tedious. This indicates that classrooms incorporating the model designed in this paper are more popular among students and more engaging compared to traditional classrooms.

IV. B. 2) Willingness to continue learning

Similar to the teaching effectiveness evaluation method, after the completion of the learning program, a “continuing learning intention scale” was distributed to the experimental subjects. The scale categorized continuing learning intentions as follows: (LW1) very willing, (LW2) willing, (LW3) neutral, (LW4) not very willing, and (LW5) unwilling. The results of the two groups of students' continuing learning intentions for folk music are shown in Table 4.

Table 4: Students have the willingness to continue learning in the same way

Group	Level	Frequency	Percentage	Cumulative percentage
Control Group	LW1	6	18.75	18.75
	LW2	8	25	43.75
	LW3	15	46.875	90.625
	LW4	2	6.25	96.875
	LW5	1	3.125	100

	Total	32	100.00	
Experimental Group	LW1	11	34.375	34.375
	LW2	14	43.75	78.125
	LW3	7	21.875	100
	LW4	0	0	100
	LW5	0	0	100
	Total	32	100.00	

In terms of willingness to continue learning under the traditional group-based teaching model, 46.875% of students in the control group held a neutral attitude (LW3), while a total of 43.75% of students (LW1) were very willing or (LW2) willing to continue learning folk music under the traditional teaching model. Overall, nearly half of the control group students expressed a willingness to continue learning folk music under the traditional teaching model. In contrast, 78.125% of the experimental group students (LW1) were very willing/(LW2) willing to continue learning under the model proposed in this paper, and no students (LW4) were somewhat unwilling/(LW5) unwilling to continue using the teaching model employed in the experiment. This indicates that the teaching model assisted by this study's model is more effective in stimulating students' enthusiasm for learning folk music, thereby promoting their in-depth exploration and study in the field of folk music, and injecting new vitality into the protection and inheritance of Chinese folk music.

V. Conclusion

This paper combines a music named entity recognition model with a link prediction model based on feature mapping and bidirectional convolutions to establish a reliable and feasible folk music relationship extraction model, providing effective research references for the current technical gaps in the protection and inheritance of Chinese folk music. The folk music relationship extraction model achieved an accuracy rate of 99.08% and an F1 score of 97.17% on the SEAD dataset. In terms of folk music entity recognition, the average values of the three evaluation metrics all exceeded 77.00%. Additionally, in practical applications, the model received positive feedback from 75% or more of folk music students within the experimental group.

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