Research on Multiple Innovative Paths and Practices of Combining Deep Learning and Knowledge Graph in Composing Choral Works

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Abstract Choral works, as an important form of musical expression, have a complex compositional process and require a deep foundation in music theory. The rapid development of artificial intelligence technology provides new possibilities for music creation. In order to solve the problems of low efficiency and limited creative ideas of traditional choral works, this study constructs a choral works creation model based on the combination of deep learning and knowledge graph. Methodologically, the Transformer and BART models are adopted as the core architecture, and the deep mining and representation learning of semantic information of choral works is realized through keyword extended graph generation, TransE knowledge representation encoder and two-layer graph attention network. Specifically, the keyword expansion graph is constructed by utilizing the knowledge map of ancient poems, the keyword semantic representation is enhanced by the multi-head graph attention mechanism, and the dual cross attention mechanism is incorporated in the BART decoder to improve the quality of text generation. The experimental results show that the model achieves 75.4%, 76.3%, and 78.4% in terms of accuracy, recall, and F1 value, respectively, which significantly outperforms baseline models such as SVM, BiLSTM, and TextCNN. The model achieves convergence at about 460 training sessions, and the convergence speed is significantly faster than the comparison model. The application practice shows that the average score of students' choral works in the experimental group reaches 86.24, which is 5.58 points higher than that of the control group. The study shows that the model can effectively support the creation of multi-topic choral works, which provides a new technical path for the intelligent development in the field of music creation.

Index Terms Deep learning, knowledge graph, choral work composition, BART model, graph attention network, intelligent composition

I. Introduction

Music, as an essential factor in today's society, has filled in all aspects of people's working life. As a form of music presentation, chorus is widely spread, such as campus chorus competition, workers' chorus competition, mass chorus competition and so on, so the existence value of chorus can not be ignored [1], [2]. At the same time, with the promotion of China's cultural policy and the rapid development of science and technology in the new era, choral music is not only a form of musical art, but also an important carrier of cultural dissemination and innovation [3]-[5].

At this stage, the creation and performance of choral works are gradually integrating more diversified forms of artistic expression, such as digital media art, modern dance and interactive performance technology [6], [7]. These integrations not only expand the dimension of choral music expression, but also reflect the modern audience's demand for diversity and interactivity of art works [8], [9]. In addition, the combination of diversified performance forms and choral singing has brought new ideas and means for the creation of choral music [10]. Modern choral works pay more and more attention to establishing a more dynamic and organic connection between music, text and visual art, and through this cross-border cooperation, choral music can express social themes and personal emotions more profoundly, so as to be closer to the aesthetic and cultural needs of the public in the new era [11]-[14]. In the face of this trend, we aim to deeply analyze how Chinese choral works can realize the diversified and innovative expression of form and content with the help of emerging digital technology in the context of the new era.

This study constructs a choral work composition model that integrates deep learning and knowledge graph, realizes the rich representation of semantic information through the construction of keyword expansion graph, learns the vectorized representation of entities and relations by using the TransE model, adopts the multilayer graph attention network to capture the complex semantic associations between keywords, and designs the double cross-attention mechanism on the basis of the BART model to realize the effective fusion of knowledge information and sequence information fusion effectively. The study verifies the effectiveness of the model through comparative

experiments on real datasets, and carries out application practices in real teaching environments to explore the practical effects and application value of the model in choral work creation.

II. Deep Learning and Knowledge Graph Based Modeling for Choral Work Creation

The creation of choral works is a challenging task in the field of natural language generation, and no mature program for choral work creation has been formed yet. In this paper, we will carry out multiple innovations of choral works, and construct a choral work creation model based on the principles of deep learning and knowledge graph.

II. A.Relevant models and technical principles

II. A. 1)　Transformer

The Transformer model is a deep learning model based on a self-attentive mechanism that efficiently learns dependencies between long sequences without recursive computation, thus avoiding the problems of gradient vanishing and gradient explosion. The model consists of an encoder and a decoder and was initially used mainly for machine translation tasks. By utilizing a self-attentive mechanism to address the performance challenges of processing long text sequences, Transformer greatly improves the capabilities of deep learning natural language processing translation models. Studies have shown that pre-trained models based on Transformer perform well in a variety of natural language processing tasks, and thus have been widely used in the field of natural language processing.

Transformer's encoder encodes the input sequence into a vector representation and the decoder converts the vector representation into an output sequence. Each encoder and decoder consists of multiple Transformerblocks, each containing a multi-headed self-attention layer, a residual network layer, and a fully connected feed-forward neural network. The self-attention mechanism can take into account the contextual relationships of all input units simultaneously. The mechanism assigns relative weights by calculating the attention score of each unit with respect to other units in the sequence. This weight can be used to indicate how important the unit is to the whole input sequence. The formula for calculating the multiple self-attention is as follows:

$$Attention\left(Q,K,V\right) = soft\max\left(\frac{QK^{T}}{\sqrt{d_{k}}}\right)V \tag{1}$$

$$head_{i} = Attention\left(Q_{i},K_{i},V_{i}\right) \tag{2}$$

$$MultiHead = Concat\left(head_{1},head_{2},\ldots,head_{n}\right) \tag{3}$$

where d_{k} is the dimension of K, and Q, K, and V represent query vectors, key vectors, and value vectors, respectively, which are computed based on the word embedding vectors X as follows:

$$Q = W^{Q}X \tag{4}$$

$$K = W^{K}X \tag{5}$$

$$V = W^{V}X \tag{6}$$

where W^{Q}, W^{K} and W^{V} are parameter weights. The attention mechanism essentially calculates the similarity weight between the query vector and the key vector, and then multiplies this weight by the value vector to get the final result. The multi-head attention mechanism, on the other hand, realizes simultaneous attention and processing of multiple information sources by splicing the output vectors of different attention heads.

II. A. 2)　Pre-trained language models

1) BERT

BERT model is a bi-directional language model based on Transformer encoder, whose core structure consists of multiple Transformer's coding layers to pre-learn deep bi-directional representations of the text from a large amount of unlabeled data [15]. The training process of BERT is divided into two phases: pre-training and fine-tuning.

The input to BERT is the embedding representation $Token_{i}$ corresponding to each word in the sentence, while each sequence is preceded by a specific categorization symbol $[CLS]$, which serves to summarize the representation information of the whole sequence. Segmentation symbols $[SEP]$ are used to separate different sentences in the sequence. The output of BERT, C and T_{i} correspond to $[CLS]$ and input $Token_{i}$ at the last

level of BERT, respectively. When dealing with token level tasks such as sequence labeling, T_i is input to the additional output layer for prediction. When dealing with some sentence-level tasks like sentiment classification, C is fed into the extra output layer to get the final answer.

2) BART

BART is a Transformer model that combines bi-directional contextual information with autoregressive features. The BART encoder, like BERT, is an auto-encoding model with bi-directional feature representations, while the decoder is an autoregressive model with uni-directional feature representations. This design makes BART perform very well on the text generation task because the left-to-right unidirectional autoregressive coding approach is more logical for text generation.

The two main processes of BART in the pre-training phase are 1) corrupting the encoder's input source text using an arbitrary noise function and 2) allowing the decoder to recover the corrupted text in an autoregressive manner. Therefore, the loss function of BART is the cross-entropy of the decoder's output with the original text.

II. A. 3)   Graph Neural Networks

In recent years, graph neural networks (GNNs) have been widely used in natural language processing tasks, such as relation extraction, named entity recognition, and event detection, due to their ability to effectively capture relevant information based on information aggregation patterns [16].

Specifically, a graph is usually defined as $G = (V, E)$, where V denotes the set of all nodes in the graph and E denotes the set of all edges in the graph. The goal of a graph neural network is to learn the feature representation of the current node using information from neighboring nodes. The learning process of node representation can be represented as follows:

$$H^k = F\left(H^{k-1}, X, A, \theta\right) \tag{7}$$

where F is the information propagation function, θ is the corresponding parameter, X represents the representation of a node, A is the adjacency matrix of the graph, and $H^k\left(H^0 = X\right)$ denotes the node representation obtained by the graph neural network after k steps of computation.

The core part of the graph neural network is the information propagation function F, which can be implemented using different implementations such as graph convolutional networks (GCN) and graph attention networks (GAT). Where unlike graph convolutional neural networks that use the same weight sentence for different neighbor nodes, graph attention networks, inspired by the self-attention mechanism, employ an attention mechanism to optimize the process of information propagation. It computes different attention weights for different neighboring nodes in the graph and uses these weights to compute the corresponding information delivery. As a result, the graph attention network performs better in most cases.

II. B. Modeling the creation of choral works
II. B. 1)   Generation of keyword expansion maps

The semantic representation of keywords is crucial for generating ancient poetic texts, and in order to enhance the semantic representation of keywords, a keyword expansion graph G_K is constructed in the encoder stage to enrich the semantic representation of keywords. In this section, it is explained how to generate and learn the keyword expansion graph G_K embedding representation from the knowledge graph G of ancient poems.

Given the keyword $k_t \in K$, first retrieve on G to obtain all the neighboring entities of the keyword k_t stored in a list, and then load the pre-trained GloVe model to generate a corresponding word vector for each entity. For each keyword entity v_i, its similarity to the neighboring entity v_j is calculated using the cosine similarity, which is shown in Equation (8) [17]:

$$\cos ine\ similarity\left(v_i, v_j\right) = \frac{v_i \cdot v_j}{|v_i| \times |v_j|} \tag{8}$$

By calculating the cosine similarity between each pair of entities, a similarity score can be obtained, which reflects the semantic proximity between the entities. The neighboring nodes of each keyword node are ranked according to the word similarity score and their potential top-k neighboring nodes are selected along with their relations to form G_K.

II. B. 2) Knowledge representation encoder

In G_K, since some keyword pairs are not directly connected and some keyword pairs are connected through multiple relations, the TransE model is used to learn the embedding representation of entities and relations. In the training process, all the triples on the one-hop, two-hop and three-hop paths of each keyword pair are first extracted, and the triples between each keyword node and its neighboring nodes are extracted. The vector representation of the triples is (v_i, r_{ij}, v_j), where v_i and v_j are the vector representations of the head entity and tail entity, respectively and r_{ij} is the vector representation of the relationship between them. The model first computes the distance metric score of the triad, which is calculated as shown in equation (9):

$$d(v_i, r_{ij}, v_j) = \left\| v_i + r_{ij} - v_j \right\|_{L2} \tag{9}$$

The score of the distance metric represents the distance between the head entity, the relationship and the tail entity in the vector space, which is used to determine whether it satisfies the $v_i + r_{ij} \approx v_j$ constraint or not, and the number of paradigms is used in the computation process in order to prevent overfitting. The model is optimized by minimizing a bounding loss function, which is calculated as shown in equation (10).

$$L = \sum_{\xi \in S} \sum_{\xi' \in S'} \left[\gamma + d(\xi) - d(\xi') \right]_+ \tag{10}$$

In order to learn the additional description of the keyword nodes, two layers of multi-head graph attention are used, the first layer is to update the keyword node v_j^N by the neighboring nodes v_i^g of the keyword and embedding the relation r_{ij}^N, to obtain the new feature vector $v_i^{g'}$ of the keyword node, and calculate the attention coefficient α_{ij} between them, which is calculated as shown in Eq. (11) and Eq. (12):

$$e_{ij} = Leaky\,\mathrm{Re}\,LU\left(W_a \left[W_q v_i^g ; W_k v_j^N ; W_r r_{ij}^N \right] \right) \tag{11}$$

$$\alpha_{ij} = soft\max(e_{ij}) = \frac{\exp(e_{ij})}{\sum_{l \in N_i^N} \exp(e_{il})} \tag{12}$$

where e_{ij} is the attention score, N_i^N is the set of neighboring nodes adjacent to the keyword node, the attention coefficient α_{ij} is obtained after softmax, W_a, W_q, W_k, W_r are the learnable weight matrices, and the new feature $v_i^{g'}$ of each keyword node can be computed after obtaining α_{ij}, and the computation method is shown in equation (13):

$$v_i^{g'} = \sigma\left(\sum_{k=1}^{K} \sum_{j \in N_i^N} \alpha_{ij}^k W_v^k v_j^g \right) \tag{13}$$

where k is the number of layers of attention in the graph attention network, α_{ij}^k is the weight coefficient of the k th set of attention, and W_v is the learnable weight matrix, which obtains the new embedding $v_i^{g'}$ after updating the keyword nodes with neighboring nodes. The second graph attention layer uses the relationship r_{ij}^R between the keyword nodes to update the representation of the keyword nodes $v_i^{g'}$ to obtain the new features $v_i^{g''}$ of the keyword nodes, and computes the attention coefficient α_{ij}, which is calculated as shown in Eq. (14) and Eq. (15):

$$e_{ij} = Leaky\,\mathrm{Re}\,LU\left(W_a \left[W_q v_i^{g'} ; W_k v_j^{g'} ; W_r r_{ij}^R \right] \right) \tag{14}$$

$$\alpha_{ij} = soft\max(e_{ij}) = \frac{\exp(e_{ij})}{\sum_{l \in N_i^R} \exp(e_{il})} \tag{15}$$

where e_{ij} is the attention score, N_i^R is the set of neighboring keyword nodes of the keyword node, the attention coefficient α_{ij} is obtained after softmax, W_a, W_q, W_k, W_r are the learnable weight matrices, and after obtaining α_{ij} the feature $v_i^{g''}$ for the second update of each keyword node can be computed, which is shown in equation (16):

$$v_i^{g''} = \sigma\left(\sum_{k=1}^{K}\sum_{j \in N_i^k} \alpha_{ij}^k W_v^k v_j^{g'}\right) \tag{16}$$

where k is the number of layers of attention in the graph attention network, α_{ij}^k is the weight coefficient of the k th group of attention, and W_v is the learnable weight matrix.

II. B. 3)　BART-based codecs

In the encoding stage of the BART model, the model converts the input keyword sequence into $w = \{w_1, w_2, \cdots, w_m\}$ after word vector embedding, which is mapped into a set of hidden states $h = \{h_1, h_2, \cdots, h_m\}$, and h_i denotes the i th hidden state, which is computed as shown in equation (17).

$$h = BARTEncoder(w) \tag{17}$$

In the decoding phase of the BART model, the number of attention layers of the decoder is increased in order to effectively utilize the semantic information provided by the knowledge representation encoder. In the decoder's cross-attention layer, the model computes two different sets of cross-attention, the first set is the cross-attention between the keyword encoder's output implicit state h and the decoder's own implicit state y, and the second is the update of the keyword embedding $v_i^{g''}$ and the cross attention between the decoder's own hidden state y, and the computation of these two sets of attention is uniformly expressed as equation (18):

$$Attention(X_1, X_2) = soft\max\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{18}$$

where X_1 and X_2 represent the two sequences to be made cross-attentive, $Q = X_1 W^Q$ is the query matrix, $K = V = X_2 W^K$ is the key-value matrix, and d_k is the dimension of the matrix used to scale the size of attention.

For the first set of cross-attention, X_1 and X_2 correspond to the decoder's own hidden state y and the keyword encoder's output hidden state h, respectively. For the second set of cross-attention, X_1 and X_2 correspond to the decoder's own implicit state y and the update keyword embedding $v_i^{g''}$, respectively, and are computed as shown in Eqs. (19) and (20) are shown:

$$\begin{aligned} AT^{KW} &= Attention(y, h) \\ &= soft\max\left(\frac{yW^Q(hW^K)^T}{\sqrt{d_k}}\right)hW^K \end{aligned} \tag{19}$$

$$\begin{aligned} AT^{KG} &= Attention(y, v_i^{g''}) \\ &= soft\max\left(\frac{yW^Q(v_i^{g''}W^K)^T}{\sqrt{d_k}}\right)v_i^{g''}W^K \end{aligned} \tag{20}$$

where W^Q and W^K are the trainable weights and d_k is the dimension of the matrix. The final decoder output is the residual concatenation of the two attentions, computed as shown in equation (21):

$$y^o = W_{att}[AT^{KW}; AT^{KG}] + y \tag{21}$$

where $W_{att} \in \Box^{dk \times 2dk}$ is the trainable weight and y^o is used to predict the token sequence.

II. C.Experimentation and Analysis

1) Experimental data

After re-labeling the topics according to the labeling rules of choral work topic classification, the data of each topic is shown in Table 1. The experimental data are divided by 8:2. The total number of topics is 15414, of which the training set and test set account for 12331 and 3083 respectively.

Table 1: Subject data information

Category	Training set	Test set	Total number of categories
Landscape pastoral	2199	550	2749
Border fortress battle	1378	344	1722
Farewell to friends	3202	800	4002
Yong Shi Huai Gu	366	92	458
Love boudoir resentment	1397	349	1746
Travel homesickness	487	122	609
Scenery lyric	2740	685	3425
Mourn the memory of people	562	141	703
Total	12331	3083	15414

2) Experimental results and analysis

In this section, the effectiveness of the choral work creation model constructed in this paper will be experimented by comparison, and SVM, BiLSTM, TextCNN models are selected as the comparison object in this experiment, and the experimental results are shown in Table 2. It can be seen that in terms of accuracy, the accuracy and recall of SVM, BiLSTM, and TextCNN models are lower than the 70% level, and the F1 value of SVM and BiLSTM models reaches the level of 72.6% and 71.9%, which is higher than that of TextCNN model (66.1%). In contrast, for the same ancient poetry dataset, the accuracy, recall and F1 value of this paper's model are the highest, reaching 75.4%, 76.3% and 78.4%, respectively, with better model performance, proving the effectiveness of this paper's model.

Table 2: Comparative experiment

Model	P (%)	R (%)	F1 (%)
SVM	66.7	68.8	72.6
BiLSTM	68.2	65.4	71.9
TextCNN	66.7	69.5	66.1
The model in this paper	75.4	76.3	78.4

The graphs of the loss degradation of this paper's model and SVM, BiLSTM, and TextCNN models during the training process are specifically shown in Fig. 1. As can be seen from the figure,the model of this paper basically realizes basic convergence at about 460 times of training, while the SVM, BiLSTM, TextCNN models converge at about 1000, 1150 and 1250 times of training, respectively. Obviously. The overall performance of this paper's model with faster Loss drop is better than SVM, BiLSTM, and TextCNN models.
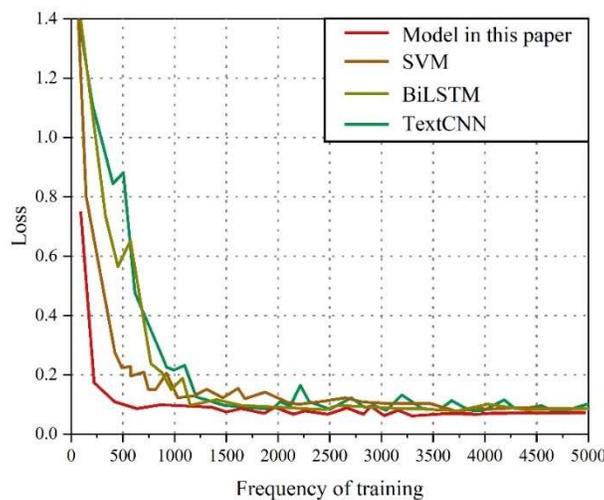

Figure 1: Loss decline process comparison

Using the choral work creation model constructed in this paper to carry out five randomized theme choral work creation experiments, each experiment will be 50 compositions, the experimental results are shown in Figure 2. As

can be seen from the figure, the choral works created by the model of this paper in the six experiments cover all the themes of landscape and garden, frontier campaign, sending off friends, history and antiquity, love and love, travel and homesickness, landscape and lyricism, mourning and remembrance of all the subjects, which can excellently complete the creation of different subjects to meet the diversified needs of the creators.
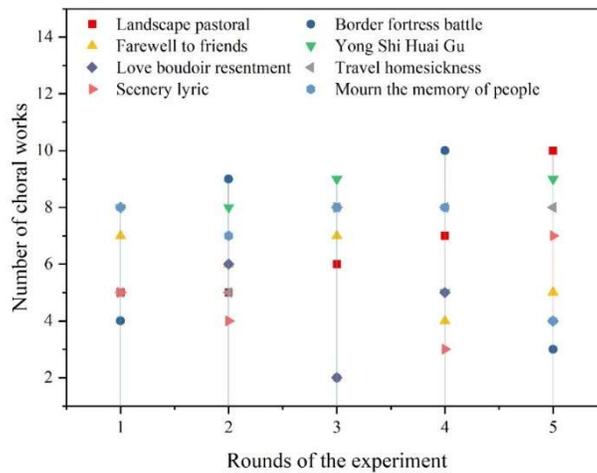

Figure 2: Experimental results of choral works creation

III. Practice of Multi-Compositional Application of Choral Work Composition Model

In order to investigate how effective the model of choral work composition constructed in this paper is in real riverbed work composition activities, this chapter will carry out a choral work multi-composition experiment in the music program of a college art school in Jiangsu Province, China.

III. A. Experimental setup
III. A. 1) Experimental Objects
The experimental subjects of this paper's research are second-year students majoring in music, using a controlled experiment, the research subjects will be divided into a control group and an experimental group, with 30 students in each group. The control group will use the traditional way of creating choral works to create, while the experimental group of students will apply the choral composition model constructed in this paper to create.

III. A. 2) Experimental environment
The creation of choral works needs to be carried out in a multimedia classroom and a recording studio, so this study supported both classrooms as experimental environments.

III. A. 3) Measuring tools
The main measurement tool used in this experiment was the Student Work Evaluation Form. At the end of the experiment students need to complete the corresponding choral work design, this study to test the creative effect of different choral work creation methods through the "Student Work Evaluation Form".

III. B. Analysis of experimental results
According to the choral work evaluation form designed in this study to score the works of the two groups of students experimental group and control group work scores descriptive statistical results shown in Table 3. From the data in the table, it can be seen that the experimental group's choral work score is 86.24 points, which is higher than the control group's score of 5.58 points.

Table 3: Students ' choral works scores

Groups	Number of people	Minimum value	Maximum value	Mean value	Standard deviation
Experimental group	30	72	98	86.24	5.688
Control group	30	58	94	80.66	8.743

After understanding the overall situation of the two groups of students' choral work scores, further statistics on the distribution of the experimental and control group's work scores were made, and the results are shown in Table

4. As can be seen from the data in the table, the proportion of students in the experimental group in the 88-100 score range is 60%, which is higher than that of the control group which accounts for 30%. In the range of 75-87 points, 61-74 points, the proportion of students in the control group is 50%, 20%, while the proportion of students in the experimental group is lower, 36.67%, 3.33%, most of the students in the control group are in the middle of the choral work creation level which indicates that the choral work creation level of the control group is lower than that of the experimental group is far more students. In short, the overall level of choral composition of students in the experimental group is higher than that of the control group.

Table 4: Performance distribution of works

Performance interval	Experimental group		Control group	
	Frequency	Percentage	Frequency	Percentage
61-74	1	3.33%	6	20.00%
75-87	11	36.67%	15	50.00%
88-100	18	60.00%	9	30.00%
Total	30	100%	30	100%

From the descriptive statistical results of the two groups of students' work performance, there is a difference between the experimental group and the control group's work performance, in order to test whether the difference is significant, it is also necessary to carry out an independent samples t-test from the six sub-dimensions of the work evaluation table (creative concept, design ideas, page design, work completeness, work optimization and related work document completeness), and the test results are shown in Table 5. As can be seen from the table, there are significant differences between the works of the two groups of students in the four dimensions of creative concept (p=0.026), design ideas (p=0.028), page design (p=0.013), and work completeness (p=0.002), while there is no significant difference in the optimization of the work as well as the completeness of the related work documents. This indicates that the choral work creation model constructed in this paper has a significant improvement effect on students' work completeness and creative ideas. Combined with the analysis of the score weights of the experimental group's students' works in each dimension (completeness of the work > completeness of the related work documents > design ideas > page design > creative ideas > optimization of the work), it can be found that the experimental group of students have a better mastery of the knowledge and skills of choral work creation. The control group, on the other hand, had a poor grasp of the completeness of the final choral work.

Table 5: Independent sample t test results of students ' work scores

Dimensions	group	N	Mean	Standard deviation	T	p
Creative ideas	Experimental group	30	7.77	1.064	2.668	0.026
	Control group	30	7.17	1.143		
Design ideas	Experimental group	30	12.64	1.21	-2.003	0.028
	Control group	30	12.72	1.413		
Page design	Experimental group	30	10.15	1.18	-2.178	0.013
	Control group	30	9.7	1.608		
Completeness of works	Experimental group	30	35.52	2.054	4.044	0.002
	Control group	30	30.77	2.805		
Optimization of works	Experimental group	30	3.72	1.088	1.365	0.326
	Control group	30	2.53	1.35		
Document integrity of related works	Experimental group	30	16.44	0.031	1.274	0.282
	Control group	30	17.77	0.793		

IV. Conclusion

The choral work creation model based on the combination of deep learning and knowledge graph shows significant superiority in multiple dimensions.

In terms of model performance, the constructed composition model significantly outperforms traditional machine learning methods on the ancient poetry dataset, with an F1 value of 78.4%, which is 5.8 percentage points higher than the 72.6% of the SVM model, proving the effectiveness of the strategy of fusing deep learning with knowledge graph. In terms of training efficiency, the model only needs 460 times of training to achieve convergence, while the

comparison model needs more than 1,000 times of training to reach a stable state, which is a significant improvement in training efficiency. In terms of practical application effect, verified by a controlled experiment in a music major of a university in Jiangsu Province, the average score of choral works of students in the experimental group is 86.24, which is 5.58 points higher than the 80.66 of the control group, and there is a significant difference in four dimensions, namely, creative concept, design idea, page design and completeness of works. The model successfully covers all the major subject categories such as landscape and garden, frontier conquest, gifting friends to send off, and aria and wistfulness, demonstrating good creative diversity and adaptability. The experimental results fully verify the feasibility and effectiveness of combining deep learning and knowledge graph in the creation of choral works, which provides important technical support and practical reference for the intelligent development of music creation, and at the same time lays a solid foundation for further research in related fields.

References

[1] Lonsdale, A. J., & Day, E. R. (2021). Are the psychological benefits of choral singing unique to choirs? A comparison of six activity groups. Psychology of Music, 49(5), 1179-1198.

[2] Balsnes, A. H. (2018). Singing for a better life: Choral singing and public health. Music and public health: A Nordic perspective, 167-186.

[3] Corbett, G. (2017). Theoartistry, and a contemporary perspective on composing sacred choral music. Religions, 9(1), 7.

[4] Meng, Y., & Liu, M. (2023). Exploring the inheritance and historical evolution of cultural values from the perspective of folk songs and chorus. Herança, 6(2), 1-13.

[5] Bennett, C. (2022). Teaching culturally diverse choral music with intention and care: A review of literature. Update: Applications of Research in Music Education, 40(3), 60-70.

[6] Copeland, P. (2017). Technology and the Choral Art: New Technologies for the Choral Musician: Inspiration and Communication. The Choral Journal, 58(1), 59-66.

[7] Alonderė, I. (2020). New media in choral practice: Virtual choir as a prophet of the new reality. Lietuvos Muzikologija, 21, 112-123.

[8] Batovska, O., BYELIK-ZOLOTARYOVA, N. A. T. A. L. I. Y. A., & IVANOVA, J. (2023). MODERN GLOBAL TRENDS IN THE DEVELOPMENT OF CHORAL PERFORMANCE. Studia Universitatis Babes-Bolyai, Musica, 68(2).

[9] Turchet, L., & De Cet, M. (2023). A web-based distributed system for integrating mobile music in choral performance. Personal and Ubiquitous Computing, 27(5), 1829-1842.

[10] Mróz, B., Odya, P., & Kostek, B. (2022). Creating a Remote Choir Performance Recording Based on an Ambisonic Approach. Applied Sciences, 12(7), 3316.

[11] Hernandez-Olivan, C., & Beltran, J. R. (2022). Music composition with deep learning: A review. Advances in speech and music technology: computational aspects and applications, 25-50.

[12] Suh, M., Youngblom, E., Terry, M., & Cai, C. J. (2021, May). AI as social glue: uncovering the roles of deep generative AI during social music composition. In Proceedings of the 2021 CHI conference on human factors in computing systems (pp. 1-11).

[13] Zhang, L. (2025). Compositional Tools Based on Artificial Intelligence for Choral Artistic Education: Enhancing Creative Skills in Choral Arrangements. Thinking Skills and Creativity, 101768.

[14] Masasabi, N. A. (2024). University Students' Experiences Using Digital Technology in Choral Music Performance. Doing Arts Thinking: Arts Practice, Research and Education, 153.

[15] Alokla Anas,Gad Walaa,Nazih Waleed,Aref Mustafa & Salem Abdelbadeeh. (2022). Pseudocode Generation from Source Code Using the BART Model. Mathematics,10(21),3967-3967.

[16] Dongdong An,Yi Yang,Xin Gao,Hongda Qi,Yang Yang,Xin Ye... & Qin Zhao. (2025). Reinforcement learning-based secure training for adversarial defense in graph neural networks. Neurocomputing,630,129704-129704.

[17] Li Duojiao,He Chenwan & Chen Ming. (2021). Text sentiment analysis based on Glove model and United Network. Journal of Physics: Conference Series,1748(3),032046-.