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THE APPLICATION OF COMPOSITION TECHNOLOGY THEORY IN COLLEGE MUSIC TEACHING BASED ON EDGE COMPUTING UNDER DIGITAL PLATFORM

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Abstract. This essay examines how music theory is used in college and university music education to help students become more adept at analyzing and understanding a wide range of acoustic activities. In this research, we leverage the benefits of edge computing and digital platforms to create a compositional network structure for diatonic composition using the Markov model, two-way gated recurrent neural network, and curve fitting. This paper's network architecture initially creates a Markov model to generate motivic melody for creating compositional knowledge rules. This model offers broad starting conditions for creating subsequent algorithmic compositions. Next, the style of the automatically gathered MIDI composition dataset is learned using a two-way gated recurrent neural network that can extract contextual note sequence information in order to create a prediction model. The test set achieves an accuracy of 88% on the proposed model by comparison experiments. The prediction model combines the input motivic melody to generate a one-part composition melody. At the same time, on the basis of the one-part composition melody, the relationship between the melodies of the two composing voices is studied, and a curve fitting method is used to model the two-part melody.

Key words: Digital platform; Edge computing; University music teaching; Technical theory of composition

1. Introduction. As music education in colleges and universities advances, interest in music composition has grown. Learners and composers are now focused not just on performing pieces but also on understanding and processing music at a deeper level [1, 2]. For music learners, it is essential to analyze and accurately master a work before performing it according to its stylistic requirements. Meanwhile, college music teachers need to continuously improve their theoretical knowledge to adapt to the increasingly diverse educational concepts of today [3, 4].

In the digital age, theoretical research on composition techniques in university music teaching must leverage digital platforms and technologies like edge computing [5]. While automatic computer composition has been explored using various machine learning methods, challenges remain. Although computer-generated music can sometimes mimic human compositions, over time, its machine-like features become apparent, diminishing the human-like qualities [6, 7]. This issue arises mainly due to the loss of musical structure and sequences that conflict with human auditory perception. To address this, automatic composition models should incorporate music's inherent structural rules, repetition, and emotional nuances, rather than just focusing on note sequences [8].

Algorithmic composition can be classified into two main categories: rule-based composition, which relies on specific musical knowledge, and machine learning-based composition, which learns composition rules through algorithms [9]. Initially, most researchers favored the rule-based approach, as it offered logical organization and clear explanations for musical behavior [10]. However, this method has limitations: music is subjective, making rule formulation challenging, and models trained this way are often genre-specific, limiting their versatility [11, 12]. For instance, the expert system CHORAL, constrained by over 350 rules, can only emulate the style of Johann Sebastian Bach.

Machine learning and deep learning methods offer greater adaptability and versatility, as they do not require extensive musical rule formulation, lowering the barrier to composition [13]. This paper focuses on the second approach, which simplifies the composition process and reduces the need for deep theoretical knowledge [14].

However, while edge computing-based methods ensure musical structure by following predefined rules, the need to manually develop numerous rules for different styles increases labor costs and contradicts the goal of

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achieving simplicity and efficiency in computer composition.

Thus, this study aims to explore a more straightforward and effective composition model and algorithm optimization path for applying composition technology theory in university music teaching under a digital platform.

2. Theoretical Model of Composition Technology Supported by Edge Computing. The musicVAE model is designed to simulate the music composition process by encoding and decoding musical sequences through a variational autoencoder architecture. This section details the specific parameters, training process, and hyperparameter adjustments used to optimize the model.

Model Architecture and Parameter Settings.

Encoder: The musicVAE model utilizes a two-layer bidirectional LSTM (Long Short-Term Memory) network as the encoder. Each LSTM layer contains 512 hidden units. The bidirectional nature of the encoder allows it to capture contextual information from both the forward and reverse directions of the musical sequence.

Latent Space: The latent space, also known as the "implicit code," is represented by a vector of 128 dimensions. This size was chosen to balance the trade-off between capturing sufficient information and maintaining computational efficiency.

Decoder: The decoder is a hierarchical LSTM network with a similar structure to the encoder. It consists of two layers, each with 512 hidden units. The hierarchical design ensures that the latent code information is consistently utilized during the decoding process, enabling the generation of coherent and contextually relevant musical sequences.

Training Process:

Dataset: The model was trained on a large dataset of MIDI files representing various genres and styles of music. The dataset was preprocessed to normalize the length and structure of the sequences, ensuring uniformity in the training samples.

Loss Function: The training process employed a combination of the reconstruction loss and the KL-divergence loss. The reconstruction loss measures the difference between the original and reconstructed musical sequences, while the KL-divergence loss ensures that the latent space distribution remains close to a standard normal distribution.

Optimization: The model was trained using the Adam optimizer with a learning rate of 0.001. The learning rate was selected after several experiments, showing the best balance between convergence speed and model stability.

Hyperparameter Tuning:

Batch Size: The batch size was initially set to 64 and later adjusted to 128 to improve training efficiency and stabilize the gradient updates.

Latent Dimension Size: Several experiments were conducted with different latent space dimensions (e.g., 64, 128, 256). A dimension size of 128 was chosen as it provided the best balance between model performance and computational requirements.

Dropout Rate: A dropout rate of 0.3 was applied to prevent overfitting. This rate was determined after experimenting with values ranging from 0.2 to 0.5, where 0.3 showed optimal regularization without compromising model capacity.

Evaluation and Fine-Tuning: The model's performance was evaluated using metrics such as reconstruction accuracy and musicality scores, which assess the coherence and creativity of the generated compositions. Based on the evaluation results, fine-tuning was conducted by adjusting the learning rate, latent space dimensions, and dropout rates. The model underwent multiple iterations of training and evaluation to achieve the desired level of performance.

Composing music is a creative and complex art activity for human beings, and it requires knowledge of basic music theory, harmony, polyphony, orchestration and composition structure, etc. How to use computers to simulate the composer's creation process and make the computer-generated compositions closer to the musician's real creation is a problem worth exploring. musicVAE is based on variational self-encoder, and the specific The structure is shown in Figure 2.1. Firstly, two layers of bidirectional encoder are used to encode music, then the implicit layer states in two directions of forward and reverse order are connected to get the implicit code", and

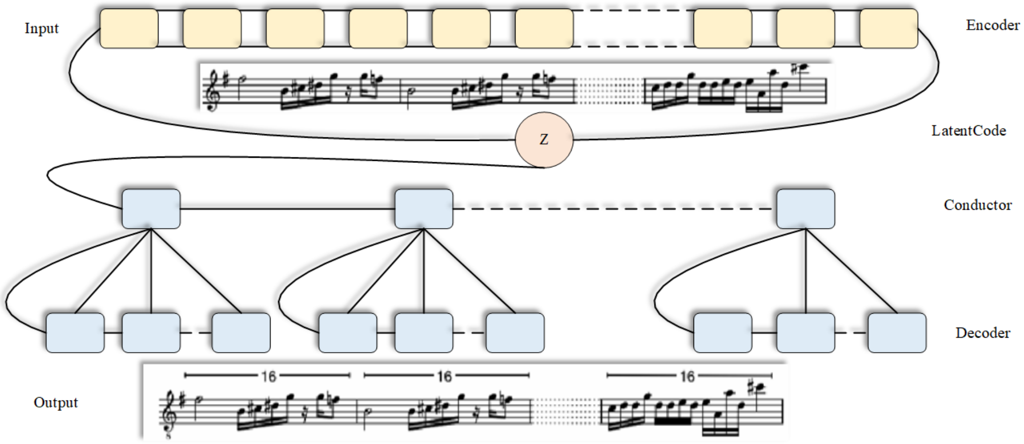

Fig. 2.1: MusicVAE architecture design.

finally a decoder is used to decode the implicit code" into music. To ensure that the information of the hidden code is always utilized in the decoding process, the decoder adopts a hierarchical design.

In the mathematical model of this study, we need to resort to the Markov model of compositional architecture, which is a relatively common mathematical statistical probability model used for sequence prediction. It is widely used in speech detection and recognition, text generation, personalized recommendation, user behavior analysis, image processing, etc. It is one of the important choices for many sequence generation problems due to its simple design and high computational efficiency [15]. The probabilities associated with different state changes in Markov models are called transfer probabilities. Suppose the sequence of states at time is j and the sequence of states at timets is j . From the definition of Markov model, it is known that the state at time is only related to the state i at time t1x, and the transfer probability is described by the mathematical formula as:

$$p_{ij} = p(i \rightarrow j) = p\left(x_t = j \mid x_{t-1} = i\right) \tag{2.1}$$

$$P = \left[p_{ij}\right]_{k \times k} = \left[\begin{array}{cccc} p_{11} & p_{12} & \cdots & p_{1k} \\ p_{21} & p_{22} & \cdots & p_{2k} \\ \vdots & \vdots & & \vdots \\ p_{k1} & p_{k2} & \cdots & p_{kk} \end{array}\right] \tag{2.2}$$

1. Matrix P:This is a k × k square matrix, representing a matrix with k rows and columns.
2. The element y in the p-matrix P is located in the jth column of the row, where the values of i and j range from $1 < i$ and$j < k$.
3. The first row of the matrix structure is composed of elements p_{11}, p_{12} ,p_{1k} . The second row is composed of elements p_{21}, p_{22}, p_{2k}, and so on, until the kth row is composed of elements p_{k1}, p_{k2}, p_{kk} .

This matrix P can be used in many fields, e.g: Linear transformations in linear algebra; Covariance matrices in statistics; Tensor representations in physics; The adjacency matrix in graph theory. The exact meaning depends on the context in which the matrix P is defined.

In the above equation, k denotes the total number of states and $P_{ij}\ (i, j = 1, 2, 3..., k)$ denotes the probability that the transition from the current state i to the next state j should satisfy.

$$0 < p_{ij} < 1 \tag{2.3}$$

$$\sum_{j}^{k} p_{ij} = 1 \tag{2.4}$$

Table 2.1: Theoretical scale structure of composition technology in college music teaching of different modes.

Mode	Scale structure
Uterine mode	2 2 3 2 3
Commercial mode	2 3 2 3 2
Mi-sol-la-do-re	3 2 3 2 2
Overtone	2 3 2 2 3
Feather mode	3 2 2 3 2

Table 2.2: Spin method of pentatonic mode.

Phonetic column name	Interval relation	Phonemic combination
B tone array	Large second degree+small third degree	Re,Mi,Sol,So,La,Do
C-tone array	Minor third degree+major second degree	Mi,Sol,La,La,Do,Re

According to the Markov process with no posteriority and the Bayesian conditional probability formula, the underlying logic of the compositional model is:

$$\pi(k) = \pi(k-1)P \tag{2.5}$$

This study will use this mathematical model as a foundation for applying compositional tone set theory concepts to the construction of motivic melodies through the fusion of folk musical elements. Through the collection and analysis of many folk song genres, we have discovered that one of the primary elements composing the melodic style of folk songs is certain sets of pentatonic triads. These triads run continuously through the piece's melody, and as the melody moves forward, various combinations of triads—which together constitute various thematic colors—make the melody present a variety of stylistic elements, much like how Western music modulates the musical structure. It contributes coherence to the music's structure. The pentatonic modes can be divided into five modes: Gong, Shang, Horn, Zheng, and Fe, each of which is composed of different triads. The scale structure of the different modes is shown in Table 2.1.

From the standpoint of interval analysis, "2" denotes the relationship between adjacent levels in the relationship between the five pentatonic scales. There are differences in the internal structure of the five scales with different pitches of the dominant tones: Gong, Shang, Horn, Zheng, and Fe. These correspond to the five pitches arranged in the numerical notation of the simple score as "1", "2", "3 ", "5", and "6". "Gong" and "Shang," "Shang" and "Jiao," "Zheng" and "Zheng," and "Zheng" and "Fe" have the main diatonic relationships. A small third relationship between adjacent levels is indicated by the letter "3". This relationship primarily exists between "horn" and "sign", as well as "feather" and "palace" and "Gong". The intervals that can occur between the intervals are three major seconds, one major third, two minor thirds, four pure fifths, and major second and minor third relationships. These interval relationships form the tritone row that is the basis for the melodic progression of the pentatonic mode.This pentatonic rotation we can divide into the following categories, as shown in Table 2.2.

The template of the above tonal column will appear frequently in the melodies of traditional Chinese folk music, constituting different melodic colors. The internal structure of the various modes in the technical theory model of composition we created for teaching music in colleges and universities is different. While the folk tuning will avoid the tonic fa and si and commonly use the tone-column melody, with fa and si rarely appearing in the strong tones, the Western tuning of Western music will follow the scale, not avoiding the tonic fa and si and frequently using the scale melody, which will bring in the tonic fa and si naturally. In Western tuning, the harmonic function is obvious, and the chord structure is emphasized more in the melody, while in traditional Chinese folk music, more emphasis is placed on the tone series, and there are some surrounding tones in the melody, often perceptually a piece will have a "national flavor", and this national flavor rationally means that the tone series will be used frequently, as shown in Table 2.3.

Table 2.3: Division structure of pentatonic modes.

Mode name	Structure
Uterine mode	A+B structure
Commercial mode	B+C structure
mi-sol-la-do-re	C+A structure
Overtone	B+B structure
Feather mode	C+C structure

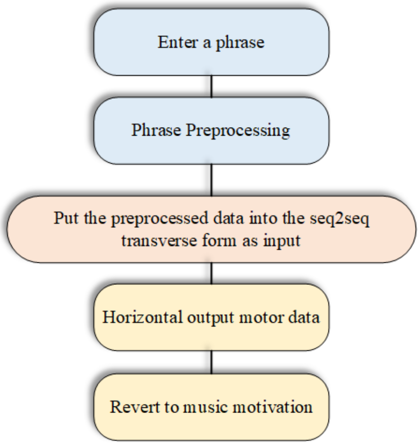

Fig. 2.2: Theoretical Model of Automatic Extraction of Music Motivation by Composing Technology in College Music Teaching.

The basis for conducting a structured generation of melodies from theoretical models of composition techniques in university music teaching is the need for a large number of musical motivation datasets as a basis for generating melodies. Since there is no previous research in this direction, there is a lack of musical motivation data sets. In order to accomplish this task of melody generation, it is necessary to rely on computers to extract a large number of musical motives from the currently available musical datasets. so a model for automatic extraction of musical motives is constructed in this paper. The flow is shown in Figure 2.2.

As shown in the flowchart, for the phrase sequence that needs to extract the motive, the first pre-processing is done to convert the phrase sequence into one-hot encoding, and then the encoding is put into the trained SEQ2 model, and the model predicts the current sequence encoding to get the musical motive encoding, and finally the encoding is reduced to the musical motive to achieve the final output effect of the composition technology model in college music teaching.

3. Methods.

3.1. Dataset and Model Runs. The dataset used in this paper comes from the Bach four-part choral corpus provided by the Python open source library. Bach, a great musician and composer of the Baroque period, wrote many four-part choral cantatas in counterpoint, each of which has a strict four-part structure with the main melody in the upper voice. Fig. 3.1 shows a fragment of the Bach Chorale BWV 334. There are 352 works in the JSB Chorale, and we expanded the dataset by transposing all works in a predefined range, resulting in 2503 cantatas. And the relationship between training set and test set will be divided by 8:2 ratio.

From a deep learning and edge computing perspective, for an input sequence of notes $(\omega_1, \omega_2, ..., \omega_n)$, the language model is modeling the probability distributionof the sequence, $P\omega$ indicating the probability of the existence of this sequence. Denote the deep learning model with parameters as $P_\theta\omega$. To make $P_\theta\omega$ approximate $P\omega$, a common approach is to maximize the objective function using stochastic gradient descent $\sum_i logP_\theta\left(\omega^I\right)$

Fig. 3.1: Bach's Praise BWV334.

Table 3.1: Discretization result of four part banknote sequence.

70	70	70	70	69	69	69	69	67	67	67	67	67	67	67	67
62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62
54	54	55	55	55	55	54	54	58	58	58	58	58	58	58	58
50	50	50	50	50	50	50	50	43	43	43	43	55	55	55	55

. However, modeling the joint probability distribution of variables is usually difficult, so the model $P_\theta \omega$ needs to be transformed into an easily solvable form, which can be obtained by the chain rule as:

$$P(\omega_1) P(\omega_2 \mid \omega_1) \ldots P(\omega_n \mid \omega_1, \ldots, \omega_{n-1}) \tag{3.1}$$

The above formula can be used as a preprocessing of the data set, and the one-way language model deals with the prediction problem, where the first n-1 words are used to predict the nth word. On this basis, the technical theory of composition in college music teaching relies heavily on cyclic repetition to build structure, and such autocorrelation is evident on multiple time scales. Therefore, in order to generate longer music fragments, melodic repetition, i.e., information extraction at different time scales, needs to be considered. The pooled attention mechanism proposed in subsection III is the core of the multi-scale Transformer automatic composition model proposed in this paper. The multi-scale Transformer model is constructed by applying pooled attention instead of self-attention to capture the autocorrelation of music at different time scales, as shown in Fig. 3.2.

The elements of the matrix are integers that represent the MIDI pitch value of the note being played, and the number of consecutive repetitions of the same number indicates the note length. Since the note with the smallest temporal value in the data set is the sixteenth note, the temporal resolution is chosen to be the sixteenth note, i.e., the quarter note (one beat) is discretized into four identical sixteenth notes. Table 3.1 shows the discretized four-voice choral music.

The selected dataset has a set of metadata corresponding to each note sequence of each voice part, including four types: sustain note, beat, key number and voice part number. Table 3.2 shows the metadata corresponding to the first note sequence. The first row indicates the presence or absence of sustain in the note at the corresponding position, marked with a Boolean value; the second row refers to the discrete notes corresponding to the sixteenth notes of a quarter note, marked with 0, 1, 2, 3 cycles; the third row specifies the key number; the fourth row indicates the serial number of the voice part to which the metadata belongs, marked with 0, 1, 2, 3 for each of the four voices The fourth line indicates the part to which the metadata belongs, and the four parts are marked with 0, 1, 2, 3 respectively.

3.2. Optimization algorithm to capture relative information. In this paper, we use a modified Transformer decoder unit, as shown in Fig. 3.3. The Transformer unit contains only two sub-layers. The use

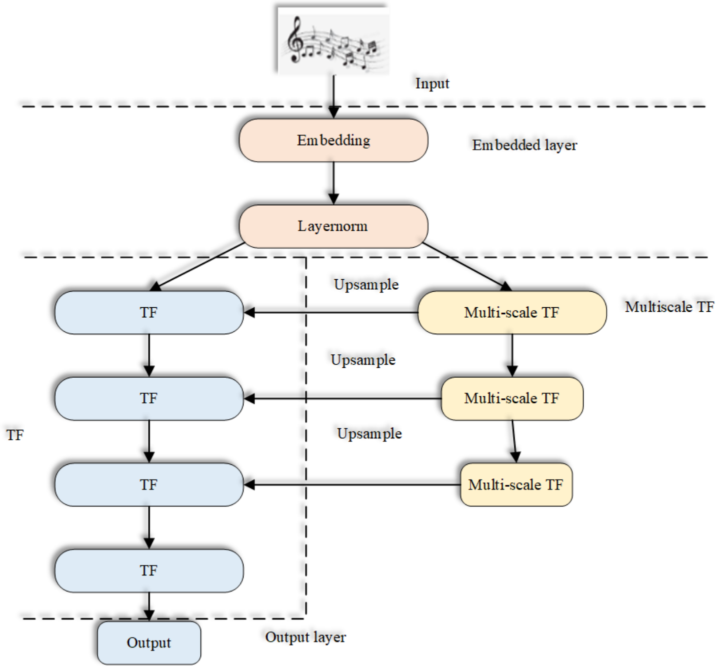

Fig. 3.2: Multi scale based automatic composition model for music teaching in colleges and universities.

Table 3.2: Metadata discretization result.

0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0
0	1	2	3	0	1	2	3	0	1	2	3	0	1	2	3
6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

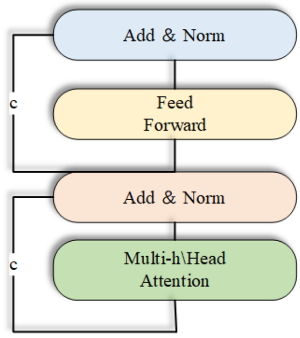

Fig. 3.3: Translated decoder unit.

of masked attention allows masking future information so that the Transformer only focuses on information from the current and previous moments. When applied to the automatic composition task, the relative position information between notes is also taken into account, so the attention mechanism used in the Transformer part adds a relative position representation.

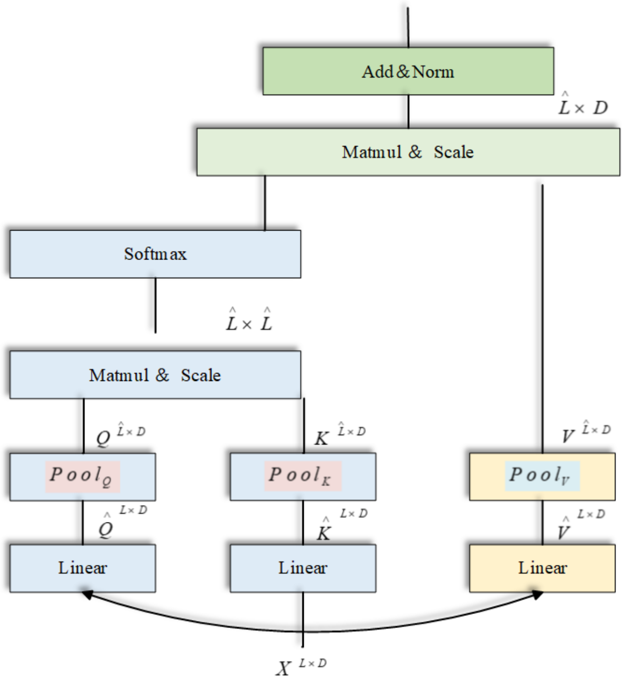

Fig. 3.4: Operation Model of Pool Attention Mechanism of Composing Technology in College Music Teaching.

To capture more relevant information, this section captures relative information in the metadata by extending the relative position representation. Since music has multiple attributes, such as time, pitch, instrument, etc. Therefore, in the model, the relative embedding of time and pitch is represented by R_t and R_p, where R_t indicates how many different sixteenth notes are between two positions and R_p indicates the difference in pitch values between notes at two positions. Therefore, the matrix representing the relative distance between any two vectors is rewritten as $S_{rel} = Q\left(R^{\top} + R_t + R_p\right)$.

The core of the multi-scale Transformer proposed in this paper is the multi-head pooling attention (MHPA) mechanism, which is a self-attentive operation mechanism that allows the Transformer unit to flexibly vary the resolution after replacing the MHA in the Transformer with MHPA. MHPA reduces the length of the sequence to be processed by pooling the input sequence. Fig. 3.4 illustrates the operational flow of the pooled attention mechanism.

In summary, the pooling attention is calculated as shown in (8) and (9). The experiments are taken,The optimization equation is obtained as:

$$Q = \left(\hat{Q}; \Theta_Q\right), K = \left(\hat{K}; \Theta_K\right), V = p\left(\hat{V}; \Theta_V\right) \tag{3.2}$$

$$PA(Q,K,V) = Soft\max\left(\frac{QK^{\top}}{\sqrt{d_k}}\right)V \tag{3.3}$$

The final output of multi-head pooled attention is obtained by considering h heads computed in parallel, each head computing pooled attention on a non-overlapping subspace of dimension D/h , and then concatenating the output results and performing one more linear transformation.

As shown in Fig. 3.5. In the training phase, G_i was trained jointly with D_i , and G_i was updated once after each K training sessions D_i , as described in the previous subsection. $K = 1$ was taken in the experiment.

The idea of GAN is also introduced after training to improve music by means of adversarial learning. Generative and discriminative models are constructed separately for each voice, with the same model structure

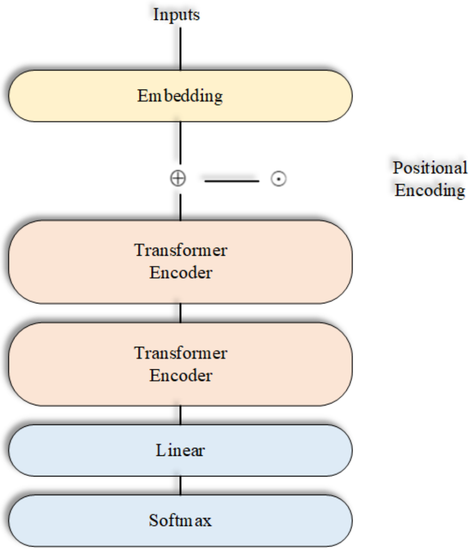

Fig. 3.5: Distinguishing Network Structure.

Table 3.3: Pseudocode for optimization of composition technology model in music teaching in colleges and universities.

Algorithm 3:	Generation algorithm 2 when training GAN
Input:	Four part note sequence V^i with length T, metadata M^i , probability distribution $p_\theta^i, i = 1, ..., I$ iteration number M
Output:	I-part note sequence V^i
1	Random initialization with uniform distribution V^i
2	For m from 1 to m do
3	Randomly select time point $t, t \in \{1, ...T\}$
4	Generate new value of V_t^i from $p_\theta^i \left(V_t^i \mathrm{I} V_{/i,t}, M^i\right)$
5	End fol
6	Return V^i

but no shared parameters. The generative model is a modified DeepBach, and the discriminative model. The pseudo-code of the generative algorithm using GAN to train the model corresponding to one voice part, using real data for the other three voices, and using G_i generation V^i is shown in Table 3.3.

The composition model studied in this paper is output in the form of probability distribution, so it is necessary to explain the sampling algorithm. V_t^i A more straightforward approach is to select the one with the highest probability, but in practical tests it has been found that this sampling approach leads to a lack of variation in the music. Therefore, this paper uses a combination of temperature sampling and top-p sampling. Fig. 3.6 shows the flow from the model output probability distribution to the sampling to get the notes.

In fact, two baseline models are trained in this section to compare with the model proposed in this paper in terms of objective metrics, as well as to compare the improved DeepBach model with DeepBach, in order to compare the multiscale design and the efficacy of relative time and relative pitch information addition. Subjective voting is used to assess the many models created by subjective experiments, which remain the best option for evaluating the generated models. Subjective voting is used to compare the musical compositions produced by various models in terms of quality.

Each model is trained separately for each of the four voices and abbreviated as S, A, T, B. Following the

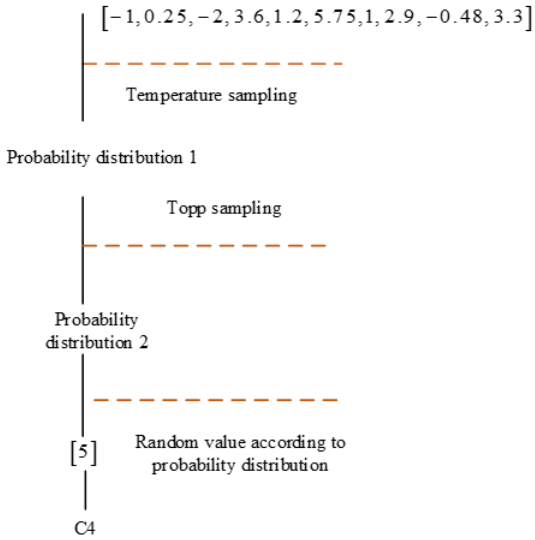

Fig. 3.6: Sampling Process of Composing Technology Model Dataset in College Music Teaching.

Table 4.1: Results of Experiment 1.

TF	0.51/0.56/0.47/0.65	0.5475
TF_REL	0.50/0.53/0.42/0.57	0.505
MTF_FT	0.44/0.50/0.39/0.57	0.475
MTF_GAN	0.42/0.50/0.35/0.55	0.455

parameter notation of section 3, the input sequence length of the model is $T = 128$, and the word embedding dimension $emb\_\dim = 16$ during the training phase. In order to judge the quality of the music generated by the model designed, the following four experiments were designed.

4. Case study. Four experiments are conducted in this paper, the first one is to compare the NLL of each model, and Table 4.1 shows the final experimental results.

Observing Table 4.1, we can know that the experimental results of the four vocal counterpart models of MTF_GAN are better than the other three, and the second vocal model of MTF_FT also reaches the optimum. The experimental results can basically illustrate the effectiveness of the multi-scale Transformer automatic composition model combined with GAN training approach proposed. In addition, comparing the results of TF and TF_REL can also illustrate the effectiveness of adding relative time and relative pitch to the Transformer.

The second one is a manual evaluation experiment. Fig. 4.1 shows the results of each model and the original Bach compositions voted as conforming to Bach's compositional style.

In Experiment 3, we built a hidden 6-layer network connection layer in the running mode of the optimization algorithm, and output the position of GRC in the first layer, then adjust the compression vector value to the interval (0, 1), and calculate the possible probability of each note output. After 12 tests, take the average value to get the test results as shown in Table 4.2 and Table 4.3.

In Experiment 4, the prediction model trained during the composition process generates a pitch for each prediction based on the input initial sequence, as shown in Fig. 4.2.

Combining the above one-part melody, the diatonic melody generated by the diatonic melody composition method designed in this paper is shown in Fig. 4.3.

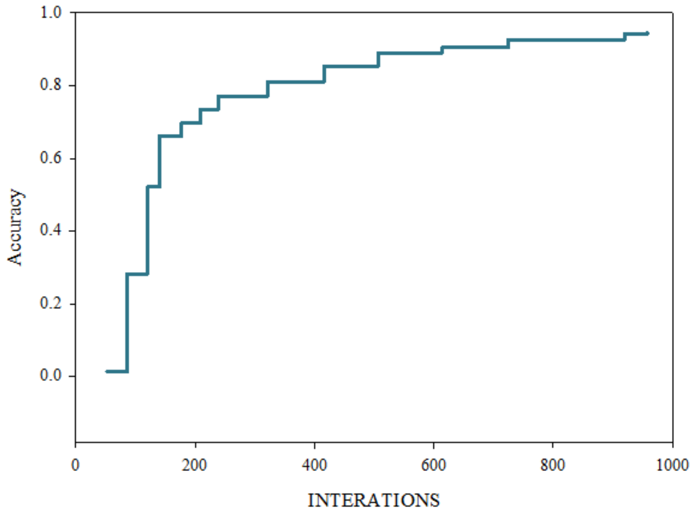

Fig. 4.1: The influence of the number of evaluation iterations on the training effect in Experiment 2.

Table 4.2: Effect of different number of neurons on accuracy in experiment 3: single layer hidden layer.

Number of neurons	128	256	512
Training set accuracy	82.39%	86.99%	97.23%
Test set accuracy	80.32%	81.39%	85.77%

Table 4.3: Effect of different number of neurons on accuracy in experiment 3 and 2 hidden layers.

Number of neurons	128	256	512
Training set accuracy	96.11%	97.47%	98.99%
Test set accuracy	84.31%	85.29%	86.53%

In this experiment, we need to further verify the accuracy and fit of the algorithm, so we will compare the composition structure optimized by this model with the relevant experiments in Google Lab, as shown in Table 4.4.

From the experimental results that, compared with other models, the algorithm model of composition technology for college music teaching designed in this paper is relatively high in F1 value, accuracy and fit, and relatively low in loss rate. Therefore, the previous experimental results can prove the excellence of our model. In addition, we also need to consider the chromatogram fitting degree to judge whether the music fitting conforms to the expected assumptions. We can get the optimized mathematical model and simplify it as:

$$V_{tr} = \sum_{i=1}^{k} V_i / \sum_{i=1}^{12} V_i, V_1 > V_2 > ...V_{12} \tag{4.1}$$

Then, based on this mathematical formula, we can judge the significant differences between different pieces of music generated in the whole model. This distribution difference shows a positive correlation with the chromatographic vector distribution. We name the scales C, D, E, G and A, and then judge the pitch contrast and energy distribution. It can be found that the C major scale occupies the largest weight, as shown in Table 4.5, which means that the model receives timbre, pitch Melodic beat and other influences.

As shown in Table **??** and Fig. 4.4, the calculation of composition technology model in college music

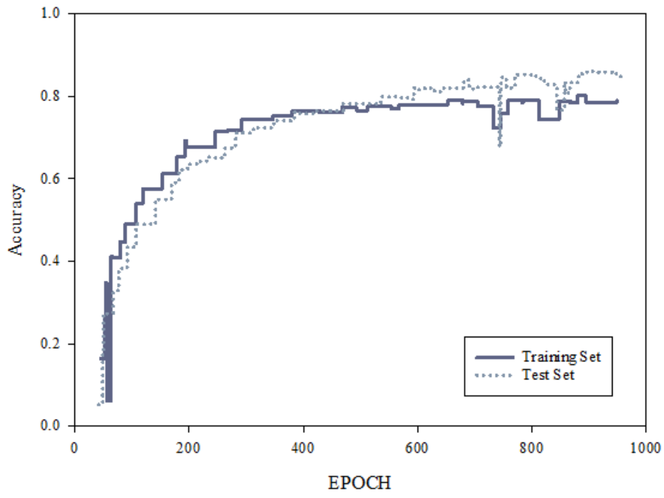

Fig. 4.2: Accuracy change process of training set and test set in Experiment 4.

Fig. 4.3: Two part Melody Created by Composing Technology Model in College Music Teaching.

teaching shows that when K=5, the contrast generated by this model is relatively high, which means that this model is more suitable for folk music teaching. For other types of music teaching and music output, more training sample sets are needed to arrange the internal structural relationships.

5. Conclusion. At the same time musical composition has existed since its emergence as a strong profession. In order to further expand the breadth and depth of music teaching in colleges and universities, and fully combine the forms of human-computer interaction, intelligent platform and edge computing with the art of music, this paper proposes a new network model for computer composition based on the LSTM model for improvement, which is proposed mainly to solve the chord repetition rate in generating chord music and the style problem of generating chord music, after the experimental results The accuracy of the test set on the proposed model reached 88%, and the music teaching and composition technology model designed in this paper is more suitable for fitting national style music.

Table 4.4: Comparison of accuracy and loss rate of algorithm model.

Network model name	Accuracy	Loss rate
Basic_ rnn	96%	0.07
Mono_ rnn	84%	0.36
Attention_ rnn	81%	0.46
Composing Model	99%	0.75

Table 4.5: Chromatographic Contrast Calculation Results of Composing Technology Model in College Music Teaching.

Song Name	Chromatographic contrast V_{tr}
Only folk songs for relatives	0.99
Basic_ Rnn Generate Songs	0.95

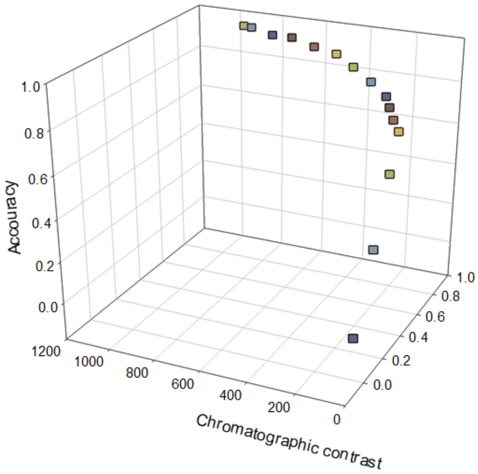

Fig. 4.4: Chromatographic contrast thermogram of composition technology model in college music teaching.

Data Availability. The experimental data used to support the findings of this study are available from the corresponding author upon request.

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