International Journal for Housing Science and Its Applications

Publish September 9, 2025. Volume 47, Issue 1 Pages 657-664

https://doi.org/10.70517/ijhsa47157

In an era where art and technology converge, artificial intelligence is driving the development of musical aesthetics and transforming aesthetic perception

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Abstract In the era where art and technology converge, the application of artificial intelligence in the field of music is becoming increasingly widespread. This paper constructs a music generation model using the Transformer, which is based on the self-attention mechanism, as the primary network architecture. Music style is measured using indicators such as chord histogram entropy, chord notes, non-chord note ratio, and style adaptability. This paper selected 10 new MIDI music pieces as research subjects to evaluate the Transformer model and explore its reliability. The results show that the performance of the model used in this paper is superior to that of other models. Other models still lag behind the Transformer model by 3% to 15% in terms of musicality metrics, demonstrating the superiority of the Transformer-based music model.

Index Terms aesthetic perception, Transformer model, self-attention mechanism, artificial intelligence, style compatibility

I. Introduction

With the continuous advancement of technology, artificial intelligence (AI) has gradually permeated various fields, including the music industry. The application of AI in the music industry not only provides music creators with more creative tools and inspiration but also offers music enthusiasts a richer and more diverse listening experience. Additionally, it has driven transformations in music aesthetics and aesthetic perception [1]-[4].

In the field of music creation, AI technology can simulate the characteristics of different music styles and blend them together to create novel and unique musical works [5], [6]. By analyzing and learning from large amounts of music data, AI can identify the features of different music styles and combine and transform them to create one-of-a-kind musical works [7]-[9]. This fusion and innovation of musical styles provides music creators with more creative possibilities and offers music listeners a wider range of musical choices [10], [11].

At the same time, AI technology can provide personalized creative support to creators based on their individual musical preferences and creative styles [12], [13]. By analyzing individual music preferences and creative styles, AI can generate music works tailored to individual needs and provide corresponding creative suggestions [14]-[16]. This personalized music creation not only meets the personalized needs of creators but also provides music enthusiasts with music works that better align with their tastes [17], [18].

AI has also had a profound impact on aesthetic experiences. AI technology can analyze an individual's music preferences and listening history to provide personalized music recommendations for music listeners [19]-[21]. Intelligent recommendation systems can recommend music works that align with an individual's preferences and listening history [22], [23]. This personalized music recommendation enables music listeners to discover and enjoy music works they love more conveniently [24], [25]. However, the application of AI in the fields of music and art also presents some challenges [26]. First, whether AI-created music and artworks possess true artistic value is a question that remains to be explored [27], [28]. Second, the application of AI may lead to the disappearance of some traditional art forms, and how to balance tradition and modernity is also a question that requires consideration [29], [30].

This paper employs the Transformer model, using self-attention mechanisms as the core mechanism to screen out more effective information. By capturing the correlations between vectors, it calculates the attention weights at each position during the encoding process. The hidden vector representation of the entire sequence is obtained through the weighted sum, and the hidden representations of the input and output are calculated to generate AI music. Indicators such as chord histogram entropy, chord notes, non-chord note ratio, and style compatibility are used to measure music style. This paper uses 10 new

MIDI music pieces as research samples to evaluate the model. The effects of Transformer model composition and traditional neural network model composition are compared to verify its reliability.

II. Research on Artificial Intelligence Empowering Music Transformation

II. A. The Influence and Application Potential of AI in the Field of Music

The rapid development of artificial intelligence (AI) is profoundly impacting every aspect of human society. Traditional music education, which falls under the realm of liberal arts and fine arts disciplines, has long emphasized theoretical research, imitation of works, and technical training, remaining in a relatively closed state. This approach struggles to fully meet the demands of the digital age for versatile musical talent. To swiftly enhance interdisciplinary integration while preserving the uniqueness of artistic disciplines, technology emerges as the optimal external force in the new era.

In the 1960s, AI first entered the field of music education, presenting unprecedented possibilities. In early explorations, the development of electronic keyboard instruments and electronic synthesizers became landmark achievements. These devices simulate the timbre of various instruments, store fixed melodies and rhythms, are easy to operate, and intelligent, providing students with opportunities for personalized creation and sharing, thereby stimulating their learning interest and musical creativity [31].

(1) In-depth exploration of intelligent music analysis

Initial intelligent music analysis primarily focused on the simple identification of notes and rhythms. With continuous technological upgrades, modern intelligent music analysis now possesses more advanced functionalities. Expansions into areas such as emotional analysis and melodic structure analysis enable AI systems to comprehensively understand students' cognition and expression of music. This deep exploration also opens up new possibilities for special music education. The system can accurately capture emotional changes in students' musical expressions, thereby better adjusting teaching strategies to meet diverse learning needs.

(2) Provision of personalized teaching plans

AI technology can tailor learning plans to meet the needs of each student. Individual differences are very significant in music teaching, and personalized teaching plans can design different types of interesting learning activities to stimulate students' interest and give them a profound learning experience, meeting the needs of different students. At the same time, accurate analysis of subject proficiency levels enables the system to provide learning content of appropriate difficulty for each student, ensuring that the teaching pace is neither too fast nor too slow, and improving the overall quality of music education.

(3) Promotion of intelligent music creation

With the continuous development of AI technology, intelligent music creation has become a highly regarded field. By training machine learning models, AI can generate relatively artistic musical works, providing students with more opportunities to participate in music creation. In traditional music creation, students may be limited by their own musical theory knowledge and creative experience, but with the introduction of AI technology, students can interact with the system to gain more creative inspiration and possibilities.

II. B. The Advantages of Artificial Intelligence in Enhancing Musical Aesthetics

(1) Improving music creation efficiency

The introduction of AI technology has significantly improved the efficiency of music creation. Traditional music creation often requires creators to invest a great deal of time and effort in conceptualization and creation, while AI can generate a large number of high-quality music works in a short period of time. This not only reduces the burden on creators, but also promotes the diversification and prosperity of music creation.

(2) Expanding the diversity of musical aesthetics

AI can generate music works in various styles and genres, greatly expanding the diversity of musical aesthetics. By integrating musical elements from different cultural backgrounds, AI can create novel and unique musical styles, bringing listeners an unprecedented aesthetic experience. This cross-cultural integration not only enriches the connotation of music art, but also promotes the exchange and dissemination of global music culture.

(3) Providing personalized music experiences

AI-based music recommendation systems use advanced algorithms to deeply analyze users' listening habits and preferences, thereby providing highly customized music content. This personalized experience not only significantly enhances user satisfaction but also effectively broadens users' aesthetic horizons. AI systems learn users' responses to different musical elements, such as melody, rhythm, and lyrics, and intelligently recommend tracks that align with users' emotional states and contextual needs.

(4) Supporting music education and research

AI technology is playing an increasingly important role in music education and research. AI can not only analyze complex musical works to help students understand music theory, harmony, and melody composition, but also enhance learning efficiency and engagement through interactive learning tools. In research, AI applications facilitate music pattern recognition, emotional analysis, and the restoration of historical musical works, providing music scholars with unprecedented depth and breadth in their research. Additionally, AI-assisted music composition tools inspire students' creativity, enabling them to discover new forms of musical expression through experimentation and exploration, thereby driving innovative development in music education and research.

III. Symbolic music generation based on Transformer

The Transformer abandons traditional CNN and RNN structures, relying solely on self-attention mechanisms to compute the latent representations of inputs and outputs. The Transformer adopts an encoder-decoder architecture, where the encoder module and decoder module are each composed of the same number of stacked encoders and decoders [32]. The basic architecture of the Transformer is shown in Figure 1. The encoder unit consists of a multi-head attention mechanism and a feedforward neural network. Similar to the encoder unit, the decoder unit also includes a multi-head attention mechanism and a feedforward neural network, but it has an additional layer of multi-head attention mechanism to focus on relevant parts of the input sequence. Additionally, residual connections are added to both the encoder and decoder units, denoted as "Add" in the figure, to prevent degradation issues during training of deep neural networks. Following this, layer normalization is applied to accelerate convergence, denoted as "Norm" in the figure [33].

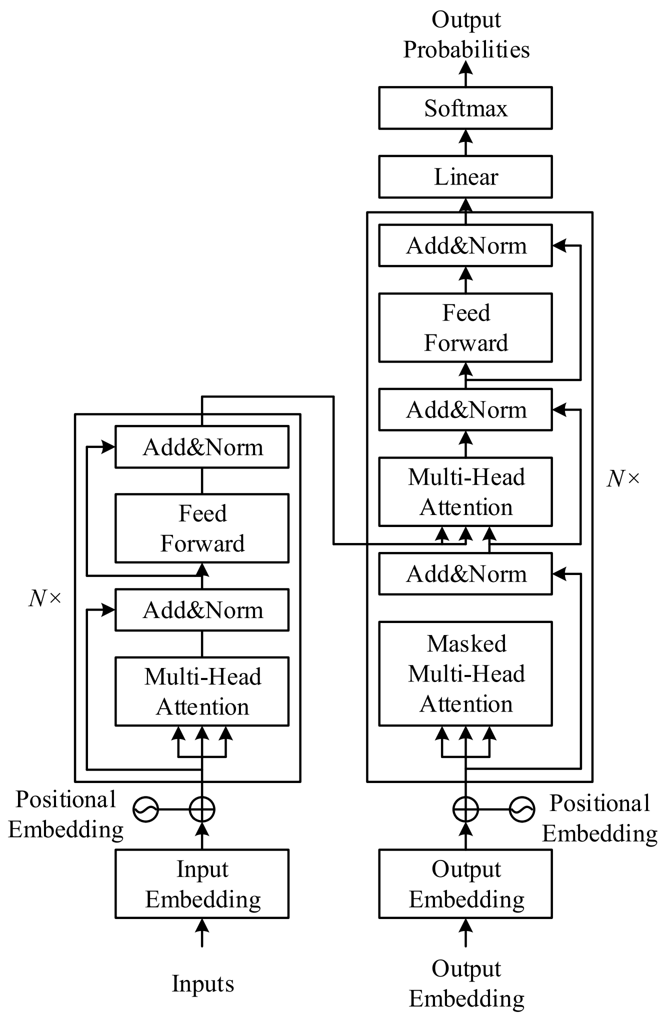


Figure 1: Basic Architecture of Transformer

The self-attention mechanism is the core mechanism of the Transformer, with the goal of filtering out more effective information. By capturing the correlations between vectors, it calculates the attention weights at each position during the encoding process and obtains the latent vector representation of the entire sequence through weighted summation. The computation process can be described as mapping the query vector and a series of key-value vector pairs to the output. The output vector is the weighted sum of the weights calculated based on the query and key applied to the value. The calculation formula is shown in Equation (1):

$$Att(Q,K,V) = softmax(\frac{QK^T}{\sqrt{d_k}})V \tag{1}$$

In equation (1), Q,K,V represent the products of the aforementioned vectors and their corresponding matrix parameters. d_k is the dimension of the vector Key. When the dimensions of two vectors are large, the variance of their dot product will also be relatively large, which may lead to the phenomenon of gradient vanishing. To maintain stable gradients during training, it is necessary to divide it by $\sqrt{d_k}$. Compared to LSTM neural networks, Transformers have stronger capabilities for modeling long sequences. In addition, Transformers can utilize self-attention mechanisms to achieve parallel computing, significantly improving the training speed of the model.

Since music has different dimensions such as time and pitch, the relative positional relationships in music sequences are particularly important for modeling. Based on this, using the original Transformer architecture as a baseline, we introduce a relative attention mechanism (RA) with relative position encoding and further improve its algorithm to capture the relative positional relationships and long-term structures in music sequences. The calculation formula is shown in Equation (2):

$$RA(Q,K,V) = softmax(\frac{QK^T + S^{rel}}{\sqrt{d_k}})V \tag{2}$$

In equation (2), S^{rel} represents the interaction between the relative embedding representation and the query vector, while the rest of the equation has the same meaning as the self-attention mechanism formula.

The experiment used two datasets, JSB-Chorale and IMAESTR-O, to represent music as a series of discrete symbols in different ways. For the former, a matrix is used for representation, with matrix rows corresponding to four different voice parts and columns corresponding to discrete sixteenth notes. For the latter, MIDI events are used to represent the data. The experiments achieved better results on the MAESTRO dataset, generating piano music with relatively consistent themes and long-term structure, with sequence lengths of approximately 2,000 notes.

IV. Aesthetic evaluation of generated music

Harmony is primarily manifested through two aspects: the accompaniment of the melody by chords and harmonic progression. The evaluation metrics for generating musical harmony primarily include three categories: chord histogram entropy (CHE), the ratio of chord tones to non-chord tones (CTnCTR), and chord pitch scores. Chord histogram entropy is calculated by normalizing the histogram of a chord sequence containing c elements and then computing its entropy. The formula is shown in Equation (3):

$$CHE = -\sum_{i=1}^{c} p_i \ln p_i \tag{3}$$

In equation (3), p_i represents the relative probability of the i th element appearing in the chord sequence. This indicator can intuitively evaluate the chord situation in the sequence. The fewer chords used in the sequence, the lower the value.

The specific calculation formula for the ratio of chord tones to non-chord tones is shown in equation (4):

$$CTnCTR = \frac{n_c + n_p}{n_c + n_n} \tag{4}$$

In equation (4), n_c is the number of chord tones in the sequence, n_n is the number of non-chord tones in the sequence, and n_p is a subset of the number of non-chord tones n_n in the sequence. The closer this value is to 1, the more harmonious the chords in the sequence are.

The chord pitch score quantifies the chordal properties of the sequence through a scoring system, as follows: For monophonic pitches, major/minor thirds, major/minor sixths, and perfect fourths/fifths in the sequence. The score is set to 1 for perfectly consonant intervals such as perfect unisons and perfect octaves, and 0 for other dissonant intervals. Additionally, in terms of style consistency, the style compatibility metric is used to assess whether the generated music aligns with the desired style. This is achieved by calculating the style configuration of the output sample and comparing it with the style configuration of the reference sample to determine if the output music matches the desired style. Generally, the higher the style compatibility between the output sample and the specified sample, the closer the styles of the two are. To better quantify the style configuration of the sample, a label is introduced. The style configuration of the sample is a vector obtained by flattening the standardized 2D histogram of the label in a specific manner. The specific calculation formula is shown in Equation (5):

$$S = \{(t_b - t_a, p_b - p_a) \mid a, b \in notes, a \neq b, 0 \leq t_b - t_a \leq 4, | p_b - p_a | \leq 20\} \tag{5}$$

In equation (5), t_i represents the start time of the i th note, while p_i is the MIDI number of the i th note.

V. Experimental Results and Analysis

V. A. Model Training Evaluation

Evaluating the quality of a piece of music is a subjective process, as everyone has different perceptions and preferences when it comes to music. However, certain criteria can be used to assess the quality of music, which can help people better understand and appreciate it.

First, melody and harmony are very important. A good melody should be able to capture the listener's attention and bring them joy and excitement. Harmony should be harmonious, creating a sense of comfort and relaxation. Second, rhythm and tempo are also crucial. A good rhythm should be able to inspire excitement and motivation, while a good tempo should provide stability and reassurance.

In addition to the musical elements themselves, the performance and singing of the music are also very important. A good performance or singing should allow the audience to feel the emotions and ideas of the music, making them feel a sense of resonance and emotion. Additionally, the recording and production of music are also very important. A good recording and production should make the music sound clear, clean, and high-quality.

Finally, when evaluating the quality of a piece of music, its innovation and uniqueness should also be considered. A good musical work should make people feel fresh and interesting, making them feel that it is one-of-a-kind. In this paper, 20 professional listeners will be selected, who have experience in playing musical instruments or are seasoned music enthusiasts; and 20 ordinary listeners, who have never played any musical instruments, will be asked to evaluate different works. The aesthetic weight of professional listeners is 1.5 times that of ordinary listeners. The average score obtained according to this scheme is the artificial score for a particular piece of music.

To compare the differences between AI aesthetic evaluation and human aesthetic evaluation, we conducted an experiment. This paper selected 10 new MIDI music pieces and informed the listeners in advance about the characteristics of MIDI music, thereby excluding factors such as emotion and timbre. These music pieces were then submitted to both AI and listeners for aesthetic evaluation. The detailed aesthetic evaluation results are shown in Table 1. As can be seen from the table, there are also differences in aesthetic evaluation among different listeners. Professional listeners showed significant differences in aesthetic evaluations of different pieces of music and tended to prefer more complex music. Ordinary listeners, on the other hand, were more enthusiastic about lively melodies and chords and were less inclined to give scores with significant differences. Additionally, while there are some differences between AI aesthetic evaluations and those of listeners, the overall differences are not significant. AI scores are closer to those of professional listeners, indicating that ordinary listeners' aesthetic evaluations are more subjective and easily influenced by personal emotional factors or differing preferences. This suggests that AI aesthetic evaluations and human aesthetic evaluations can complement each other, providing more comprehensive and accurate results for music scoring.

Table 1: Different iterations of the music score

Music	Style	Professional audience score	Average audience score	Final score	Model score
MIDI1	Gloom	93.7	90.4	92.5	93.6
MIDI2	Gloom	93.5	91.7	92.9	94.5
MIDI3	Warmth	88.5	90.3	89.4	87.9
MIDI4	Warmth	93.6	93.4	93.7	92.9
MIDI5	Brightness	85.8	93.4	89	87.7
MIDI6	Brightness	89.1	93.6	91	90.5
MIDI7	Enthusiasm	89.3	91.3	90.2	90.5
MIDI8	Enthusiasm	90.2	91.3	90.8	90.6
MIDI9	Peace	90.3	90.5	90.5	90.4
MIDI10	Peace	94.7	91.2	93.4	93.7

Specifically, the training termination time is controlled by adjusting the number of iterations of the Transformer model. When the loss function reaches a certain threshold, training is stopped and music is generated. Defining this threshold becomes a key issue. Since there are already two methods for evaluating the quality of a MIDI piece of music, training can be stopped at different iteration counts, and different pieces can be generated according to the same rules. By scoring the different pieces, the iteration count with the highest score can be identified. For each iteration count, different pieces are selected, and their average scores are taken. The results are shown in Table 2.

Table 2: Different iterations of the music score

Iteration number	Artificial score	Model score	Number of music
10k	Ungraded	/	3
15k	Ungraded	64.7	3
20k	61.4	64.2	4
25k	63.3	66.8	5
30k	66.5	70.0	7
35k	73.8	72	8
40k	75.2	78	9
50k	78.6	80	6
60k	77.4	73.4	6
80k	73.6	73.1	6
100k	73.9	73.6	6

V. B. Comparison of results from different models

To compare the performance of Transformer models and traditional neural network models in music composition, this paper uses both models to expand the same musical segments and evaluates the aesthetic quality of the generated music. The selected segments range from 2 to 32 seconds in length. Six short musical segments of varying lengths were selected for expansion. It can be observed that as the original segment length increases, the music scores generated by both models also increase. The comparison results are shown in Table 3. Additionally, it is evident that the models used in this paper outperform those created using the Keras deep learning framework, with scores generally exceeding those of the Keras models by more than 10 points.

Table 3: Keras depth learning framework is compared to transformer model

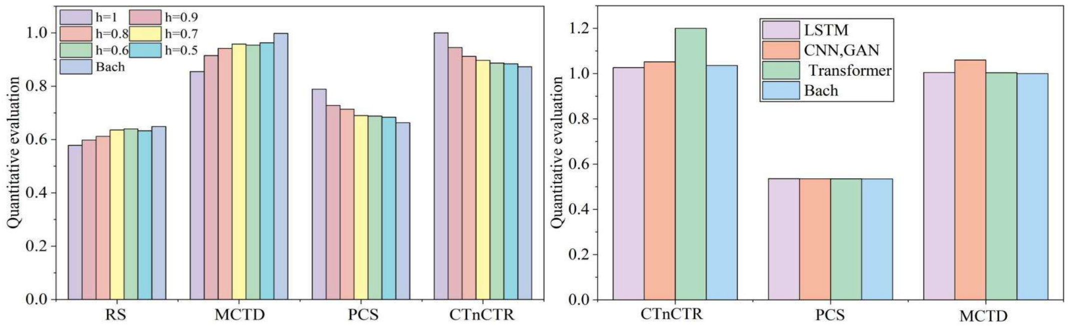
Music	Duration	Keras framework scores	Transformer model score	Fractional difference
Music 1	2s	63.3	76.3	12.2
Music 2	6s	64.5	75.5	11.3
Music 3	11s	65.2	77.8	12.0
Music 4	15s	65.3	77.4	12.4
Music 5	24s	65.0	77.5	12.2
Music 6	32s	66.9	78.9	12.4

V. C. Music Measurement Indicators

Experiments on validation set accuracy cannot fully prove the superiority of the model, as the harmony in music is more closely related to human auditory experience due to the unique nature of music.

This paper uses three metrics—string, melody, and harmony—to measure musicality. The models compared were trained on different datasets using three types of models: Transformer, LSMT, CNN, and GAN, and were compared with Bach's original work metrics. The experimental results demonstrate that all three models are nearly identical to Bach's original work in terms of musicality metrics, as shown in Figure 2. Due to differences in experimental parameter settings, the metrics in this paper cannot be compared across models. However, when compared to Bach's original work, the models proposed in this paper are nearly identical to Bach's metrics under the current evaluation metrics (with an error margin of less than 2%). The Transformer model still has a 3% to 15% gap in musicality metrics compared to Bach's original works, demonstrating the superiority of the Transformer-based music model. In the task of providing harmony for a given melody, the model proposed in this paper is already very close to the level of human composers. Among them, the RS metric is a quantitative evaluation of the generated music by professional musicians, normalized to a range of 0.2 to 1. h is the gamma sampling coefficient. The ratio of chord tones to non-chord tones (CTnCTR). Melody-chord tone distance (MCTD). Note-chord consistency score (PCS).

This paper measures the musicality of generated choral music. We selected Bach's choral music from the test set to compare the metrics of the generated music, with the input being the notation of Bach's samples. The closer the metrics of the generated music are to those of Bach's original work, the better the metrics. The figure shows that in terms of the metric measuring the match between generated notes and chords, the generated samples are already very close to Bach's original work. The model fits different harmonic distributions, leading to some dissonance in the generated harmonic relationships. After transposition, the model's input pitches are only shifted up or down, and the interval relationships remain unchanged, while interval relationships are directly related to harmony.



(a)Musical metric representation (b)Comparison of indexes

Figure 2: metrics for music

VI. Conclusion

Artificial intelligence is emerging as a key driver of transformation and creation in music. This paper establishes a Transformer model that uses self-attention mechanisms to calculate inputs and outputs, thereby creating appropriate music. By evaluating and comparing performance with representative models, the paper reveals the positive role of artificial intelligence in advancing musical aesthetics and aesthetic perception. Research indicates that the model proposed in this paper, when combined with human aesthetic judgment, can provide more comprehensive and accurate results for music scoring. When comparing different models, it is evident that the Transformer model used in this paper outperforms other models in terms of the quality of the music they generate. Additionally, under current evaluation metrics, the model achieves results comparable to those of Bach's works, with an error margin of less than 2%.

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