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An Exhaustive Survey to Understand Music Generation based on Artificial Intelligence

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ABSTRACT

Music generation is a creative process that requires the ability to understand melody, rhythm, harmony, structure, and emotional expression. Although music has long been viewed as a human-centered artistic domain, the development of Artificial Intelligence has opened new opportunities for automatic music generation with minimal human intervention. **This study aims** to analyze the use of AI algorithms in music generation, identify commonly used approaches, and examine existing gaps in producing high-quality musical compositions. The study reviews several **AI-based methods,** including recurrent neural networks, Deep Composer, WaveNet, memetic algorithms, generative adversarial networks, reinforcement learning, and transformer-based models. In addition, publicly available music datasets and GAN-based synthetic data generation are considered to support the training process. The **findings** indicate that deep learning models are effective in learning musical patterns, while reinforcement learning and transformer-based preprocessing can improve sequence understanding, adaptability, and structural coherence. However, current models still face challenges in duplicating specific artist styles, maintaining complete song structure, and generating music with strong uniqueness. Therefore, integrating deep learning, reinforcement learning, GAN-based synthetic data, and transformer preprocessing offers a promising direction for improving AI-generated music quality and supporting future research in automatic music composition.

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1. INTRODUCTION

Technological advancements have made human life easier and more efficient. With the emergence of Artificial Intelligence, many tasks can now be performed automatically with minimal human intervention [1]. AI has been widely applied in various fields, including e-commerce, education, healthcare, robotics, gaming, social media, finance, marketing, and digital content creation. However, its application in automatic music generation still requires further exploration because music is not only based on technical patterns, but also involves creativity, emotion, rhythm, melody, harmony, and artistic expression [2].

Automatic music generation refers to the process of composing musical pieces using computational models and intelligent algorithms with minimal human involvement [3]. The use of AI in music generation provides several advantages, such as reducing production costs, accelerating the composition process, and supporting creative experimentation. Nevertheless, generating music through AI remains challenging because musical creativity requires an understanding of music cognition, performance context, human emotion, and long-term musical structure. Therefore, AI-based music generation must be able to produce compositions that are not only technically correct, but also meaningful, coherent, and pleasant to listeners.

This study is also aligned with the Sustainable Development Goals (SDGs) [4], particularly SDG 3 on Good Health and Well-being, SDG 4 on Quality Education, SDG 8 on Decent Work and Economic Growth, and SDG 9 on Industry, Innovation, and Infrastructure. AI-generated music can support well-being through therapeutic, relaxation, and emotional support applications. It can also improve creative learning by helping students, musicians, and content creators explore music composition more easily [5]. In addition, the development of AI-based music systems can strengthen innovation in the creative industry and open new opportunities for digital music production, content creation, and intelligent entertainment technology.

Based on [6], several AI models have been used for music generation, including Recurrent Neural Networks, Deep Composer, WaveNet, memetic algorithms, Generative Adversarial Networks, reinforcement learning, and transformer-based models. However, existing studies still show several limitations, such as difficulties in producing complete songs with strong structure, maintaining uniqueness, and duplicating the style of a specific artist. Therefore, this study aims to provide an analytical review of AI algorithms for automatic music generation and identify possible improvements through emerging technologies such as deep learning, reinforcement learning, GAN-based synthetic data generation, and transformer preprocessing. The Study specifically aim to answer the following research questions:

- RQ1: Which AI algorithms are mostly used for generation of music? Which problem they aim to solve?
- RQ2: Identify the gaps which have not been addressed?
- RQ3: How the gaps can be addressed using emerging AI technologies? Also find dataset which have been used.

This study analyzes previous works related to AI-based music generation and proposes a hybrid approach that integrates deep learning, reinforcement learning, GAN-based synthetic data generation, and transformer-based preprocessing. This approach is expected to improve the ability of AI systems to learn musical patterns, generate more diverse compositions, and produce music with better structure, adaptability, and coherence. Therefore, the study contributes to the development of intelligent music generation systems and provides a foundation for future research in AI-assisted creative technology.

2. LITERATURE REVIEW AND RELATED WORK

2.1. Artificial Intelligence in Music Generation

Artificial Intelligence has become an important technology in supporting creative processes, including automatic music generation [7]. Automatic music generation refers to the process of composing musical pieces with minimal human intervention by using intelligent algorithms and computational models. In recent years, AI has been widely applied in various fields such as education, healthcare, robotics, e-commerce, gaming, and social media [8]. However, its application in automatic music composition is still developing and requires further exploration. Music generation is considered a complex task because music is not only built from sound patterns, but also involves rhythm, melody, harmony, emotion, and creative structure.

AI-based music generation offers several advantages compared to traditional music production. It can reduce production costs, accelerate the composition process, and assist musicians or content creators in producing new musical ideas. Nevertheless, the process also faces several challenges. Musical creativity requires a model that can understand music cognition, performance context, human emotion, and artistic expression. Therefore, AI models must be able to generate music that is not only technically correct, but also meaningful and pleasant to listeners [9].

2.2. Deep Learning Approaches for Music Generation

Deep learning has been widely used in music generation because of its ability to learn complex patterns from large datasets [10]. One of the common approaches is the use of Recurrent Neural Networks, which are suitable for processing sequential data such as melody and rhythm. RNN-based models are able to generate short musical sequences by learning note transitions and temporal relationships. However, these models still have limitations, especially in generating a complete song with clear structure, theme, and uniqueness [11].

To overcome these limitations, several advanced deep learning architectures have been developed. Hierarchical RNN is one example that uses different layers to generate different musical components. The lower layer can be used to generate melodies, while the higher layer can generate chords and drum patterns. This approach allows the system to create more structured music. In addition, WaveNet has also been applied to symbolic music generation. The use of dilated convolution layers in WaveNet helps the model encode musical structure more explicitly, resulting in better performance in generating musical sequences.

2.3. Deep Composer and Artist Style Duplication

Deep Composer is one of the important models in AI-based music generation. This model applies deep neural hashing and retrieval techniques to generate multi-instrument songs [12]. Unlike traditional models that only imitate a general music genre, Deep Composer attempts to learn how specific music segments are arranged. This makes the model more capable of producing music that reflects the style of a particular artist.

The concept used in Deep Composer is closely related to intelligent duplication. Intelligent duplication refers to the effort to artificially duplicate or clone the musical characteristics of a specific composer or artist [13]. For example, an AI model may attempt to learn how a composer arranges melodies, harmonies, and song structures. However, existing studies show that no AI model has fully succeeded in perfectly duplicating the unique style of a particular artist. This indicates that artist-style duplication remains an important research gap in AI music generation.

2.4. Generative Models in Music Composition

Generative models are also widely used in music composition because they are designed to create new data based on learned patterns [14]. One of the most popular generative models is the Generative Adversarial Network. GAN consists of two main components, namely the generator and the discriminator. The generator produces synthetic data, while the discriminator evaluates whether the generated data is similar to real data. In the context of music generation, GAN can be used to generate synthetic music data that supports the training process [15].

Besides GAN, other generative approaches such as CVAE-GAN have also been used in emotion-based AI music generation [3]. This model is useful for generating music that reflects specific emotional characteristics. The use of generative models is important because music generation requires creativity and variation. By using synthetic data and generative learning, AI systems can produce more diverse musical outputs and reduce dependency on limited original datasets.

2.5. Reinforcement Learning and Transformer-Based Music Generation

Reinforcement learning has strong potential in AI-based music generation because it allows the model to improve its output through reward-based learning [16]. In reinforcement learning, the system learns by taking actions and receiving rewards based on the quality of its decisions. This approach can be applied to music generation by evaluating whether the generated music meets certain criteria, such as rhythm consistency, melody quality, and structural coherence.

Transformer models also provide significant advantages for music generation. Unlike traditional sequential models, transformers are able to capture long-range dependencies more effectively through attention mechanisms. This ability is important because music often contains repeated patterns, long-term structure, and relationships between different musical parts. In the proposed study, transformer architecture is used as a preprocessing layer to prepare music data before it is processed by the deep learning and reinforcement learning architecture. This combination is expected to improve the quality, coherence, and creativity of generated music.

2.6. Research Gap

Based on [17–19], AI-based music generation has shown promising progress, but several research gaps remain. First, existing models still have difficulty generating complete songs with strong structure, theme, and uniqueness. Second, duplicating the style of a specific artist remains a major challenge because musical identity is influenced by complex creative and emotional factors. Third, many previous models use deep learning, reinforcement learning, GAN, or transformer architectures separately, while hybrid integration among these approaches is still limited [20].

Therefore, this study attempts to address these gaps by combining deep learning, reinforcement learning, GAN-based synthetic data generation, and transformer-based preprocessing. The integration of these approaches is expected to produce more adaptive and high-quality AI-generated music. This hybrid approach can also provide a stronger foundation for future research in automatic music composition, especially in improving musical structure, creativity, and style representation [21].

3. PROPOSED WORK

A deep learning model is proposed based on this study analysis of deep learning and reinforcement learning algorithms. Deep learning and reinforcement learning have different process flow so the study merged the architectures to get state of art results [22]. The study took help of public available data and merged it with synthetic generated data points to proceed [23]. These datasets contain symbolic and structured music data that can be used for training artificial intelligence models. Several public sources were considered, including music generation datasets based on LSTM, automatic music generator datasets, and variational autoencoder-based music datasets. These datasets were selected because they provide suitable input for training deep learning models in recognizing musical patterns, note sequences, rhythm, and structural characteristics. Datasets for music generation are as follows:

- https://www.kaggle.com/code/karnikakapoor/music-generation-lstm/data [24].
- https://www.kaggle.com/code/anubhavjin/automatic-music-generator-dl/data [25].
- https://www.kaggle.com/code/basu369victor/generate-music-with-variational-autoencoder/data [26].

After collecting these datasets, the data were organized into a hybrid dataset to support the proposed music generation model. The original datasets provide structured musical information, including note sequences, rhythm patterns, and melodic characteristics, while synthetic data generated through GAN is used to enrich data variation [23]. This combination is important because a more diverse dataset can help the model learn broader musical patterns and reduce dependency on limited original data sources. Therefore, the hybrid dataset becomes the main input for the deep learning and reinforcement learning architecture to generate more adaptive and structured music outputs. The synthetic data generation process used in this study is presented in Figure 1.

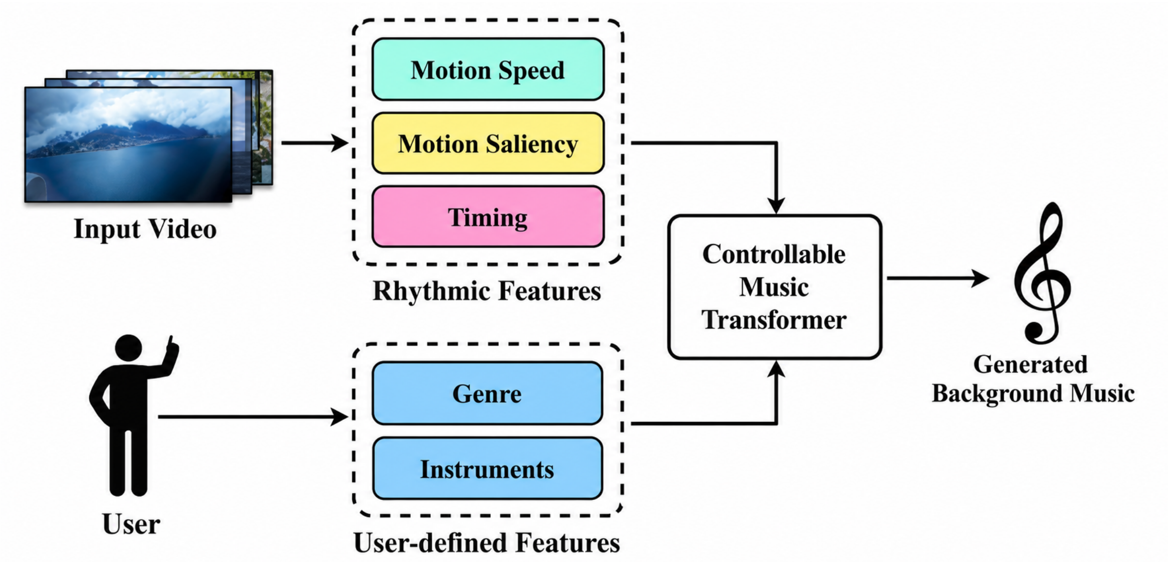

Figure 1. GAN Synthetic Music Data Generation

Figure 1 presents the GAN-based synthetic music data generation process. The model receives input from video data and user defined features to generate background music. Rhythmic features, such as motion speed, motion saliency, and timing, are extracted from the input video to capture movement patterns and rhythm context. Meanwhile, user-defined features, including genre and instruments, are used to control the style and characteristics of the generated music. These features are then processed by a controllable music transformer to produce background music that is more flexible, adaptive, and aligned with the intended musical context.

After the hybrid dataset is prepared through the combination of public music datasets and GAN-based synthetic data, the next stage focuses on processing the data using a deep reinforcement learning architecture. This stage is essential because the generated music output should not only follow learned musical patterns, but also maintain rhythm consistency, structural flow, and adaptive decision-making during the generation process. Deep learning is used to recognize complex musical features from the dataset, while reinforcement learning helps the model select appropriate actions based on feedback [27]. This process supports the development of more intelligent and adaptive creative technology, which is aligned with SDG 9 on Industry, Innovation, and Infrastructure. In addition, AI-based music generation can contribute to SDG 3 on Good Health and Well-being by supporting the creation of music for relaxation, emotional support, and digital therapeutic media. Therefore, the integration of neural networks and reinforcement learning provides a stronger foundation for generating music that is more coherent, adaptive, and beneficial for digital creative applications. The deep reinforcement learning architecture used in this study is presented in Figure 2.

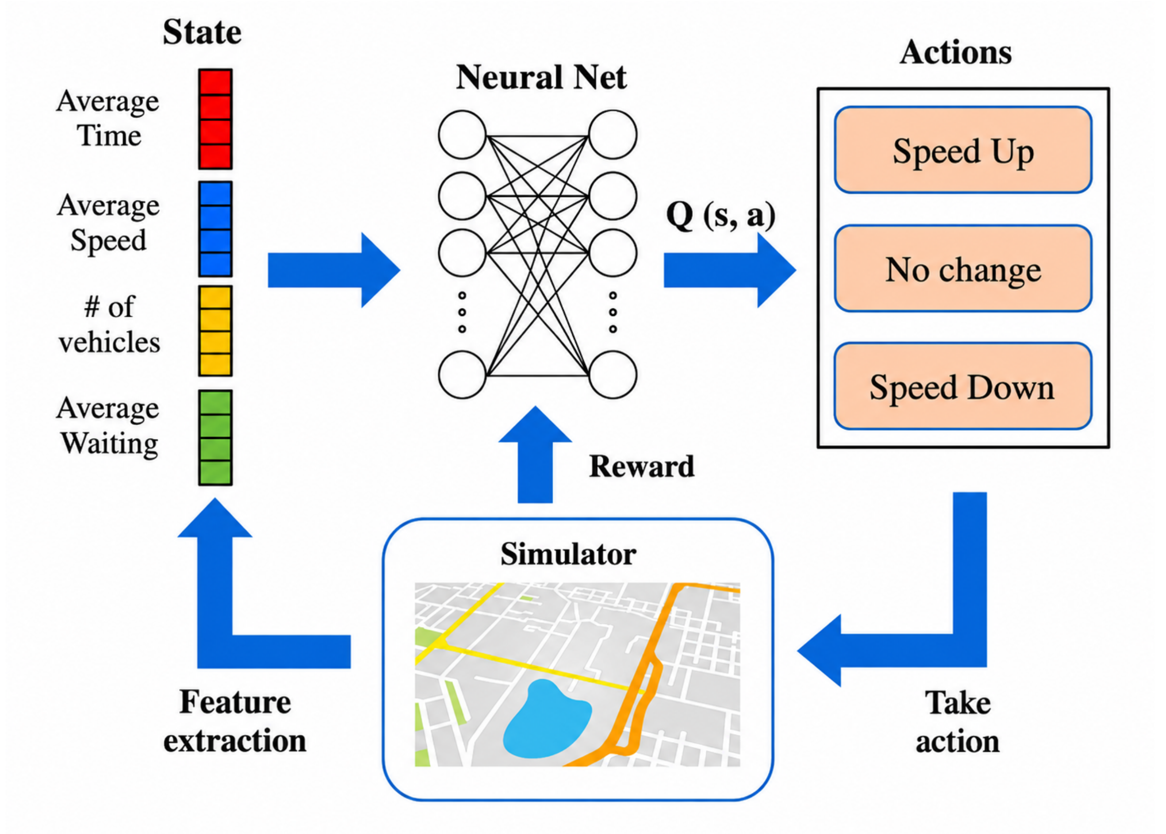

Figure 2. Deep Reinforcement Learning Architecture for Music Generation

Figure 2 presents the deep reinforcement learning architecture used to support the proposed music generation process. The architecture begins with feature extraction, where input characteristics are transformed into state representations. These states are processed by the neural network to estimate actions through the Q(s, a) function [28]. After an action is selected, the system receives a reward to improve the next generation process. In AI-based music generation, this mechanism helps evaluate musical consistency, sequence structure, and output quality [29]. This approach is relevant to SDG 4 because it can support music composition learning and creative AI education. It also supports SDG 8 by opening opportunities for digital music production, content creation, and creative industry innovation.

After the deep reinforcement learning architecture processes the hybrid dataset, the next stage applies a transformer model as a preprocessing layer to improve the representation of musical sequences. This step is needed because music data contains temporal patterns, note relationships, rhythm transitions, and long-term dependencies that must be understood before the generation process. By using transformer-based preprocessing, the model can organize input data more effectively and prepare stronger sequence representations for producing generated music samples. The transformer preprocessing layer used in this study is presented in Figure 3.

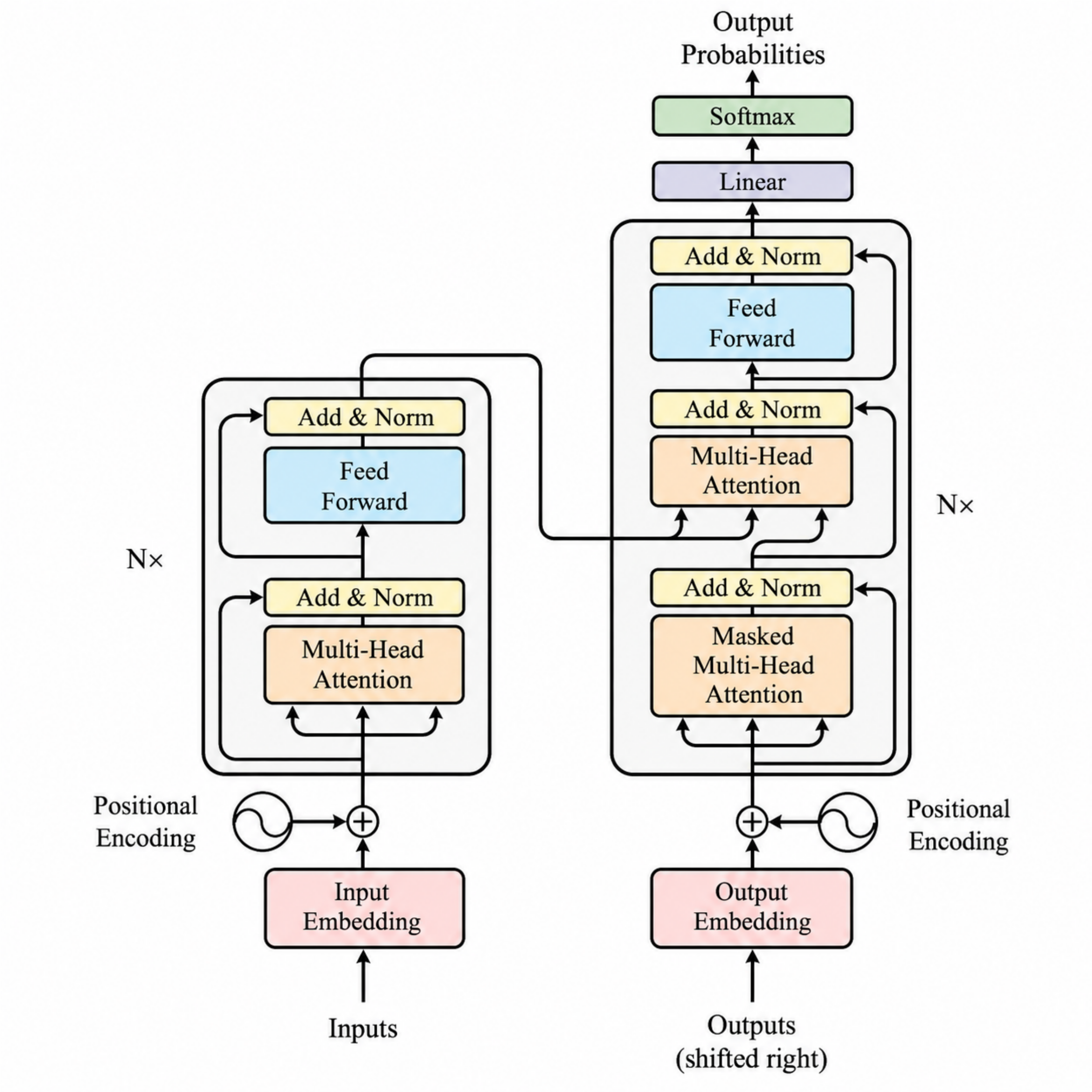

Figure 3. Transformer As Preprocessing Layer

Figure 3 shows the transformer architecture used as a preprocessing layer in the proposed music generation model. The process begins with input embedding and positional encoding, which help the model understand the order and position of musical sequences. The multi-head attention mechanism then captures relationships between different parts of the input data, while the feed-forward layer refines the extracted features. In the decoder section, masked multi-head attention and output embedding are used to process shifted outputs before generating output probabilities through linear and softmax layers. In this study, the transformer layer supports the model in learning complex musical structures, improving sequence understanding, and preparing data for more coherent AI-based music generation.

4. RESULT AND DISCUSSION

The results of this study indicate that artificial intelligence can be applied as a promising approach for automatic music generation by combining deep learning, reinforcement learning, GAN-based synthetic data generation, and transformer-based preprocessing. Based on [6], several AI models have been used for music generation, including Recurrent Neural Networks, Deep Composer, WaveNet, memetic algorithms, Generative Adversarial Networks, reinforcement learning, and transformer models. Each method contributes differently to the music generation process. RNN is useful for processing sequential melody patterns, WaveNet supports symbolic music generation, GAN helps generate synthetic music data, while transformer models improve the understanding of long-range musical relationships [30]. However, the findings also show that these models still face challenges in producing complete songs with strong structure, uniqueness, and artist-specific style representation.

Table 1. Comparative Analysis of AI-Based Music Generation Methods

Method	Main Function	Strengths	Limitations
RNN	Learns sequential note and melody patterns	Effective for sequence modeling and short melody generation	Weak in producing full-song structure, theme, and uniqueness.
Deep Composer	Retrieves and arranges music segments to mimic artist style	Supports multi-instrument generation and artist-style modeling	Cannot fully duplicate the unique style of a specific artist.
WaveNet	Encodes symbolic music structure using dilated convolutions	Improves structural encoding and sequence quality	Still limited in complete composition coherence.
GAN	Generates synthetic music data for training	Enriches data diversity and supports creative variation	Output quality depends on training stability and data quality.
Reinforcement Learning	Optimizes music generation through reward-based decisions	Improves adaptability, consistency, and decision-making	Requires suitable reward design and iterative training.
Transformer	Captures long-range relationships in musical sequences	Strong sequence understanding and structural coherence	Needs large data and higher computational resources.

Based on Table 1, each AI-based music generation method provides different contributions to the development of automatic music composition. RNN is effective for learning sequential note and melody patterns, but it still has limitations in producing complete songs with strong structure and uniqueness. Deep Composer supports multi-instrument generation and artist-style modeling, although it cannot fully duplicate the unique style of a specific artist. GAN contributes to synthetic music data generation, which helps enrich dataset diversity, while reinforcement learning improves adaptability through reward-based decision-making [31]. In addition, transformer models provide stronger sequence understanding by capturing long-range relationships in musical data. Therefore, the comparison shows that no single method is sufficient to address all challenges in AI-based music generation, making the hybrid integration of GAN, transformer, deep learning, and reinforcement learning a more promising approach for improving the quality and coherence of generated music.

The proposed approach addresses these limitations by organizing public music datasets and synthetic generated data into a hybrid dataset. This dataset supports the model in learning broader musical patterns, including note sequences, rhythm, melody, and structural characteristics. The use of GAN-based synthetic data improves data variation and reduces dependency on limited original datasets. As presented in Figure 1, rhythmic features and user-defined features are processed to generate background music that is more adaptive to the intended style. This result suggests that synthetic data generation can support the development of more flexible AI-based music generation systems.

The deep reinforcement learning architecture presented in Figure 2 further supports the music generation process through a reward-based learning mechanism. The model extracts important features, represents them as states, processes them through a neural network, and selects actions based on the Q(s, a) function. Through this process, the model can continuously evaluate and improve the generated musical sequence. This mechanism is important because music generation requires not only pattern recognition, but also decision-making to maintain consistency, rhythm, and structure in the generated output.

Furthermore, the transformer preprocessing layer presented in Figure 3 strengthens the model's ability to understand musical sequence relationships. Input embedding and positional encoding help the model recognize the order of musical elements, while multi-head attention captures relationships between different parts of the music data. This supports better sequence representation before the data is processed by the main generation model. Therefore, the integration of transformer preprocessing with deep learning and reinforcement learning can improve the coherence, adaptability, and structural quality of AI-generated music. To summarize the overall process, the proposed workflow connects dataset collection, GAN-based synthetic data generation, transformer preprocessing, deep reinforcement learning, and output evaluation. The complete workflow is presented in Figure 4.

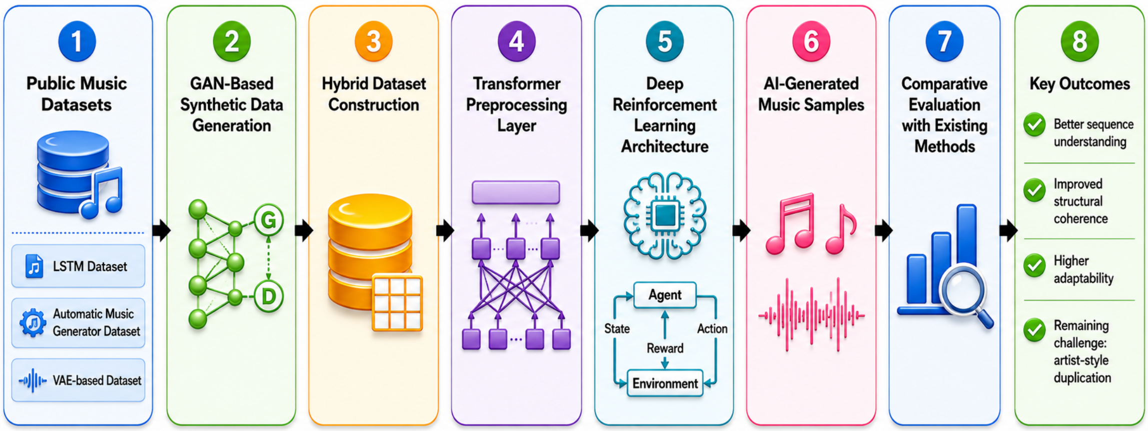

Figure 4. Proposed Hybrid AI Music Generation Workflow

Figure 4 presents the overall workflow of the proposed hybrid AI music generation model. The process begins with public music datasets, including LSTM-based, automatic music generator, and VAE-based datasets, which are then enriched through GAN-based synthetic data generation. The original and synthetic data are combined into a hybrid dataset to provide broader musical patterns for training. After that, the transformer preprocessing layer is applied to improve sequence representation and capture long-range relationships in musical data. The processed data are then used in the deep reinforcement learning architecture to generate AI-based music samples. Finally, the generated outputs are compared with existing methods to identify the main outcomes, including better sequence understanding, improved structural coherence, higher adaptability, and the remaining challenge of artist-style duplication. This workflow shows that the proposed hybrid approach provides a more complete framework for improving the quality of automatic music generation.

Overall, the results show that the proposed hybrid approach provides a stronger framework for automatic music generation compared to using a single AI model. The combination of GAN, transformer, deep learning, and reinforcement learning supports better data preparation, feature extraction, sequence understanding, and adaptive music generation. Nevertheless, this study still has limitations because the evaluation mainly focuses on architectural analysis and generated music samples. Future studies should include quantitative evaluation, expert-based listening tests, user perception analysis, and comparison with real musical compositions to measure the quality, creativity, and emotional value of AI-generated music more objectively.

5. MANAGERIAL IMPLICATIONS

The findings of this study provide practical implications for managers, digital music producers, creative industry practitioners, and AI-based application developers. The proposed hybrid AI approach can help organizations reduce the time and cost required to produce background music, especially for digital content, advertising, games, films, educational media, and online platforms. By using user-defined features such as genre and instruments, managers can develop more personalized music generation systems that match specific content needs. This can support faster creative production while still allowing human creators to guide the artistic direction of the generated music.

From a strategic perspective, AI-based music generation can become a valuable tool for companies that rely on large-scale content production. Managers can use this technology to create music prototypes, generate alternative compositions, and support creative experimentation before final production. However, implementation should be supported by clear policies regarding copyright, data ownership, artist rights, and ethical use of AI-generated content. Human supervision remains important to ensure that the generated music is appropriate, original, and aligned with the intended emotional and commercial purpose. Therefore, the adoption of AI in music generation should not replace human creativity, but should be positioned as a collaborative tool to improve efficiency, innovation, and creative decision-making in the music and digital media industries.

6. CONCLUSION

This study concludes that Artificial Intelligence provides a promising approach for automatic music generation by integrating deep learning, reinforcement learning, GAN-based synthetic data generation, and transformer-based preprocessing. The findings show that deep learning architectures play an important role in learning musical patterns, while reinforcement learning supports adaptive decision-making during the generation process. In addition, the use of public music datasets combined with synthetic data helps enrich musical variation and supports the development of more structured AI-generated music samples.

The proposed hybrid approach contributes to addressing several limitations found in previous AI-based music generation models. Existing methods still face challenges in producing complete songs with strong structure, uniqueness, and artist-specific style representation. By applying a transformer as a preprocessing layer, the model can better capture long-range relationships in musical sequences, while reinforcement learning helps improve consistency and output quality through reward-based evaluation. Therefore, this study provides a useful framework for researchers and practitioners working in the field of AI-assisted music composition.

For future research, further studies should conduct more comprehensive testing using quantitative evaluation metrics, expert listening assessments, and user perception analysis to measure the quality of AI-generated music more objectively. Future work can also explore more advanced architectures, such as explainable AI, diffusion models, and real-time interactive music generation systems. In addition, ethical issues related to copyright, artist-style duplication, and ownership of AI-generated music should be examined to ensure that the development of AI music generation remains responsible, creative, and beneficial for the digital music industry.

7. DECLARATIONS

7.1. About Authors

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7.2. Author Contributions

Conceptualization: BR; Methodology: AI; Software: NP; Validation: SP; Formal Analysis: BR and AI; Investigation: NP; Resources: SP; Data Curation: BR; Writing Original Draft Preparation: AI and NP; Writing Review and Editing: NP and AI; Visualization: SP; All authors, BR, AI, NP, and SP, have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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7.5. Declaration of Conflicting Interest

The authors declare that they have no conflicts of interest, known competing financial interests, or personal relationships that could have influenced the work reported in this paper.

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