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SYMPHONY OF CODE: THE INTERSECTION OF ARTIFICIAL INTELLIGENCE (AI) AND MUSIC COMPOSITION

Abstract

The advent of artificial intelligence (AI) has transformed various creative industries, but its impact on music composition is yet to be fully explored by most composers. Despite the creative abilities of composers, they find it difficult to bring their ideas and works to limelight due to lack of exposure on the use of AI. This study investigates the transformative role of machine learning in music generation, aiming to provide a comprehensive framework for understanding AI's application in the compositional process. Qualitative content analysis method was employed in this study. Findings revealed that hybrid AI Systems can be trained to understand and process the unique rhythmic, melodic, and harmonic nuances of African music. However, the Machine Learning Algorithm (MLA) falls short in capturing the musical nuances of African indigenous music, as it is limited by the training data set derived from the works of Western composers. Based on these findings, this study recommends the development of hybrid AI music generation systems that can be trained to understand the musical nuances of African music. Also, infusion of human creativity and emotional intelligence should be pivotal in future research on AI music generation systems.

Keywords: Artificial Intelligence (AI), Intersection, Music Composition, Symphony

Introduction

AI's influence is felt across various aspects of modern life, including music creation. The current capabilities of AI are particularly compelling, due to advancements in computational power and new technologies like deep learning systems. This paper explores the evolving relationship between AI and music composition, it highlights how machine learning techniques contribute to musical creation. The goal is to investigate how AI, through various models, enhances music composition while examining the strengths and weaknesses of these models. Music generation can be categorized into two main types: extractive and abstractive. Extractive music generation creates short musical phrases based on existing input music, merely selecting key sections using an algorithm. Conversely, abstractive music generators take in whole pieces and create entirely new compositions without pulling directly from the source, generating original phrases instead. Recent developments in music generation have primarily relied on GANs (Generative Adversarial Networks), a machine learning model which is categorized as abstractive music generator that produce audio in formats like MIDI or raw waveforms. GANs have shown remarkable success in generative tasks. Since generative models cannot understand some of the nuances of African music, but with a structured training process, GANs can be trained with the datasets found in African music, leading to the innovation of systems that can both interpret and generate African music.

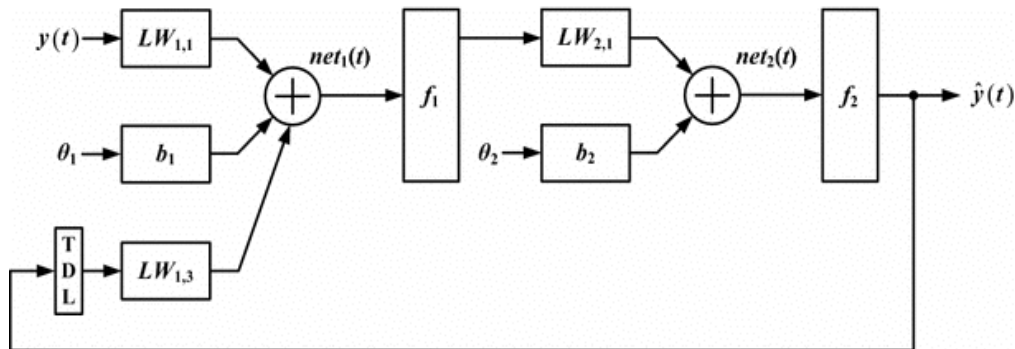
Challenges Faced by Composers

While the African continent possesses an abundance of compositional talents, a persistent technological gap prevents many composers from effectively conveying their creative concepts. Traditional Western-focused musical tools often lack the semantic range needed to interpret the rhythmic complexities and tonal subtleties inherent in African indigenous music. This absence of culturally responsive systems results in a significant notational barrier, where composers find themselves unable to transcribe their ideas into a format that honors their original intent. Such limitations do not merely represent a technical inconvenience but act as a profound constraint on the evolution of African art music. Taofeek, Mande and Oko (2025) noted that Nigerian music industry is facing lack of proper digital and technological structure in music marketing and distribution in Nigeria as this does not enable artists gain global audience, exposure and markets. There exists an obvious need for models tailored to address these issues.

Types of Music Generation Models

According to Data Science Dojo Staff (2024), there are five categories of AI music generation models but the two main categories are discussed below.

1. Autoregressive Models

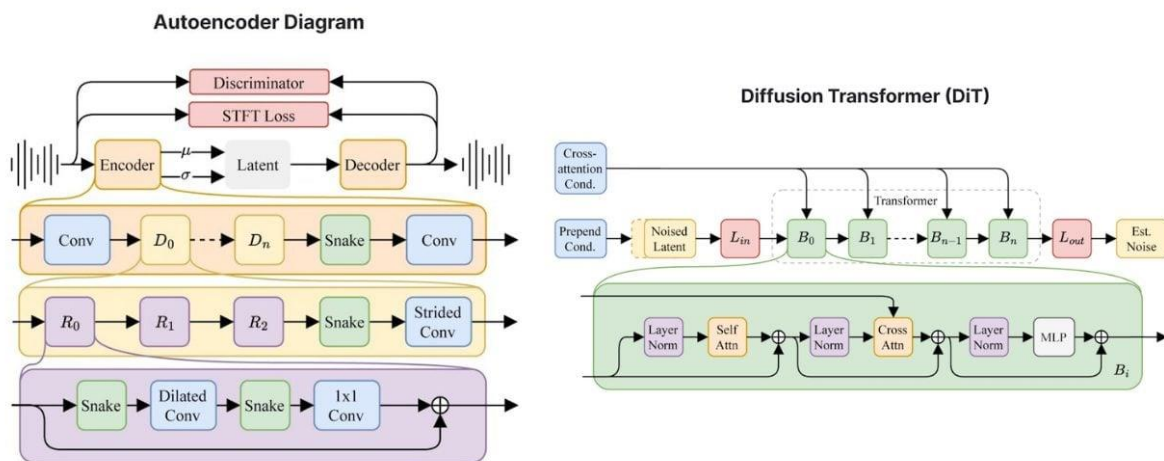


Overview of the architecture of an Autoregressive Model – Source: ResearchGate

These models are a foundational method in AI music generation, where they predict future elements in a sequence based on past ones. The signal flow proceeds primarily from left to right, beginning with the input $y(t)$ and ending with the estimated output $\hat{y}(t)$, while also incorporating feedback and time-dependent components. On the left side of the diagram, the input signal $y(t)$ is fed into a block labeled $LW_{1,1}$, which represents a weighted linear transformation. In parallel, a parameter Θ_1 enters a bias block labeled b_1 . Additionally, a time-dependent signal passes through a block labeled TDL (Tapped Delay Line), whose output is connected to another weighted block labeled $LW_{1,3}$. The outputs of $LW_{1,1}$, b_1 , and $LW_{1,3}$ are combined at a summation node, indicated by a circular symbol with a plus sign. The result of this summation is denoted as $net_1(t)$. The signal $net_1(t)$ is then passed through a nonlinear transformation block labeled f_1 , which functions as an activation or processing function for the first layer. The output of f_1 is subsequently fed into a second weighted block, $LW_{2,1}$. At the same time, a second parameter Θ_2 is applied through a bias block labeled b_2 . These two signals are summed at a second summation node, producing $net_2(t)$. The signal $net_2(t)$ is then processed by a second nonlinear function f_2 whose output represents the final estimated signal $\hat{y}(t)$. From this output, a feedback path is shown looping back toward the

earlier part of the system, indicating that past outputs may influence future computations. This feedback, together with the tapped delay line, suggests that the model accounts for temporal dynamics and memory effects.

2. Diffusion Models



Overview of the Stable Audio 2.0 architecture – Source: stability.ai

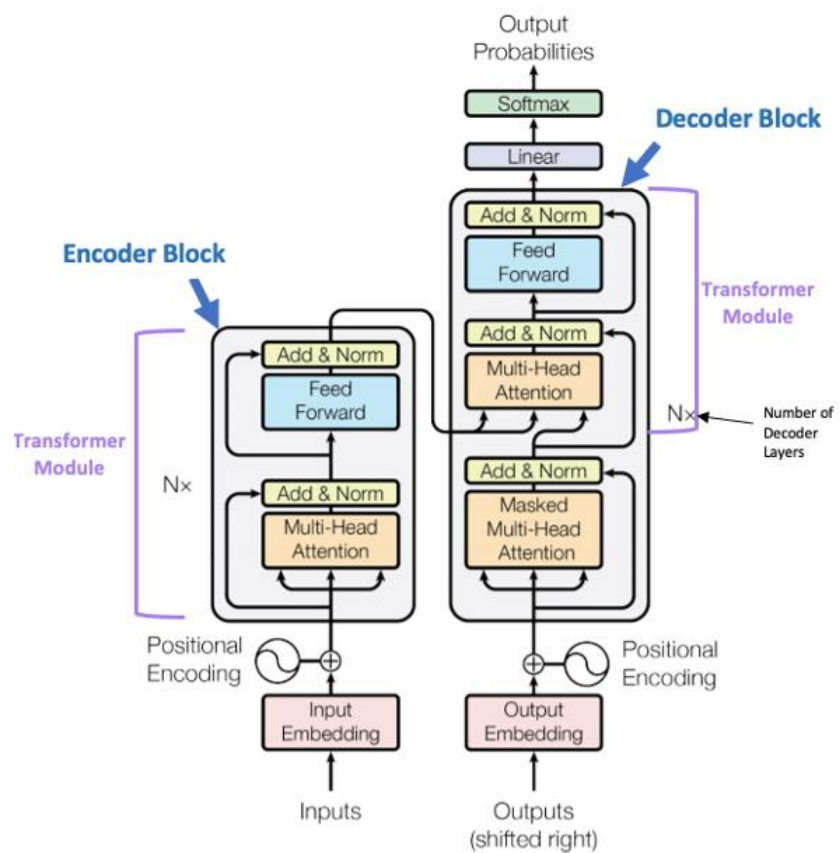
These operate by reversing a diffusion process that gradually adds noise to the data and then learns to undo this process to create new data. The layout is divided into two main parts: an autoencoder diagram on the left and a diffusion transformer (DiT) on the right, with a clear flow of information between the two systems. The visual style uses colored blocks, arrows, and labeled components to indicate signal transformations, conditioning paths, and learning objectives. On the left side, the autoencoder diagram begins with an audio waveform input, depicted as a stylized signal icon. This input is processed by an encoder, which transforms the signal into a latent representation. The latent space sits between the encoder and decoder and serves as a compact, learned representation of the original signal. From this latent representation, the decoder reconstructs an output waveform. Above the encoder–decoder pathway, two supervisory components are shown: a discriminator and an STFT loss block,

both connected to the reconstructed output. These elements indicate that the autoencoder is trained using adversarial loss and short-time Fourier transform-based spectral loss to improve perceptual and frequency-domain fidelity. Below the main encoder–latent–decoder path, several stacked processing blocks illustrate the internal structure of the encoder and decoder networks. These blocks include convolutional layers, residual blocks labeled R_0 , R_1 , and R_2 , dilated convolutions, strided convolutions, and multiple nonlinear activation functions labeled “Snake.” The diagram shows progressive down sampling through blocks labeled D_0 to D_n , followed by nonlinear transformations and convolutional layers. Skip connections and additive junctions are also present, indicating residual learning and feature reuse throughout the network. Together, these components emphasize a deep, hierarchical feature extraction process designed to efficiently encode audio signals. On the right side of the diagram is the Diffusion Transformer (DiT). The latent representation produced by the autoencoder is first noised, forming a “noised latent” input that enters the diffusion process. Conditioning information is added through prepend conditioning and cross-attention conditioning blocks, which feed contextual signals into the transformer. A linear layer labeled L_{in} projects the input into the transformer’s internal representation. The transformer itself is shown as a sequence of blocks labeled B_0 , B_1 , up to B_n . Each block contains a structured arrangement of layer normalization, self-attention, cross-attention, and a multilayer perceptron (MLP). Arrows indicate residual connections around these subcomponents, highlighting the iterative refinement of representations typical of transformer architectures. The conditioning signals are repeatedly injected into these blocks, allowing external information to guide the diffusion process at multiple stages. At the end of the transformer stack, a loss block labeled L_{out} computes the training objective, and the final output estimates the noise component, which is characteristic of diffusion-based generative models. This estimated noise is used during training to guide the denoising process and during inference to progressively generate or refine latent representations.

AI Music Generation Systems

1. MuseNet: OpenAI's AI-Powered Music Generation System

In 2019, OpenAI launched MuseNet, an AI model capable of generating complex compositions spanning multiple genres and different instruments. MuseNet is built on a deep neural network trained on diverse musical datasets, enabling it to blend styles, tempo and produce harmonized pieces. With MuseNet, OpenAI showcased the power of AI in simulating human-like creativity, sparking conversations about the future of music. (Jeffrey Lupker, 2025).



Transformer architecture of MuseNet – source: miro.medium.com

Training Dataset: The Musical Foundation of MuseNet

Musenet is built on a deep neural network with transformer kernels from Sparse Transformer. It analyzes MIDI files and builds an internal musical vocabulary to model its training data. With similar unsupervised technology as GPT-2, it could be said that the music generation algorithms have their maps of harmonic theory that were not directly programmed by a human. (Ezra Sandzer-Bell, 2023). Musenet’s dataset is somewhat diverse, with sixteen musical “styles” in total. It leans into classical music like Mozart, Bach, Chopin, or

Rachmaninoff. The transformer model in MuseNet is designed for sequential data learning, predicting subsequent notes based on an input sequence of musical notes. Ultimately, an encoding programme was employed to combine pitch, volume, and instrument attributes into one expressive token.

The transformer model breaks down compositions into tokens that represent notes, chords, instrument choices, or timing intervals, processing them in parallel instead of sequentially. This means it can recognize long-range dependencies between musical elements, so that the pieces maintain stylistic coherence throughout. Given its training on a massive dataset of MIDI compositions across genres, MuseNet can emulate styles from classical symphonies to jazz improvisations and pop melodies, showcasing its genre adaptability by recognizing complex relationships between musical elements. Moreover, MuseNet takes advantage of Sparse Transformers, focusing on significant patterns rather than clutter, which boosts the speed and quality of its output while maintaining structured and engaging compositions. MuseNet's transformer architecture is redefining AI-driven music creation, facilitating long-form musical consistency, multi-instrument integration, and genre adaptability. Utilizing advanced sequence prediction and self-attention mechanisms, MuseNet produces intricate compositions that uphold artistic coherence while enabling creative exploration.

Unique Features That Set MuseNet Apart

Key features contributing to MuseNet's ability to generate high-quality, stylistically diverse compositions include:

- **Multi-Instrumental Composition:** MuseNet can create music using up to 10 different instruments, allowing for rich and layered arrangements. Whether users seek orchestral pieces or contemporary digital music, MuseNet delivers varied instrumental combinations.
- **Genre Blending:** MuseNet excels at mixing musical genres, allowing users to prompt it to create pieces that blend classical with jazz or combine electronic beats with orchestral melodies, making it a valuable asset for experimental music.
- **Composer and Instrument Tokens:** MuseNet facilitates user guidance in its output based on selected composers or instruments, ensuring the music aligns with historical or contemporary styles. These instrument tokens refine orchestration to meet desired soundscapes.
- **Interactive Music Generation:** MuseNet offers both simple mode, allowing users to hear pre-generated samples, and advanced mode, where users can input musical

prompts for customized compositions. This interactivity makes it a compelling tool for musicians seeking AI assistance.

- **Long-Term Musical Structure:** Unlike other AI models that produce short fragments, MuseNet maintains a structured long-term composition, utilizing its deep architecture to remember musical themes over extended sequences, ensuring continuity and progression.

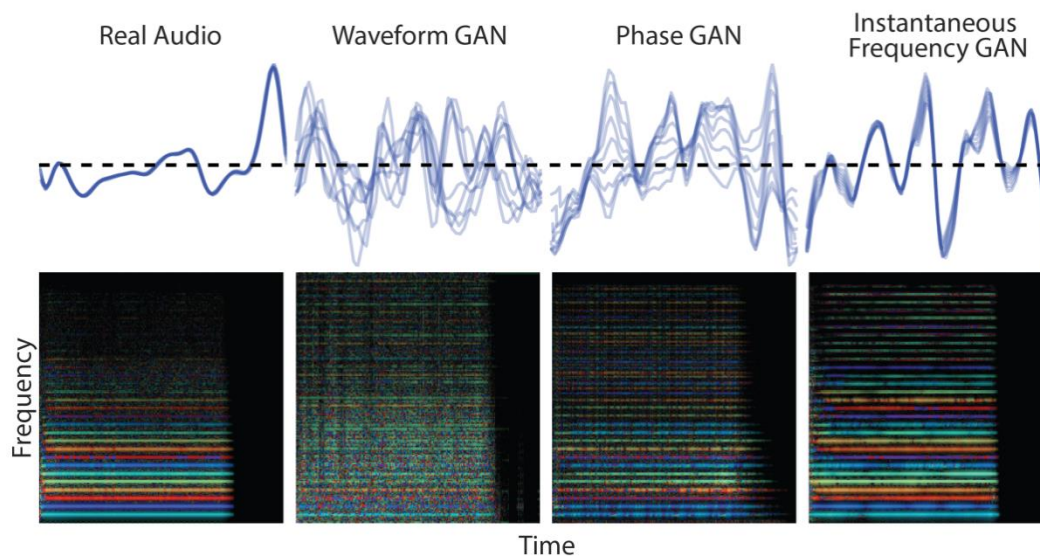
2. Magenta (Google)

Magenta, developed by Google, employs a diverse array of deep learning models to generate and manipulate music, enhancing creativity with AI. Google Magenta elaborated a novel approach called Differential Digital Signal Processing (DDSP) that incorporates deep neural networks with preconditioned digital signal processing techniques, reaching state-of-the-art results, especially in timbre transfer applications (Francesco Ganis, Erik Frej Knudsen, Søren V. K. Lyster, Robin Otterbein, David Südholt, Cumhuriyet, 2021). Each model plays a role in aspects of music generation, from melody creation to sound synthesis. A foundational model in Magenta is Performance RNN, designed for expressive piano performances by learning from existing musical sequences. Unlike simple MIDI generators that produce rigid notes, Performance RNN captures nuances of human performance, such as timing variations and articulation, which makes its outputs feel more natural. Another vital model is MusicVAE, a variational autoencoder (VAE) that allows seamless transitions between musical sequences. The Variational Autoencoder (VAE) has proven to be an effective model for producing semantically meaningful latent representations for natural data. However, it has thus far seen limited application to sequential data, and, as we demonstrate, existing recurrent VAE models have difficulty modeling sequences with long-term structure.

To address the issue mentioned above, this work proposes use of a hierarchical decoder, which first outputs embeddings for subsequences of the input then uses these embeddings to generate each subsequence independently. This structure encourages the model to utilize its latent code, thereby avoiding the "posterior collapse" problem, which remains an issue for recurrent VAEs. (Adam Roberts, Jesse Engel, Colin Raffel, Curtis Hawthorne, Douglas Eck, 2019). This model excels at capturing the realism of acoustic instruments like violins, flutes, and guitars. One of Magenta's groundbreaking models is GANSynth, which employs Generative Adversarial Networks (GANs) to synthesize high-fidelity audio. GANs consist of a generator and a discriminator that compete to create increasingly realistic sound samples. Unlike sequential models that generate waveforms piece by piece, GANSynth produces entire

musical notes or phrases in parallel, significantly boosting speed and quality. By utilizing adversarial learning, GANSynth ensures that AI-generated sounds replicate the tonal richness of real instruments.

Magenta's architecture is uniquely crafted to blend multiple AI approaches, enabling both melody creation and high-fidelity sound synthesis. Whether through RNN-based expressive performances, VAE-powered style blending, WaveNet sound processing, or GAN-driven audio refinement, Magenta embodies a sophisticated fusion of AI and creativity, pushing the boundaries of music production.



How GAN works –Source: <https://magenta.tensorflow.org/>

Training Dataset

Magenta uses several datasets to train its models, ensuring diversity in musical styles. Key datasets include:

- Bach Doodle Dataset – Comprising 21.6 million harmonizations from Google's Bach Doodle experiment, providing classical music patterns.
- CocoChorales – A dataset of 240,000 audio mixtures designed for generating four-part ensembles in the style of Bach chorales.
- Expanded Groove MIDI Dataset (E-GMD) – Featuring 444 hours of human drumming performances, it's one of the largest datasets for expressive drumming.
- Groove MIDI Dataset (GMD) – Containing 1,134 MIDI files and nearly 22,000 measures of human-performed drumming.
- MAESTRO Dataset – Comprising 200 hours of virtuoso piano performances, finely aligned between note labels and audio.

- NSynth Dataset – A collection of 305,979 musical notes from 1,006 instruments, showcasing variations in pitch and timbre.

These datasets endow Magenta with a wide array of musical elements, enabling it to create stylistically diverse and structurally sound compositions.

Model Architecture

Magenta employs various deep learning architectures for music generation and manipulation. Some notable models include:

- NSynth (Neural Audio Synthesis) – A WaveNet-based autoencoder designed for synthesizing audio, enabling realistic, expressive sounds.
- DDSP (Differentiable Digital Signal Processing) – Merging deep learning with traditional sound processing to synthesize realistic instrument tones.
- MusicVAE – A variational autoencoder that enables smooth transitions between melodies and styles.
- Performance RNN – A recurrent neural network trained on expressive piano performances, generating dynamic compositions.
- Sketch-RNN – While mainly focused on visual art, it highlights Magenta's creative sequence generation capabilities.

GANSynth: Magenta's GAN-Based Music Model

A significant advancement in Magenta is its incorporation of Generative Adversarial Networks (GANs) into music synthesis. GANs involve two neural networks: a generator and a discriminator, working against each other to produce refined outputs.

- Parallel Waveform Generation – GANSynth generates entire audio sequences in parallel instead of sequential audio generation, improving speed and quality.
- Instrument Timbre Modeling – The generator learns to develop high-fidelity musical samples while the discriminator evaluates and refines these outputs for realism.
- High-Resolution Sound Synthesis – GANSynth excels in creating expressive instrument tones, enhancing the accuracy of synthesized sounds.
- Adversarial Learning Process – The GAN model continually hones its capacity to produce natural-sounding music through adversarial feedback.

Unique Features

Magenta's unique features that enhance AI-driven music composition include:

- **AI-Assisted Music Generation** – Magenta provides tools for musicians to collaborate with AI, generating melodies, harmonies, and rhythms that can be refined further.
- **Genre Adaptability** – Its models can create music across various genres, from classical to pop, jazz, and electronic.
- **Interactive Tools** – Magenta includes interactive applications like the Magenta Studio plugin for real-time music creation assistance.
- **Open-Source Framework** – Built on TensorFlow, Magenta is accessible to developers and researchers for experimentation and contributions to its development.
- **Integration with MIDI and Audio Processing** – Magenta supports both MIDI composition and audio synthesis, making it versatile for digital and live music production.

Flow Machines

Flow Machines is an AI system designed to help musicians and composers generate original music. Unlike straightforward algorithmic composition, it combines machine learning with creative intelligence, assisting artists in producing innovative and stylistically diverse works. Developed under the European Research Council and further developed by Sony Computer Science Laboratories (Sony CSL), Flow Machines exemplifies a collaborative approach to AI music creation rather than relying solely on automation.

Training Dataset: The Foundation of AI Creativity

Flow Machines trained on a vast array of musical compositions, drawing from classical, jazz, pop, and electronic genres. Its database, known as the Flow Machines Database (FMDB), contains thousands of pieces, allowing the AI to recognize common harmonies, chord progressions, melodic structures, and rhythmic patterns across various musical traditions.

Genre-Specific Learning: Flow Machines doesn't generate random sequences; it learns from past compositions to create music that feels natural and adheres to existing genre characteristics.

- **Style Transfer Capabilities:** The system analyzes specific composers and genres, generating new pieces that imitate their style while introducing fresh variations.
- **Multi-Instrumental Training:** The database includes compositions with various instruments, allowing Flow Machines to create full orchestral arrangements rather than isolated melodies.

Model Architecture: How Flow Machines Generates Music

Flow Machines employs a hybrid method, blending rule-based techniques with deep learning models to maintain coherence and creative diversity in its compositions. Some key architectural elements include:

- **Markov Models:** Flow Machines uses Markov chains to predict the next musical sequence based on learned probability distributions, ensuring logical progression.
- **Constraint Satisfaction Algorithms:** These techniques maintain traditional structures in compositions, preserving harmonic integrity and rhythmic coherence.
- **Neural Networks:** The system integrates deep learning models to refine musical compositions, capturing patterns from training data for emotionally expressive outputs.
- **Style Adaptation and Transfer:** Flow Machines can modify output according to composer preferences, giving users the ability to mimic specific styles like classical symphonies or jazz improvisations.

Unique Features That Make Flow Machines Stand Out

Flow Machines differentiates itself from other AI music generators through several unique features:

- **Human-AI Collaboration** is designed to assist rather than replace musicians, Flow Machines allows human artists to refine AI-generated music.
- **Multi-Instrumental Composition**, generates music for various instruments, ensuring rich and layered arrangements.
- **Adaptive Learning**, its flow machines improve its output based on user feedback, growing more refined with each interaction.
- **Interactive Composition Tools**, in which users can modify harmonic progressions, melodies, and rhythms, maintaining control over the final piece.
- **Style Emulation**, its flow machines can produce music in the style of specific composers, promoting exploration of different artistic influences.
- **Historical and Modern Applications**, its use includes the AI-assisted song “Daddy’s Car,” in the style of The Beatles, showcasing its capability of replicating established musical traditions.

Having discovered how these models work, there is need to develop models trained to understand African traditional musical idioms and nuances for proper representation of its music. Meanwhile, translating a complete composition from traditional notation to a list of events can typically result in a cumbersome list of data. Binding data to variables helps to efficiently enclose data in abstraction, thus greatly facilitating its manipulation in the programming environment. (Cope David, 2003)

Methodology

This study employed a qualitative content analysis methodology. We reviewed literature on AI and music, followed by an in-depth evaluation of three major AI music generation systems: OpenAI's MuseNet, Google's Magenta, and Sony's Flow Machines.

Selection Criteria:

- (i) Publicly accessible or well-documented systems.
- (ii) Employ machine learning techniques, including GANs and RNNs.
- (iii) Have been utilized in academic or commercial music production.

Each system was analyzed based on:

- (i) Technical architecture (e.g., GANs, RNNs, transformers)
- (ii) Output quality and coherence
- (iii) Ability to model emotional expression
- (iv) Level of human involvement required.

Findings were categorized into strengths, limitations, and future potential.

Results

Analysis of the three AI music systems revealed several key insights:

MuseNet (OpenAI), utilizes a transformer-based model trained across diverse music styles, producing structurally sound and stylistically versatile music. However, it often lacks emotional depth, and long-term coherence can occasionally falter in extended pieces.

Magenta (Google), prioritizes creativity and the synergy between humans and machines. It features tools like MusicVAE and NSynth, excelling in generating melodic concepts and variations but falling short in harmonically rich compositions.

Flow Machines (Sony), employs Markov and hybrid models for complete song generation, excelling at stylistic imitation and genre-based compositions, but it necessitates substantial human input for lyrics and arrangements.

The comparative findings indicate that different generative music systems exhibit distinct strengths and limitations. GAN-based systems, such as those developed within the Magenta project, tend to excel at producing structurally cohesive compositions, resulting in outputs that feel more internally consistent. In contrast, Transformer-based models like MuseNet demonstrate a broader range of stylistic variation, allowing them to adapt more flexibly across genres and musical forms. Despite these advances, emotional nuance remains a common shortcoming across all systems, with generated music often lacking the depth and expressiveness of human-created works. As a result, effective collaboration between human creators and AI systems continues to be essential for achieving high-quality and musically compelling outcomes.

Discussion of Results

The findings emphasize the potential and limitations of present AI systems in music composition. Although system with GANs as in the case of Magenta shows impressive structuring and generative capabilities, the absence of emotional expressiveness remains a notable shortcoming. This is largely due to the nature of training data, which often lacks contextual depth and emotional metadata. Furthermore, the collaborative models seen in Magenta highlight a promising direction where AI acts as a creative assistant rather than a replacement, aligning with the idea of AI augmenting human creativity and allowing composers to explore new musical territories. The emotional gap in AI-generated music underscores the need for models that can interpret and integrate affective data, perhaps through multimodal learning that incorporates audio, lyrics, and listener feedback for improved human-like expressiveness. Ethical considerations, especially concerning authorship and originality, become increasingly relevant as AI capabilities grow, blurring the lines between human and machine creativity.

Conclusion

AI and machine learning are transforming the music composition landscape. This study has demonstrated that models are trainable; therefore, they can be trained to understand the musical nuances in African music with the use of the right data set. Utilizing GANs appears particularly promising for enhancing coherence and stylistic accuracy. However, the future lies in developing hybrid systems that combine various models' strengths and weave in emotional intelligence. Future research should prioritize improving emotional modeling in AI systems, creating tools that support human-AI collaboration, and navigating ethical concerns regarding authorship and creativity. With thoughtful integration, AI has the potential not only to create music but also to inspire new artistic expressions.

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