From Tradition to Innovation: A Review of AI Music Generation Models, Datasets, and Evaluation Techniques

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Abstract: AI-driven music generation has evolved significantly through deep learning, enabling autonomous composition across diverse styles. This study reviews AI models for monophonic music generation, from traditional approaches such as rule-based systems and Markov Chains to modern architectures such as RNNs, LSTMs, GRUs, CNNs, GANs, VAEs and Transformers models. Here we reviewed cutting edge AI music generation models and discussed emerging commercial tools and ethical challenges with future research need in this domain. Key datasets for AI driven monophonic music generation with their sizes and features are examined and tabulated. We evaluate model effectiveness through objective metrics, subjective assessments and hybrid approach by analyzing strengths, limitations, and future directions. Applications of AI driven monophonic music generation in various domains are also mentioned in the last section. The review emphasizes the need for hybrid architectures, improved evaluation frameworks, and diverse datasets to enhance AI-generated music's expressiveness and accessibility.

Keywords: Music Generation; Deep Learning Models; Generative AI Models; Sequence Prediction; Neural Networks

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Introduction

Music, a cornerstone of human culture, has been revolutionized by AI's ability to compose pieces emulating human-created works. AI-driven music generation employs deep learning, statistical modeling, and symbolic representations to create melodies, harmonies, and rhythms [10]. This study focuses on monophonic music generation, which forms the foundation of traditions like folk songs and classical education.

Early music generation used rule-based systems and Markov Chains, producing predictable compositions due to limited learning capacity. Deep learning models especially RNNs, LSTMs, GRUs, CNNs, GANs, VAEs, and Transformers have superseded these approaches, enabling more sophisticated pattern recognition. While polyphonic models have advanced considerably, monophonic generation remains less explored, requiring specialized approaches for melody and emotional intent. Recent hybrid architectures like CNN-Transformers and VAE-RNNs show promise in improving expressiveness.

This research examines model architectures from rule-based systems to deep learning models, analyzes datasets for size, diversity, and representation formats, and evaluates frameworks using different objective metrics (FAD, Wasserstein Distance etc) and subjective assessments. Monophonic music generation impacts several domains: music therapy and relaxation tools, educational applications, AI-human collaborative composition systems, and cross-cultural music preservation. By analyzing models and identifying improvements, this research bridges AI-generated and human-composed music, fostering advancements in creativity and accessibility.

Related work

The evolution of AI-driven music generation can be categorized into traditional approaches and deep learning- based models. Traditional methods, including rule-based systems, Markov Chains, and statistical techniques, laid the foundation for computational AI music composition but were limited in expressiveness and adaptability [10]. Deep learning models, on the other hand, have revolutionized music generation, capturing intricate temporal dependencies and stylistic nuances. This section provides a detailed review of both traditional and modern deep learning models for monophonic music generation, highlighting their advantages, limitations, and recent advancements.

I.Traditional Approaches in AI Music Generation

A. **Rule-Based Systems:** Rule-based systems operate on predefined music theory rules, encoding harmonic progressions, rhythmic patterns, and melodic structures based on classical composition techniques. Rule based models and their details are shown in table 1 covers basically traditional approaches in AI music generation. These models ensure theoretical correctness and stylistic consistency; they lack adaptability and produce deterministic outputs lacking natural variation. Complex compositions require increasingly sophisticated rule sets, making manual rule formulation impractical.

B. **Markov Chains:** Markov models generate music using probabilistic state transitions, where each note is predicted based on previous notes. Markov chain models and their details are shown in table 1 covers Flow Machines (Sony CSL), Markov Music Generator, Jazz Improviser AI, BachBot and Google's Coconet. Effective for short melodic structures and computationally efficient, they fail to capture long-term musical dependencies, often producing structurally weak and repetitive compositions lacking global coherence.

C. **Statistical Methods:** Early AI-generated music utilized Hidden Markov Models (HMMs), Gaussian Mixture Models (GMMs), and Bayesian Networks to improve upon simple Markov Chains by incorporating hidden states for unobservable musical structures. Statistical models and their details are shown in table 1 focuses Hidden Markov Model (HMM) Music Generator, Gaussian Mixture Model (GMM) for Melody Generation, Bayesian Network Composer, MusicVAE (Statistical + Deep Learning) and Symbolic AI for Music Analysis. They are more adaptable than Markov Chains and useful for capturing stylistic constraints, these methods lack deep hierarchical understanding and struggle with complex polyphonic music.

Table 1. Traditional Approaches in AI Music Generation

Model	Year	Type	Description	Access
Rule Based Systems				
EMI	1981	Rule	Uses stored patterns for new compositions	[51]
CHORAL	1991	Rule	Harmonizes Bach chorales with tonal rules	[52]
HARMONET	1992	Rule	Automates melody harmonization with classical rules	[53]
AIVA	2016	DL+Rule	Generates emotional soundtracks with theory constraints	[54]

MoVE	2022	Rule+VAE	Uses theory rules within VAE for harmonic coherence	[55]
Performance Net	2021	HRNN+Rule	Models timing and dynamics for realistic performance	[56]
DeepScore	2020	Rule+CNN	OMR system for sheet music to digital format	[57]
Computoser	2014	Rule+Prob	Combines rules with probability algorithms	[58]
Gamelan	2020	Rule	Interactive melody generator for Gamelan music	[59]
Sibelius AI	2019	Rule+ML	Uses symbolic AI for stylistic constraints	[60]
Melomics	2013	Rule+GA	Evolutionary principles with music theory rules	[61]
Markov Chains				
Flow Machines	2016	Markov+AI	Combines Markov with constraint satisfaction	[62]
Markov Gen	2005	Markov	Models note transition probabilities	[63]
Jazz AI	2011	Markov	Uses first/second-order models for jazz	[64]
BachBot	2017	LSTM+MCMC	Integrates Markov with deep learning	139
Coconet	2019	MCMC+CNN	Markov-based structure for score completion	[65]
Statistical Methods				
HMM Gen	1999	HMM	Hidden states for melodic sequences	[66]
GMM Gen	2007	GMM	Probabilistic modeling for variations	[67]
Bayesian Net	2012	Bayesian	Probabilistic graphs for chord progression	[68]
MusicVAE	2018	VAE+Stat	Deep generative model with statistical priors	[127]
Symbolic AI	2015	Stat+Symb	Rule-based with probabilistic techniques	[69]

II. Deep Learning Models for AI Music Generation

Deep learning has transformed AI-generated music by enabling data-driven learning of musical patterns, structures, and styles. Unlike traditional models, deep learning architectures capture long-term dependencies, polyphonic relationships, and stylistic variations. The most prominent deep learning models are explained below with their type in table 2.

A. Recurrent Neural Networks (RNNs) for Music Generation: RNNs effectively model sequential data by capturing temporal dependencies in melody generation. RNNs excel at modeling short-term dependencies and melodic patterns, they struggle with long-term dependencies due to vanishing gradients, often producing compositions that lack global coherence. A study by Eck and Schmidhuber (2002) [16] demonstrated their effectiveness in generating coherent melodies from MIDI data, but maintaining structural consistency over extended sequences remains challenging.

B. Long Short-Term Memory Networks (LSTMs) & Gated Recurrent Units (GRUs): LSTMs and GRUs address long-range dependency issues through gated information flow mechanisms, enabling selective retention of musical context [7]. These architectures excel at capturing temporal dependencies for both melody and polyphonic generation; they remain computationally expensive and struggle with highly diverse datasets. Studies by Huang and Wu (2021) [11] and Patil et al. (2023) [4] demonstrate their effectiveness in generating complex harmonic structures and jazz improvisations, though maintaining consistent quality across extended sequences remains challenging.

C. Transformer-Based Models: Transformers, leveraging self-attention mechanisms instead of recurrence, efficiently model long-range dependencies in music generation. These architectures excel at capturing both local motifs and global structures in music, they remain computationally expensive and require large training datasets. Studies by Vaswani et al. (2017) [15] demonstrate their effectiveness in tasks like melody generation, harmonization, and multi-instrumental composition, though generating highly structured music still requires domain-specific adaptations.

D. Convolutional Neural Networks (CNN): CNNs, originally designed for image processing, excel at capturing local patterns in spectrograms and audio data. These architectures effectively analyze time-frequency features for audio synthesis and texture generation; they work better in hybrid configurations with RNNs and Transformers. Studies by Esling et al. (2018) [14] demonstrate their effectiveness in learning latent representations of timbre and synthesizing high-quality soundscapes, though generating structured music still requires domain-specific adaptations.

E. Sequence-to-Sequence (Seq2Seq) and Variational Autoencoders (VAEs) Models: Seq2Seq models, initially developed for machine translation, utilize encoder-decoder architecture for music generation tasks. VAEs generates multitrack music with inter track depemdency, specified genres using style attributes and regularize enhanced music coherence. These models excel at tasks like melody continuation and harmonization; they often struggle with fixed-length vector representation limitations. Studies by Li et al. (2021) [7] and Zhang et al. (2023) [2] demonstrate their effectiveness in generating orchestral arrangements and harmonically rich pieces, though maintaining coherence in longer sequences remains challenging.

F. Generative Adversarial Networks (GAN): GANs utilize adversarial training between generator and discriminator networks to create realistic musical sequences. GANs excel at generating complex, multi-track compositions and capturing intricate musical structures, they face challenges with training stability and musical consistency. Studies by Tokui et al. (2022) [12] demonstrate their effectiveness in generating rhythmic patterns for electronic dance music, though maintaining coherence across longer sequences remains challenging.

G. Autoregressive Models: Autoregressive models predict each element in a sequence based on preceding elements, creating coherent and contextually appropriate outputs. Recent research by Huang et al. (2021) [10] demonstrates their effectiveness in symbolic music generation and raw audio synthesis, though computational challenges in sequential processing remain a limitation for real-time applications.

H. Neural Networks with Traditional DSP Modules: Neural networks effectively learn complex patterns and nonlinear relationships in audio signals. These models combine efficient learning with precise signal processing and enhance performance in low-data scenarios by leveraging predefined DSP rules; they face challenges with rigid DSP modules limiting adaptability and neural networks requiring extensive training to generalize across different audio domains.

I. Neural Networks with Reinforcement Learning: Neural networks combined with RL enable adaptive music generation through reward-based learning. These models excel at optimizing musical outputs based on defined reward functions and capturing higher level patterns, they face challenges with computational cost and reward function design. Studies by Mosin et al. (2024) [1] demonstrate their effectiveness in creative music generation, though careful reward tuning remains crucial for maintaining musical coherence.

J. Self-Supervised Learning Hybrids (SSL): Self-supervised learning enables models to learn musical patterns without labeled datasets by integrating SSL with Transformers, RNNs, and VAEs. These models excel at learning from unlabeled data and improve generalization for unseen musical styles, they remain computationally expensive for large-scale training. Recent studies demonstrate their effectiveness in capturing complex musical structures and generating diverse compositions, though optimization challenges persist for real-time applications.

Table 2. Deep Learning-Based AI Music Generation Models

Model	Year	Type	Description
Recurrent Neural Networks (RNNs)			
DeepJ	2016	CNN+RNN	Generates rock music via CNN features, RNN modeling [70]
SampleRNN	2017	H-RNN	Multi-scale RNN for raw audio generation [71]
MelNet	2019	MS-RNN	Multi-layered RNN for audio spectrograms [72]
MAGNet	2020	CNN+RNN	Music Autoregressive Network combining CNNs and RNNs [73]
AMS-GAN	2020	GAN+RNN	Anticipation-RNN in GAN for musical coherence [144]
Music Autotranslator	2018	Seq2Seq RNN	Translates melodies between styles via sequence learning
BeatGAN	2019	GAN+RNN	RNN-based temporal modeling for drum beats [145]
JazzGAN	2018	GAN+RNN	RNN-based jazz improvisation generation [146]
MoGAN	2018	GAN+RNN	Smooth genre transitions via RNN generation [148]
RL-Duet	2019	RL+RNN	Real-time duet generation with RL and RNNs [49]
Neural Parametric Singing Synthesizer	2017	Seq2Seq RNN	Voice synthesis from scores and lyrics
HRNN	2019	H-RNN	Multi-level structure modeling [74]
Cross-Modal Music Retrieval	2019	RNN	Cross-modal music representation learning [75]
ORGAN	2017	GAN+RNN+RL	GAN with RL objectives for music generation [151]
VRAE	2014	RNN+VAE	Latent space learning with RNN-VAE hybrid [76]
SALAMI-Net	2020	CNN+RNN	Structural segmentation modeling with attention
Deep AutoRegressive Networks	2019	Auto-RNN	Sequential note/chord prediction from context
PerformanceNet	2019	H-RNN	Models expressive timing and dynamics
Lead Sheet	2018	Seq2Seq RNN	Melody and chord generation learning

Generation			
Dance2Music	2021	Seq2Seq RNN	Music generation from dance movements [123]
Long Short-Term Memory Networks (LSTMs)			
DeepBach	2016	Bidirectional LSTM	Generates Bach-style chorales using bidirectional LSTM networks [77]
PerformanceRNN	2017	LSTM	Models expressive timing and dynamics in MIDI performance generation [78]
MelodyRNN	2016	LSTM	Generates monophonic melodies using stacked LSTM layers [79]
AttentionRNN	2019	LSTM+Attention	Enhances long-range dependencies in music sequences with attention mechanisms [80]
MuseGAN	2017	LSTM+GAN	Integrates LSTMs within a GAN framework for multi-track symbolic music generation [140]
C-RNN-GAN	2016	LSTM+GAN	Uses an LSTM-based generator with a CNN-based discriminator to generate coherent music sequences [81]
BachBot	2017	LSTM	Generates chorale harmonization in the style of Bach using deep LSTM networks [82]
Folk-RNN	2016	LSTM	Generates folk-style melodies by training on folk music datasets [83]
LakhNES	2018	LSTM	Generates chiptune music in NES style using LSTM networks [84]
VirtuosoNet	2020	LSTM	Models expressive piano performances using hierarchical LSTM layers [85]
MusicVAE	2018	VAE+LSTM	Combines variational autoencoders with LSTMs for diverse melody generation [127]
Biaxial LSTM	2017	LSTM	Processes time and pitch axes simultaneously for polyphonic music generation [86]
IBM Watson Beat	2018	LSTM	Generates music based on emotional intent using LSTM networks [87]
ChoraleRNN	2015	LSTM	Models multi-voice chorale harmonization using LSTM networks [88].
DeepJazz	2016	LSTM	Generates jazz improvisations by learning from jazz MIDI transcriptions [89]
Bi-directional LSTM with Attention	2020	Bi-LSTM+ Attention	Uses bi-directional LSTMs with attention to improve sequence modeling [90]
Differential Music	2021	LSTM	Employs novel interval encoding in an LSTM-based model for melody and harmony generation [91]
LSTM-Based Music Generation System	2019	LSTM	A generic system for automatic music generation using LSTMs [92]
Three-layered LSTM for Music generation	2021	LSTM	Explores a three-layered LSTM architecture to generate music in ABC notation [93]
LSTM-Based Music Generation with dataset preprocessing	2018	LSTM	Introduces effective preprocessing techniques to enhance LSTM-based music generation [94]
MIDI-Sandwich2	2019	Hierarchical LSTM with Attention	Generates multi-track MIDI compositions by modeling the hierarchical structure of music [95]

Enhanced LSTM Music Generator	2023	LSTM+Adaptive Attention	Improves long-range musical coherence with adaptive attention mechanisms integrated into LSTM networks [96]
Interactive LSTM Music Composer	2024	LSTM+RL	A real-time composition system that integrates LSTM networks with reinforcement learning for interactive music generation [97]
Multi-Scale LSTM Music Generator	2024	LSTM+Multi-Scale Processing	Leverages multi-scale LSTM architectures to capture both short-term motifs and long-term structure [98]
Gated Recurrent Units (GRUs)			
Jazz Improvisation GRU Model	2023	GRU	Uses GRU networks to generate jazz improvisations from MIDI datasets [99]
Real-Time GRU Melody Continuation	2021	GRU	Employs GRUs for real-time melody continuation [100]
Multi-Instrument GRU Composer	2020	GRU	Utilizes GRU architectures for multi-instrument compositions [101]
Adaptive GRU Music Generator	2023	GRU+Adaptive Mechanisms	Integrates adaptive GRU layers for dynamic musical context [102]
Multi-Scale GRU Music Generator	2024	GRU+Multi-Scale Processing	Leverages multi-scale GRU networks for both short-term motifs and long-term structure [103]
Transformer-Based Models			
Music Transformer	2019	Transformer	Generates polyphonic music with relative positional encoding [153]
MuseNet	2019	Autoregressive Transformer	Multi-instrument compositions via transformer-based modeling [152]
Pop Music Transformer	2020	Transformer	Specializes in pop music patterns and structures [106]
Groove Transformer	2020	Transformer	Models expressive drumming with relative attention [107]
Hierarchical Music Transformer	2019	H-Transformer	Captures multi-level structure in notes, bars, phrases [108]
Transformer-Seq2Seq	2019	Transformer	Translates melodies to rich accompaniments [109]
Interactive Transformer Composer	2023	Transformer+Interactive	Real-time interactive composition with transformer modules [110]
Multi-Scale Transformer	2024	MS-Transformer	Captures both local motifs and global structure [111]
Enhanced Music Transformer	2023	Transformer	Improved attention mechanisms for long-range dependencies [104]
MusicBERT	2021	BERT	Pre-trained transformer for music understanding [105]
Convolutional Neural Networks (CNNs)			
WaveNet	2016	Deep CNN	Uses dilated causal convolutions to generate raw audio waveforms [154]
Coconet	2017	CNN	Employs convolutional networks to in-fill missing parts of music scores [112]
PopMAG	2018	CNN+Transformer	CNN layers extract short-range melodic features with Transformer for long range dependencies [113]
MusicBERT	2020	CNN+Transformer	CNN-based embedding layers with Transformer encoder for monophonic generation [114]
Dance Dance Convolution	2019	CNN	Models rhythmic patterns in dance music using convolutional layers [115]
MusicSketchNet	2020	CNN+RNN	Generates rough musical sketches via CNN-based feature extraction [116]
Neural FM Synthesizer	2019	CNN	Predicts FM synthesis parameters using CNN architectures [117]
DDSP	2020	CNN+DSP	Combines neural networks with DSP modules for synthesis [159]
Enhanced CNN Music Generator	2023	CNN	Improved CNN architecture with enhanced feature extraction [118]

Interactive CNN Music Composer	2024	CNN+Interactive	Integrates CNNs with interactive components for real-time composition [119]
Sequence-to-Sequence (Seq2Seq) Models			
Music Autotranslator	2018	Seq2Seq RNN	Translates melodies from one musical style to another by learning cross domain mappings [120]
Neural Parametric Singing Synthesizer	2017	Seq2Seq RNN with Attention	Synthesizes expressive singing voice waveforms from musical scores and lyrics [121]
Lead Sheet Generation with Deep Learning	2018	Seq2Seq RNN with Attention	Generates lead sheets by modeling relationships between melodic lines and chord progressions [122]
Dance2Music	2021	Seq2Seq RNN with Attention	Translates dance motion sequences into synchronized musical compositions [123]
SING Model	2020	Seq2Seq RNN with Attention	Generates singing voice spectrograms from musical scores, focusing on expressive synthesis [124]
Adaptive Seq2Seq Music Generator	2023	Seq2Seq RNN with Adaptive Attention	Incorporates adaptive attention mechanisms to dynamically adjust to musical context for enhanced generation [125]
Interactive Seq2Seq Music Composer	2024	Seq2Seq RNN with RL	Enables real-time interactive music composition through sequence-to-sequence framework with reinforcement learning [126]
Variational Autoencoders (VAEs)			
MusicVAE	2018	VAE+LSTM	Learns the latent space of musical sequences using a VAE with an LSTM based decoder [127]
MuseGAN	2017	VAE+GAN	Integrates VAEs with GANs for expressive multi-track music generation [140]
MuseVAE	2020	VAE	Utilizes VAEs for generating multi-track music with inter-track dependency capture [194]
MIDI-VAE	2018	VAE+LSTM	Combines VAEs with LSTM-based encoder-decoder architectures for structured music generation [128]
StyleVAE	2018	Conditional VAE	Generates music in specified genres by conditioning on style attributes [129]
MuseMorphose	2021	Transformer based VAE	A conditional Transformer-based VAE enabling controllable music generation through attribute morphing
Musika!	2021	VAE+GAN	Combines VAEs and GANs for style-conditioned music generation and style transfer
Music FaderNets	2021	VAE with attribute Controllers	Learns disentangled latent representations to control musical attributes such as pitch and rhythm [130]
MoVE	2021	VAE with Theory Constraints	Incorporates music theory rules into the VAE framework for harmonically coherent music [131]
NVidia's Jukebox	2020	VQ-VAE-2 + Autoregressive Transformer	Generates raw audio songs with singing by combining VQ-VAE-2 and autoregressive transformers [155]
MIDI-VQVAE	2020	VQ-VAE	Uses vector quantization in a VAE framework to discretize the latent space for improved music generation [132]
Google's Piano Genie	2019	Autoencoder	Translates simple inputs into complex piano compositions using an autoencoder approach [133]
Enhanced VAE Music Generator	2023	VAE	Employs advanced encoder-decoder architectures and regularization for enhanced music coherence [134]
Hierarchical VQ-VAE Music Generator	2024	Hierarchical VQ-VAE	Leverages a hierarchical architecture and vector quantization to capture both short-term and long-term musical structure [135]
VAE-GAN Music Composer	2023	VAE+GAN	Integrates VAE and GAN frameworks for refined music composition through adversarial training [136]
Generative Adversarial Network (GAN)			
HarmonyGAN	2020	GAN	Generates polyphonic music by learning harmony and rhythm simultaneously [11] [137]
CompMusicGAN	2021	GAN	Produces compositions tailored to specific styles by conditioning on auxiliary features [138]
MultiGAN	2023	GAN	Generates multi-instrument compositions with intricate musical textures [139]
MuseGAN	2017	VAE+GAN	Integrates VAEs with GANs for expressive multi-track music generation [140]

MuseGAN Hybrid	–	GAN+RNN	Incorporates RNN-based components within GAN framework for melody generation
MuseGAN Extended	–	GAN+VAE+Attention	Enhances MuseGAN with VAEs and attention for improved representation learning
MidiNet	2022	CNN-GAN+LSTM	Utilizes CNNs with GANs and LSTM modules for melody generation [141]
C-RNN-GAN	2016	RNN+GAN	Employs RNN-based generator with CNN-based discriminator [142]
GANSynth	2018	GAN	Synthesizes high-fidelity audio focusing on timbral quality [143]
Musika	2021	VAE+GAN	Combines VAEs and GANs for style-conditioned generation and transfer
DeepArtist	2020	GAN+CNN	Generates music aligned with specific emotional tones using GANs
AMS-GAN	2020	GAN+RNN	Integrates Anticipation RNN within GAN framework [144]
BeatGAN	2019	GAN+TCN	Uses TCNs in GAN framework for drum pattern generation [145]
JazzGAN	2018	GAN	Produces jazz improvisations conditioned on chord progressions [146]
ChordGAN++	2019	GAN	Improves melody generation through enhanced chord conditioning [147]
MoGAN	2018	GAN	Generates music with smooth style transitions [148]
Melody Generation with GANs	2019	GAN+LSTM	Adversarially trains generator for realistic melodies [149]
Style Transfer GAN	2020	CycleGAN	Applies CycleGAN for style transfer between genres [150]
Autoregressive Models			
MuseNet	2019	Autoregressive Transformer	Generates multi-instrument music note-by-note using transformer-based autoregressive modeling [152]
Music Transformer	2019	Transformer with Relative Positional Encoding	Uses self-attention to capture long-term dependencies in polyphonic music generation [153]
WaveNet	2016	Deep Autoregressive CNN	Generates raw audio waveforms sample-by-sample using dilated causal convolutions [154]
Jukebox	2020	VQ-VAE2+Autoregressive Transformer	Generates raw audio songs with singing by combining vector quantized VAEs and autoregressive transformers [155]
Transformer-XL for Music Generation	2019	Autoregressive Transformer with Long-Term Memory	Extends the transformer architecture to capture longer dependencies for music generation [156]
Deep Auto Regressive Networks	2019	Autoregressive RNN	Sequentially generates music by predicting each note or chord based on prior context [157]
MusicGen	2023	Autoregressive Transformer	A state-of-the-art model by Meta AI that generates music from textual descriptions and raw audio using autoregressive techniques [158]
Neural Networks with Traditional DSP Modules			
NeuroDSPNet	2018	CNN+DSP	A hybrid system combining deep neural networks with DSP techniques for audio synthesis and enhancement
HarmonicNet	2018	CNN+DSP	Uses a CNN-based feature extractor with DSP-based harmonic analysis for precise note detection and music transcription
OpenAI's DDSP	2020	Neural Networks+ DSP Modules	Integrates deep learning with traditional DSP to generate realistic instrument sounds by predicting synthesizer parameters
DDSP++	2023	Enhanced Neural DSP	An improved version of DDSP featuring advanced neural architectures and expanded DSP integration for more expressive sound synthesis
Neural DSP Synthesizer	2024	Neural Networks+ DSP	Combines neural networks with conventional DSP modules to model complex audio transformations and generate high-quality synthesized music
Reinforcement Learning-Based Models			
SeqGAN	2017	GAN with RL	Utilizes policy gradient methods to generate discrete sequences, applicable to music generation [160]
MusicRL	2023	RNN+RL	Employs reinforcement learning to generate music by optimizing reward functions based on musical attributes [161]

RL-Duet	2019	RL with RNN	Enables collaborative, real-time duet generation using RL integrated into a recurrent network framework [162]
RL Music Composer	2019	Deep Q-Network	Generates music by optimizing a reward function based on music theory rules[163]
Interactive RL Composer	2023	RL+Neural Networks	Facilitates real-time interactive music composition through RL framework[164]
Multi-Scale RL Generator	2024	RL+Multi-Scale	Integrates RL with multi-scale architectures for both short-term and long-term structure [165]
Self-Supervised Learning (SSL) Hybrid Models			
REMUS	2023	SSL-Transformer Hybrid	Uses contrastive learning with a Transformer encoder to model musical sequences without labeled data [173]
MIDI-SSL	2024	VAE-SSL Hybrid	Integrates self-supervised embeddings with a VAE latent space to enhance melody variation and structure learning [174]
SSL-MusicGen	2023	SSL+Transformer	Leverages self-supervised pre training for improved music understanding and generation [175]
ContrastiveMusic	2024	SSL+CNN	Uses contrastive learning to capture musical features without explicit supervision [176]
MusicBERT-SSL	2023	SSL+BERT	Enhances music representation learning through masked prediction tasks [177]
SSL-Harmony	2024	SSL+GAN	Combines self-supervised learning with adversarial training for improved music generation [178]

III. Discussion on Cutting Edge Models in AI Music Generation

The field of AI music generation has evolved dramatically in recent years, driven by breakthroughs in deep learning architectures, multimodal integration, and ethical considerations. Below is an expanded analysis of cutting-edge models and trends, supported by references from industry developments and academic research.

A. **Transformer-Based Models:** Transformer architectures have become the backbone of modern AI music systems due to their ability to model long-range dependencies and integrate cross-modal data.

MusicLM (Google): MusicLM leverages large-scale Transformers to generate music from text prompts, enabling precise control over genre, mood, and instrumentation. Its semantic conditioning mechanism allows users to describe scenes (e.g. ”a melancholic violin solo at dusk”) and receive stylistically coherent outputs [166]. Recent iterations incorporate relative positional encoding, improving coherence in multi-minute compositions [166].

MIDI-GPT: A specialized Transformer model for multitrack music composition, MIDI-GPT supports track-level infilling and attribute-based generation (e.g., instrument type, note density). Unlike earlier models, it avoids duplicating training data and guarantees instrument-specific outputs, making it ideal for professional workflows [167].

Udio: A commercial platform using a Hybrid Transformer-VAE architecture, Udio enables real-time collaboration where multiple users co-compose tracks with distinct roles (e.g., lead melody, percussion). Its training data is ethically sourced, addressing copyright concerns while maintaining high fidelity [167].

B. **Diffusion Models and Autoregressive Hybrids:** Diffusion models have emerged as a powerful alternative to GANs, offering higher audio fidelity and robustness against mode collapse.

Riffusion: This diffusion-based model generates music by denoising visual spectrogram representations. Users input text prompts e.g upbeat electronic dance music, and riffusion synthesizes tracks in seconds, though outputs may lack the depth of human-composed music [168].

Hydra II (Rightsify): Trained on 1 million copyright-cleared songs, Hydra II combines diffusion with text to music functionality. It supports 800+ instruments and 50+ languages, focusing on instrumental music to avoid vocal deepfake controversies [168].

Noise2Music: A hybrid model integrating diffusion with autoregressive components, Noise2Music refines outputs iteratively. This approach ensures contextual alignment between notes, preserving melodic integrity even in complex compositions [169].

AudioCraft: Meta's latest audio generation model combines diffusion with self-attention mechanisms to produce high- fidelity music from text descriptions. Its multi-stage architecture allows for fine-grained control over musical attributes while maintaining coherent structure.

MusicLDM: A latent diffusion model that operates in compressed latent space, enabling faster generation while preserving quality. It incorporates semantic conditioning to better align generated music with textual descriptions.

C. **Hybrid Architectures:** Hybrid models bridge symbolic and audio domains, enhancing both interpretability and expressiveness. Recent developments demonstrate significant advantages in combining multiple architectures.

MuseCoco: This two-stage framework first generates symbolic MIDI sequences using rule-based constraints, then converts them into high-fidelity audio via neural synthesis. MuseCoco's hybrid design is particularly effective for classical and jazz genres, where structural clarity is paramount [166].

VAE-Transformer Hybrids: Models like MusiciAI combine Variational Autoencoders (VAEs) with Transformers to encode latent spaces of musical styles. Users can interpolate between emotions (e.g., joy to sorrow) while the Transformer ensures long-term coherence. This architecture is widely used in therapeutic applications for mood-aligned music generation [166].

CNN-RNN Architecture: Recent models integrate CNNs for local feature extraction with RNNs for temporal modeling. For instance, DeepJ combines convolutional layers for harmonic analysis with LSTM networks for melodic progression, achieving more coherent long-term structure in generated pieces.

GAN-VAE Fusion: Systems like MuseGAN incorporate VAEs within GANs to improve training stability and output diversity. This combination allows for better control over musical attributes while maintaining generation quality [140].

D. **Real-Time and Interactive Systems:** Modern AI systems are increasingly designed for live performance and dynamic adaptation.

IBM Watson Beat: Watson Beat uses reinforcement learning (RL) to adjust melodies in real time based on physiological signals (e.g., heart rate). For instance, during a live concert, the system can shift from a calm piano melody to an energetic synth riff in response to audience engagement metrics [166].

Interactive AI Studios: Platforms like Loudly integrate AI with digital audio workstations (DAWs), allowing producers to remix tracks dynamically. Loudly's playback engine combines 170,000+ audio loops in real time, adapting to user-defined chord progressions [170].

E. **Emotion-Conditioned Generation:** Emotion-aware models are reshaping how music aligns with human affect.

Suno: Suno's multi-modal embedding system maps text descriptions to emotional contours. For example, the prompt "a triumphant orchestral crescendo" triggers dynamic shifts in tempo and instrumentation, leveraging attention mechanisms to emphasize key motifs [171].

AIVA: AIVA generates cinematic scores conditioned on emotional labels (e.g., "epic," "suspenseful"). Its LSTM-Transformer hybrid architecture adjusts rhythmic dynamics and pitch variance to evoke specific moods, making it a favorite among filmmakers [172].

EmotiVAE: A specialized VAE architecture that learns to map between emotional descriptors and musical features. The model can interpolate between different emotional states while maintaining musical coherence.

F. **Emerging Commercial Tools and Ethical Challenges:** The commercialization of AI music tools has accelerated, raising important concerns about copyright, industry integration, and ethical considerations.

Copyright and Originality: Models like MusicGen employ "theory-trained" algorithms to avoid plagiarism concerns, yet platforms like Boomy face scrutiny for enabling AI-generated music monetization without clear royalty frameworks [168].

Industry Integration: Commercial platforms like Mureka and Soundraw democratize music creation through AI, focusing on thematic consistency through motif-based generation and royalty-free track creation, though outputs often require human refinement for professional use [172].

Ethical Considerations: The industry grapples with fundamental challenges including attribution rights, fair compensation models, preservation of human creativity, and cultural appropriation concerns. These issues necessitate developing comprehensive frameworks that balance innovation with artistic integrity.

Challenges of Technical and ethical Development: The latest AI music models demonstrate unprecedented capabilities while facing key challenges as technical advancement of multimodal integration combining text, audio, and visual inputs shows promise [170], while enhanced user control through attribute-based interfaces improves generation quality [167]. Hybrid architectures merging multiple model types demonstrate superior performance in maintaining musical coherence.

Ethical Development of **i**ndustry progress requires standardized licensing models for AI-generated music [172], robust attribution systems for crediting both AI and human contributions, and fair compensation structures for AI-assisted compositions. Copyright concern and use of unlicensed works to train generative AI must be addressed [49][50].

Future Research focus on priorities includes developing emotion-aware models, cross-cultural learning systems, and sophisticated real-time collaboration tools. While originality and copyright challenges persist, hybrid architectures and emotion-aware systems promise to enhance human-AI musical collaboration rather than replace human artistry.

IV. Datasets for AI-Driven Monophonic Music Generation:

High-quality datasets are fundamental for training models that can produce coherent and stylistically accurate melodies. This section examines key datasets and their characteristics. Common data formats for monophonic music generation includes MIDI, ABC notation, and symbolic representations, each offering different levels of detail and ease of use. MIDI provides precise timing and velocity information, while ABC notation excels in folk music representation. The key requirements are sufficient size and diversity for monophonic model training. Consistent annotation quality for ensuring the data is accurate, reliable, and useful for training machine learning models. Clear metadata (tempo, key, genre), balanced genre representation and accurate transcriptions. The notable monophonic dataset in terms of size, feature and description is shown in table 3.

The necessity for more diverse, well-structured datasets is that future datasets must address current limitations to advance AI-driven monophonic music generation. Key priorities include expanding genre coverage beyond western classical and pop music, incorporating detailed expressive annotations (dynamics, articulation, phrasing), maintaining rigorous data quality standards, and increasing overall dataset sizes. Additionally, datasets should include cultural metadata and stylistic annotations to enable more nuanced music generation across diverse traditions. These improvements will enhance AI models' ability to generate authentic, emotionally resonant compositions while preserving cultural authenticity.

Table 3. The Notable Monophonic Music Datasets

Dataset	Size	Features and Description	Access
ABC Notation	500K+ tunes	Folk and traditional music in ABC notation with rich metadata	[17]
MAESTRO	200+ hours	Synchronized MIDI-audio piano performances with alignment	[18]
Irish Folk	50K+ tunes	Celtic melodies for stylistic music generation	[19]
Nottingham	1,200 tunes	Traditional British/American folk tunes in MIDI	[20]
POP909	909 songs	Pop songs with detailed structural annotations	[21]
NSynth	305K notes	High-quality audio from 1,006 instruments	[22]
dMelodies	1.3M melodies	Two-bar sequences with controlled variations	[23]

mono-midi	100K+ files	Monophonic MIDI files for transposition studies	[24]
MuseScore	17K scores	Monophonic scores in MusicXML format	[25]
Good-Sounds	12K samples	Professional instrument recordings	[26]
OMR	15K sheets	Optical Music Recognition dataset	[27]
ORCHSET	64 excerpts	Symphonic music with melody annotations	[28]
CVC-MUSCIMA	1K images	Handwritten music score images	[29]
MUSCIMA++	140K symbols	Enhanced music notation dataset	[30]
DeepScores	300K scores	Typeset scores for OMR development	[31]
HOMUS	11K symbols	Handwritten music symbols dataset	[32]
MusicCaps	5.5K pairs	Music-text pairs with expert descriptions	[33]
Lakh MIDI	176K files	Diverse MIDI collection for retrieval	[34]
URMP	44 pieces	Multi-modal performance dataset	[35]

V. Evaluation methodology for AI generated Monophonic Music:

AI-generated music evaluation requires both subjective assessments and objective metrics and this section examines key methodologies.

Subjective Evaluation: It centers on human judgment to assess musicality and emotional expressiveness. In human listening tests experts and non-experts evaluate samples for overall appeal, melody coherence, and emotional impact using Likert scales. This resembles musical Turing tests, determining if AI-generated music matches human composition quality [36]. While in the structured Surveys, participants rate specific elements like pitch accuracy, rhythm coherence, and melodic continuity. These quantified opinions enable model comparisons [37]. Then comparative studies carried out side-by-side model output comparisons which help determining relative performance in expressiveness and style adherence [38].

Objective Evaluation: It uses computational metrics based on s**tatistical measures** as pitch distribution analysis using KL divergence, entropy for measuring sequence diversity, Frechet Audio Distance (FAD) and Wasserstein Distance for distribution comparison. Some note-level metrics can also use for objective evaluation such as Raw Pitch Accuracy (RPA), Chromatic Pitch Accuracy (CPA), Rhythm coherence measures and structural coherence metrics.

Hybrid/Combined Methodologies: It integrates both subjective and objective methods by pre-screening which use objective metrics to filter samples before human evaluation [39]. Automated quality prediction carried out where machine learning models predict human ratings based on objective features [40]. Standardized Frameworks where development of universal evaluation protocols combining quantitative measures with human judgment is one of the hybrid approaches of evaluation.

VI. Applications of AI Monophonic music generation:

Folk and Traditional Music: Folk-RNN generates melodies adhering to regional styles (Rajasthani, Irish, Celtic), preserving musical heritage [139]. BachBot creates authentic-sounding solo instrumental pieces using LSTM networks [138].

Educational Applications: MelodyRNN demonstrates musical concepts through generated examples [134], while Piano Genie enables interactive learning [41]. AIVA combines rule-based systems with deep learning for music theory education [94].

Creative Applications: DeepJ generates jazz improvisations for solo instruments [42], while IBM

Watson Beat creates emotion-conditioned melodies [144]. Dance2Music generates synchronized music from movement [43].

Research Applications: MusicVAE explores latent spaces for melody generation [127], while RL-Duet enables AI-human collaborative compo- sition [44]. Researchers analyze generated melodies to study musical creativity [64].

Commercial and Therapeutic Uses: AIVA and MuseNet assist in quick music production [94] [13]. CalmAI generates personalized melodies for stress reduction [45], while Spotify's AI DJ creates adaptive playlists [46].

Gaming and Interactive Media: WaveNet adapts music to gameplay events [154], while MuseMorphose enables dynamic soundtrack generation based on narrative progression [48].

Conclusions

This comprehensive review of AI-driven monophonic music generation reveals several key findings. Deep learning models have significantly improved music generation capabilities, with hybrid architectures showing particular promise. However, challenges persist in achieving true creativity and maintaining consistent macro-structures. Dataset limitations include genre bias, lack of expressive annotations, and inconsistent encoding formats. More diverse, multimodal datasets are needed for advancement. While combining objective metrics with subjective assessments provides a foundation, standardized evaluation protocols are needed to capture musical quality comprehensively. The field must address copyright concerns, fair compensation mechanisms, and cultural preservation issues. Future directions include developing hybrid architectures combining symbolic and audio generation, integrating emotion-aware and cross-cultural learning systems, enhancing real-time collaborative tools, and establishing robust evaluation frameworks. The future of AI music generation lies in balancing technological innovation with human creativity, ensuring AI serves as an enhancement rather than replacement for human musical expression.

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