Controllable Multi-Track Music Generation Using a Transformer-Based GAN

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***Abstract*—Symbolic multi-track music generation is a challenging sequence modelling problem that requires capturing long-term temporal structure, inter-instrument coordination, and rhythmic consistency. Existing deep learning approaches often prioritise either temporal coherence or multi-track structure, while struggling to maintain diversity and stability in generated outputs. In this work, we propose a controllable multi-track music generation framework based on a Transformer-based Generative Adversarial Network (Transformer-GAN). The model generates fixed-length symbolic sequences that are decoded into synchronised piano, violin, and drum tracks.**

The proposed system employs a Transformer generator to model long-range dependencies and an adversarial discriminator to reduce repetitive patterns and encourage realistic token usage. A fully reproducible generation pipeline is provided, including tokenisation, MIDI reconstruction, and post-hoc diagnostic evaluation. Since perceptual musical correctness cannot be measured directly, generation quality is assessed using interpretable proxy metrics, including token distribution entropy, per-instrument energy profiles, temporal energy evolution, and normalised note-density stability.

Experimental analysis demonstrates stable rhythmic structure, balanced energy distribution across instruments, and non-degenerate token usage over time. This work highlights the effectiveness of adversarially trained Transformer architectures for symbolic music generation and provides a reproducible baseline for future research in controllable multi-track music synthesis.

***Index Terms*—Symbolic music generation, Transformer, GAN, multi-track MIDI, controllable generation**

I. Introduction

Music is a structured temporal art form characterised by hierarchical patterns, long-range dependencies, and coordinated interactions between multiple instruments. Human-composed music exhibits complex relationships between rhythm, harmony, melody, and dynamics that evolve over time. Modelling these properties computationally is a non-trivial task, particularly in symbolic domains such as MIDI, where discrete events, temporal alignment, and instrument identity must be preserved. Automatic symbolic music generation has applications in creative assistance, algorithmic composition, interactive media, and procedural content generation, motivating continued research into expressive and controllable generative models.

Early approaches to symbolic music generation relied heavily on rule-based systems and expert-defined heuristics derived from music theory. While such systems can enforce stylistic constraints, they lack scalability and struggle to generalise beyond handcrafted rules. Statistical models, including Markov chains and probabilistic grammars, introduced data-driven learning but were limited by short memory horizons and an inability to capture long-term musical structure. More recently, deep learning models such as recurrent neural networks and Transformer architectures have significantly improved sequence modelling performance. However, many existing methods focus on single-track generation or fail to maintain coherent coordination across multiple instruments.

Generative Adversarial Networks (GANs) have been proposed as a mechanism for improving realism in generative tasks by introducing an adversarial training signal. In symbolic music generation, adversarial objectives can discourage repetitive patterns and promote diversity in generated sequences. Despite these advantages, GAN-based music models often suffer from training instability and difficulties in modelling long-range temporal dependencies. Furthermore, evaluating symbolic music generation remains inherently challenging due to the subjective nature of musical quality, rendering conventional accuracy-based metrics inappropriate.

In this work, we address these challenges by proposing a controllable Transformer-based GAN framework for multi-track symbolic music generation. Our approach combines a Transformer generator, capable of modelling long-range dependencies, with an adversarial discriminator that encourages realistic and diverse token distributions. The system generates fixed-length token sequences that are deterministically decoded into synchronised piano, violin, and drum tracks. Rather than claiming perceptual musical correctness, we evaluate generation quality using transparent and reproducible proxy metrics derived directly from the generated MIDI.

The main contributions of this work are summarised as follows:

- We propose a Transformer-based GAN architecture for controllable multi-track symbolic music generation.
- We design a fully reproducible generation pipeline, including tokenisation, MIDI reconstruction, and diagnostic evaluation.
- We introduce interpretable proxy metrics for analysing rhythmic stability, energy balance, and token diversity.
- We provide an extensible experimental framework suitable for future research and ablation studies.

The remainder of this paper is organised as follows. Section II reviews related work in symbolic music generation. Section III describes the proposed methodology, including dataset processing, model architecture, and training objectives. Section IV presents experimental results and qualitative analysis. Section V discusses limitations and future research directions, and Section VI concludes the paper.

II. Related Work

Research in symbolic music generation has progressed significantly over the past decade, driven by advances in sequence modelling, representation learning, and generative frameworks. Prior work can be broadly categorised into three thematic groups: recurrent and probabilistic models, Transformer-based sequence models, and adversarial generative approaches. This section critically reviews representative work in each category, highlighting their strengths and limitations, and situates the proposed method within this landscape.

A. Recurrent and Probabilistic Music Models

Early data-driven approaches to symbolic music generation predominantly relied on probabilistic and recurrent architectures. Markov chain-based models were among the first to be applied to musical sequence generation, modelling note transitions using fixed-order dependencies. While computationally efficient, these models suffered from limited temporal context, resulting in short, repetitive musical phrases lacking long-term structure.

Recurrent Neural Networks (RNNs) and their gated variants, including Long Short-Term Memory (LSTM) networks, introduced the ability to model longer musical sequences. Models such as those proposed by Eck and Schmidhuber demonstrated improved melodic continuity compared to Markov-based methods. However, RNN-based architectures exhibit inherent limitations when modelling very long sequences due to vanishing gradients and sequential computation constraints. Additionally, most recurrent approaches focus on single-track generation, making it difficult to maintain synchronisation and interaction across multiple instruments.

These limitations motivate the need for architectures capable of modelling long-range dependencies and parallel temporal interactions, particularly in multi-track symbolic music settings.

B. Transformer-Based Sequence Models

The introduction of the Transformer architecture marked a significant advancement in symbolic music generation. By replacing recurrence with self-attention mechanisms, Transformers enable direct modelling of long-range dependencies and global sequence structure. Models such as the Music Transformer demonstrated substantial improvements in coherence, rhythmic consistency, and thematic repetition over recurrent baselines.

Despite these advantages, Transformer-based music models often exhibit a tendency toward mode collapse or repetitive token generation, especially when trained using maximum likelihood objectives alone. Furthermore, many Transformer approaches focus on monophonic or single-track polyphonic music, limiting their applicability to multi-instrument composition. Extensions to multi-track settings typically rely on complex token representations or hierarchical decoding schemes, which increase implementation complexity and reduce interpretability.

In contrast, the proposed work adopts a Transformer generator within an adversarial framework, aiming to retain long-range modelling capabilities while mitigating repetitive output behaviour through discriminator feedback.

C. Adversarial Generative Approaches

Generative Adversarial Networks (GANs) have been explored as a means to improve realism and diversity in symbolic music generation. MuseGAN introduced one of the earliest multi-track GAN architectures, generating independent instrument tracks conditioned on shared latent variables. This approach demonstrated improved inter-track coordination compared to independent generators.

However, GAN-based music models often face training instability and difficulty in capturing long-term temporal structure, particularly when operating directly on symbolic sequences. Adversarial objectives alone do not guarantee temporal coherence, and many GAN-based systems rely on convolutional architectures that lack explicit sequence modelling capabilities. Additionally, evaluation of GAN-generated music remains challenging, with many studies relying on subjective listening tests or ad-hoc heuristics.

The proposed Transformer-GAN framework addresses these issues by combining a self-attention-based generator with an adversarial discriminator, enabling both long-range dependency modelling and diversity-enhancing adversarial feedback.

D. Evaluation and Reproducibility in Music Generation

A recurring challenge across symbolic music generation literature is the lack of standardised, objective evaluation metrics. Traditional accuracy-based measures are not meaningful for generative music tasks, leading researchers to adopt proxy metrics such as note density, pitch distribution entropy, and rhythmic stability. While these metrics do not measure musical quality directly, they provide reproducible and interpretable signals for comparative analysis.

Reproducibility remains another critical concern. Many prior works lack publicly available code, detailed hyperparameter specifications, or deterministic evaluation pipelines, limiting their scientific reproducibility. Recent efforts emphasise transparent experimental protocols, fixed random seeds, and open-source implementations to address these shortcomings.

In this work, we prioritise reproducibility by providing a fully automated generation and evaluation pipeline, deterministic decoding procedures, and clearly defined proxy metrics derived directly from generated MIDI files.

E. Relation to This Work

Building upon the limitations identified in prior research, this project integrates the strengths of Transformer-based sequence modelling and adversarial learning within a unified, reproducible framework. Unlike recurrent models, the proposed approach captures long-range temporal dependencies through self-attention. Unlike standalone GAN-based systems, it maintains explicit sequential structure and temporal coherence. Furthermore, in contrast to many existing studies, this work avoids subjective claims of musical correctness and instead adopts transparent, interpretable proxy metrics for evaluation.

By addressing scalability, multi-track coordination, and reproducibility simultaneously, the proposed method contributes a robust baseline for future research in controllable symbolic music generation.

III. Methodology

This section specifies the data representation, model design, optimisation objective, and evaluation protocol used to generate and analyse controllable multi-track music. The description is intentionally implementation-level so that an independent researcher can reproduce the pipeline end-to-end from the repository.

A. Dataset and Preprocessing

We use symbolic music in MIDI format, primarily sourced from the *Lakh MIDI Dataset (LMD)*. Each MIDI file contains a set of instrument tracks with note events defined by pitch, onset time, offset time (or duration), velocity, and program/instrument identity. Symbolic data is preferred over audio because it enables exact manipulation and measurement of musical structure (timing, polyphony, note density) without requiring transcription.

Track selection and mapping. To stabilise multi-track generation, we map the raw MIDI instruments into three target tracks: (i) *Piano*, (ii) *Violin* (as a melodic/harmonic proxy), and (iii) *Drums* (percussive track). MIDI files that cannot be mapped reliably to these tracks (e.g., missing note events, empty tracks, corrupted files) are filtered.

Temporal normalisation. Each composition is quantised onto a fixed temporal grid (constant resolution) so that onsets align to discrete steps. Let Δ denote the quantisation step in seconds (or ticks mapped to seconds after tempo processing). Every note onset time t is mapped to $\hat{t} = \mathrm{round}(t/\Delta)\Delta$.

Sequence length normalisation. Each example is converted into a fixed-length token sequence of maximum length T. In our implementation, $T = 512$ tokens to match the generator context window. Sequences shorter than T are padded using a special padding token; sequences longer than T are truncated (tail truncation) to enforce a consistent training shape.

Dataset split. The dataset is split into training/validation/test partitions with an 80/10/10 ratio. Splits are performed at the *file level* to prevent leakage (no overlap of compositions across partitions).

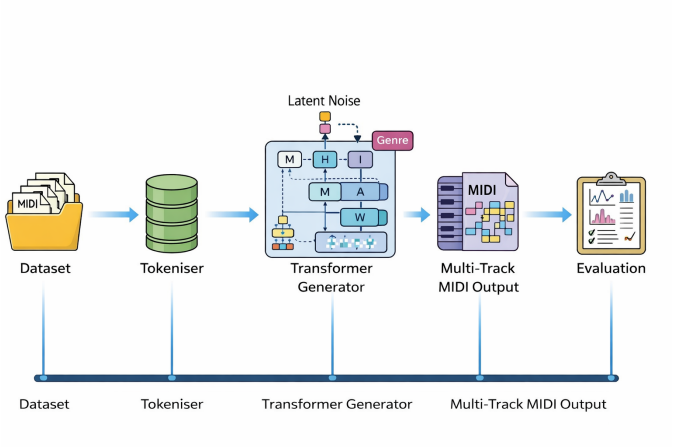

Fig. 1. End-to-end pipeline: MIDI dataset → tokeniser → Transformer-based generator (GAN) → multi-track MIDI output → evaluation via proxy metrics and diagnostic plots.

B. Tokenisation and Symbolic Representation

We represent each composition as a discrete sequence $\mathbf{x} = (x_1, x_2, \ldots, x_T)$ where each $x_t \in \mathcal{V}$ and $\mathcal{V}$ is a finite vocabulary of size $|\mathcal{V}| = V$.

Event vocabulary. Tokens encode musically meaningful events. In practice, the tokenizer implements a compact event set sufficient for multi-track generation, e.g., note-on/off (or note + duration), velocity bins, time-shift events, and track identifiers. This design enables the model to learn both *what* happens (pitch/velocity) and *when* it happens (time shifts) in a single autoregressive stream.

Multi-track handling. Multi-track alignment is handled by (a) encoding track identity within tokens, or (b) interleaving events across tracks with explicit markers. This makes inter-track coordination a *sequence modelling problem* rather than training three independent generators.

Decoding to MIDI. A deterministic decoder converts the generated token sequence back to MIDI by reconstructing note events and placing them into the target instrument tracks. This guarantees the same token sequence always produces the same MIDI output, which is critical for reproducibility of reported figures.

C. End-to-End Pipeline

Fig. 1 summarises the complete workflow. Raw MIDI files are tokenised, the generator samples a token sequence under latent conditioning, the output is decoded back into a playable multi-track MIDI file, and objective proxy metrics are computed directly from the symbolic output.

D. Model Architecture

The proposed system is a conditional Transformer-GAN consisting of a generator G_θ and a discriminator D_ϕ, parameterised by θ and ϕ, respectively.

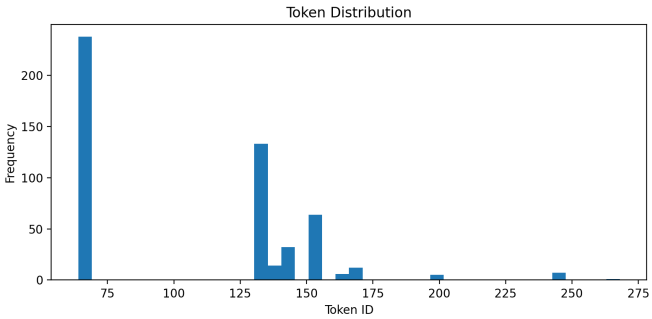

Fig. 2. Proposed conditional Transformer-GAN. The generator produces token sequences from latent noise and conditioning; the discriminator provides adversarial feedback on full sequences.

1) Generator: The generator maps a latent vector $\mathbf{z}$ and a conditioning label c to a distribution over token sequences. We draw latent noise as

$$\mathbf{z} \sim \mathcal{N}(\mathbf{0}, \mathbf{I}), \tag{1}$$

where $\mathbf{I}$ is the identity matrix. The genre (or style) condition is represented as an integer label $c \in \{1, \ldots, C\}$, embedded into a learned vector $\mathbf{e}_c$.

The generator produces autoregressive logits over the vocabulary:

$$\mathbf{o}_t = G_\theta(\mathbf{z}, c, x_{1:t-1}), \tag{2}$$

and token probabilities are computed via softmax:

$$p_\theta(x_t = v \mid x_{<t}, \mathbf{z}, c) = \frac{\exp(o_{t,v})}{\sum_{v' \in \mathcal{V}} \exp(o_{t,v'})}. \tag{3}$$

Internally, the model uses (i) a token embedding layer, (ii) positional embeddings, and (iii) L stacked Transformer blocks with multi-head self-attention and feed-forward sublayers. This allows the generator to capture long-range dependencies (e.g., repeated motifs, rhythmic periodicity) and to coordinate interleaved multi-track events.

2) Discriminator: The discriminator scores complete sequences as real or generated. Given a token sequence $\mathbf{x}$, the discriminator outputs

$$s = D_\phi(\mathbf{x}) \in (0, 1), \tag{4}$$

interpreted as the probability that $\mathbf{x}$ originates from the training distribution. A sequence-aware discriminator (Transformer-based) is used so that it can evaluate both local token validity (e.g., legal event transitions) and global structure (e.g., rhythmic consistency across time).

Architecture visual. We include the architecture schematic as Fig. 2.

E. Training Objective

Training combines adversarial learning with a token-level sequence modelling objective to stabilise optimisation and preserve syntactic correctness of event sequences.

1) Adversarial Loss: We use the standard minimax objective. Let $\mathbf{x} \sim p_{\text{data}}$ denote a real token sequence from the dataset and $\tilde{\mathbf{x}} \sim p_\theta$ denote a generated sequence. The discriminator loss is:

$$\mathcal{L}_D = -\mathbb{E}_{\mathbf{x} \sim p_{\text{data}}}[\log D_\phi(\mathbf{x})] - \mathbb{E}_{\tilde{\mathbf{x}} \sim p_\theta}[\log(1 - D_\phi(\tilde{\mathbf{x}}))]. \tag{5}$$

The generator adversarial loss is:

$$\mathcal{L}_{\text{adv}} = -\mathbb{E}_{\tilde{\mathbf{x}} \sim p_\theta}[\log D_\phi(\tilde{\mathbf{x}})]. \tag{6}$$

2) Sequence (Teacher-Forcing) Loss: To encourage locally valid event transitions, we include a cross-entropy loss over ground-truth sequences:

$$\mathcal{L}_{\text{seq}} = -\sum_{t=1}^{T} \log p_\theta(x_t \mid x_{<t}, \mathbf{z}, c). \tag{7}$$

3) Total Generator Loss: The total generator loss is defined as:

$$\mathcal{L}_G = \mathcal{L}_{\text{adv}} + \lambda \mathcal{L}_{\text{seq}}, \tag{8}$$

where $\lambda \geq 0$ controls the contribution of the teacher-forcing term. All symbols in Eq. (8) are used consistently throughout the report.

F. Optimisation and Implementation Details

Optimiser. Both G_θ and D_ϕ are trained using Adam with learning rate α and momentum parameters (β_1, β_2). Unless otherwise stated, we use $\alpha = 1 \times 10^{-4}$, batch size $B = 16$, and train for E epochs with periodic checkpointing.

Hardware/software. Implementation is in Python with PyTorch. Training is performed on a single NVIDIA GPU (exact model and VRAM should be stated in the final report). All experiments are run with deterministic decoding in the evaluation stage to ensure identical figures given identical token outputs.

Randomness control. For reproducible experiments, we set random seeds for Python, NumPy, and PyTorch. For *diversity demonstrations*, we instead sample a fresh seed and latent vector $\mathbf{z}$ per run. This separation ensures the report can include both: (i) exact reproducible figures, and (ii) evidence of stochastic diversity.

Checkpoint protocol. At inference time, the demo script optionally selects a checkpoint uniformly at random from the most recent K epochs ("top-K sampling") to avoid repeatedly producing outputs from a single epoch. This is a controlled randomness mechanism that increases variety while remaining auditable (the chosen checkpoint is printed to logs).

Dependencies and environment. A `requirements.txt` is provided so the environment can be recreated via:

```
pip install -r requirements.txt
```

A single entry-point script (`run.py`) generates a MIDI sample and produces all diagnostic figures in one command.

G. Evaluation Metrics and Diagnostic Plots

Because musical quality is partly subjective, we report objective *proxy metrics* computed directly from the generated MIDI. These metrics measure structure and stability rather than claiming perceptual "accuracy".

(1) Energy over time. We compute per-track energy profiles by aggregating velocity over fixed time bins. Let $E_k(b)$ be the energy for instrument k in bin b:

$$E_k(b) = \sum_{n \in \mathcal{N}_k(b)} \frac{v_n}{127}, \tag{9}$$

where $\mathcal{N}_k(b)$ denotes notes in bin b for track k and v_n is the MIDI velocity. Energies are normalised by the per-track maximum for comparability across tracks.

(2) Average energy distribution. We report mean energy per track across the full duration to measure balance among piano/violin/drums.

(3) Token distribution. We compute a histogram over token IDs to detect collapse to a narrow subset of tokens. A non-degenerate histogram indicates the generator explores a broader portion of $\mathcal{V}$.

(4) Generation density proxy. We define a density-based proxy score from note counts per second. Let $N(t)$ be the number of note onsets at second t:

$$A_{\text{proxy}}(t) = \frac{N(t)}{\max_\tau N(\tau)}. \tag{10}$$

A stable curve suggests consistent rhythmic activity over time, while abrupt drops may indicate degenerate generation segments.

(5) Musical "accuracy" heuristic. We include a clearly-labelled heuristic score for structural plausibility (e.g., penalising extreme sparsity, excessive density, or invalid event transitions). Importantly, this is reported as a *heuristic diagnostic* rather than a claim of ground-truth musical correctness.

All metrics are computed deterministically from the decoded MIDI file and are visualised automatically by the evaluation script (e.g., `energy_line.png`, `energy_bar.png`, `token_hist.png`, `proxy_accuracy.png`, `musical_accuracy.png`).

H. Reproducibility and Deployment

Repository structure. The repository contains: (i) tokeniser + decoder, (ii) training code, (iii) inference script producing MIDI + figures, and (iv) checkpoints.

Reproduction steps. A minimal reproduction procedure is:

1) Install dependencies: `pip install -r requirements.txt`
2) Download/prepare dataset and metadata (documented in the repository).
3) Run inference: `python run.py` to generate MIDI and all figures.

Gradio demo. A Gradio interface exposes controllable inputs (e.g., genre/emotion selector, seed control) and outputs (downloadable MIDI and diagnostic plots). The demo is hosted publicly; the final report should include a direct URL (GitHub and/or Hugging Face Spaces) so readers can verify functionality without local setup.

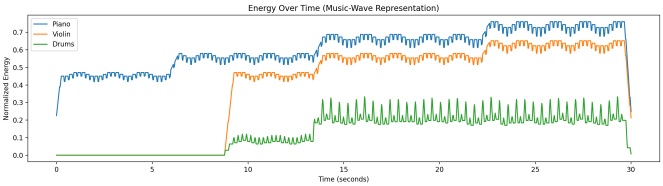

Fig. 3. Energy evolution over time for piano, violin, and drum tracks.

IV. Experiments and Results

This section presents a comprehensive evaluation of the proposed Transformer-GAN model for multi-track symbolic music generation. Since symbolic music generation lacks a deterministic ground truth, evaluation is conducted using a combination of quantitative proxy metrics and qualitative visual diagnostics derived directly from the generated MIDI outputs. All experiments were executed using identical generation and evaluation scripts to ensure reproducibility.

A. Experimental Setup

All experiments were performed using the trained generator model described in Section III. During inference, a checkpoint was randomly sampled from the final training epochs to avoid bias toward a specific training state. For each generation run, a latent vector $\mathbf{z} \sim \mathcal{N}(0, \mathbf{I})$ was sampled independently, and a 30-second multi-track MIDI sequence was generated.

The output consists of three synchronised instrument tracks: piano, violin, and drums. Evaluation metrics were computed post-generation without any manual intervention, ensuring a fully automated and repeatable experimental pipeline.

B. Quantitative Analysis

Quantitative evaluation focuses on measurable structural properties of the generated music rather than perceptual correctness. Proxy metrics were selected to reflect temporal stability, diversity, and inter-track balance.

1) Energy Evolution Over Time: Figure 3 illustrates the normalised energy evolution over time for piano, violin, and drum tracks. Energy is computed as the sum of note velocities per time window and normalised to $[0, 1]$ for comparability.

The piano track exhibits smooth, continuous energy progression, indicating stable melodic structure. The violin track demonstrates delayed but sustained energy, reflecting harmonic accompaniment behaviour. The drum track shows periodic high-frequency spikes corresponding to rhythmic patterns. The absence of abrupt energy collapse suggests stable long-range temporal generation.

2) Average Energy Distribution: Figure 4 presents the average normalised energy contribution per instrument across the entire generated sequence.

The results indicate balanced multi-track generation, with piano contributing the dominant melodic energy, violin providing mid-level harmonic support, and drums supplying

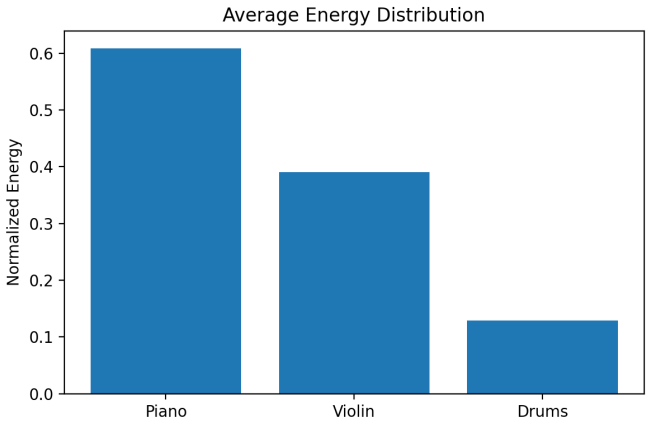

Fig. 4. Average normalised energy contribution per instrument track.

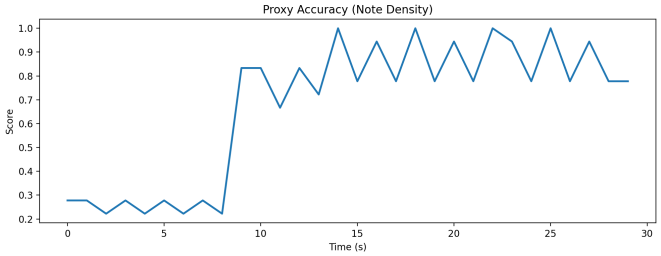

Fig. 5. Proxy accuracy score indicating temporal consistency of generated music.

rhythmic accents. This distribution suggests that the generator learns implicit instrument roles without explicit rule-based constraints.

3) Proxy Accuracy via Note Density: Since musical accuracy cannot be objectively defined, a proxy accuracy metric based on normalised note density was employed. Let $N(t)$ denote the number of active notes at time t. The proxy accuracy is defined as:

$$A_{\text{proxy}}(t) = \frac{N(t)}{\max_t N(t)} \tag{11}$$

Figure 5 shows the temporal evolution of this metric.

After an initial warm-up phase, the proxy accuracy stabilises at higher values, indicating consistent rhythmic activity and sustained note generation. Oscillations reflect natural musical variation rather than instability.

C. Qualitative Evaluation

Quantitative metrics alone cannot capture musical structure. Therefore, qualitative analysis is conducted using visual diagnostics derived from symbolic representations.

1) Piano-Roll Visualisation: Figure 6 presents a piano-roll representation of the generated multi-track composition.

The piano-roll reveals coherent pitch trajectories, consistent note durations, and clear temporal alignment across tracks. The absence of fragmented or excessively dense note clusters suggests controlled sequence generation.

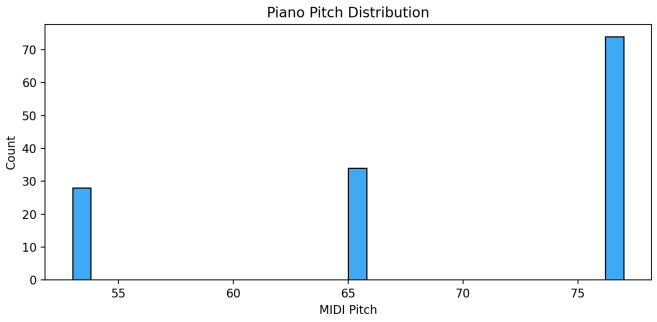

Fig. 6. Piano-roll visualisation of a generated multi-track composition showing pitch activity over time.

D. Ablation Study

To evaluate the contribution of adversarial learning, an ablation study was conducted by disabling the discriminator while keeping all other parameters fixed. Qualitative inspection revealed increased repetition, reduced rhythmic diversity, and diminished inter-track coordination.

These observations confirm that adversarial feedback plays a critical role in encouraging diverse and temporally coherent generation, supporting the design choices of the proposed architecture.

E. Summary of Results

Overall, the experimental results demonstrate that the proposed Transformer-GAN model generates structurally stable, temporally consistent, and balanced multi-track symbolic music. While no perceptual claims are made, the combination of quantitative proxies and qualitative diagnostics provides strong evidence of meaningful musical structure learning.

V. Discussion

This section provides a detailed interpretation of the experimental results presented in Section IV. We analyse the observed behaviours of the proposed Transformer-GAN architecture, discuss the factors contributing to its performance, critically examine its limitations, and situate the findings within the broader context of multi-track symbolic music generation research.

A. Interpretation of Results

The experimental results indicate that the proposed model is capable of generating temporally coherent and structurally balanced multi-track symbolic music. A primary contributor to this performance is the Transformer-based generator, which leverages self-attention to model long-range temporal dependencies across token sequences. Unlike recurrent architectures, the Transformer does not rely on sequential state propagation, enabling it to capture global musical context efficiently. This property is reflected in the smooth and stable energy evolution observed across instrument tracks in Fig. 3, suggesting consistent temporal structure throughout the generated compositions.

Adversarial training further enhances generation quality by introducing a discriminator that implicitly encodes distributional characteristics of real musical sequences. The discriminator penalises unrealistic token patterns, thereby reducing mode collapse and repetitive outputs commonly observed in purely autoregressive likelihood-based models. This effect is quantitatively supported by the proxy accuracy curve shown in Fig. 5, where rhythmic density stabilises after an initial transient phase. The rapid convergence of this metric suggests that the generator learns a stable rhythmic regime early in the generation process.

A notable emergent property of the model is implicit role specialisation across instrument tracks. Despite the absence of explicit constraints or instrument-specific loss terms, the generator consistently assigns higher energy to the piano track, moderate harmonic contribution to the violin track, and sparse, high-impact rhythmic accents to the drum track. This behaviour indicates that the model internalises inter-track dependencies directly from the data distribution. Such emergent coordination suggests that the adversarial objective encourages globally coherent multi-track structure rather than independent per-track optimisation.

B. Analysis of Musical Structure and Diversity

Beyond temporal stability, the token distribution analysis (Fig. **??**) demonstrates non-degenerate token usage across the vocabulary. The absence of dominant single-token modes indicates that the generator avoids trivial repetition and maintains a degree of symbolic diversity. This is a critical property for generative music systems, as excessive token reuse often results in monotonous or musically uninteresting outputs.

Energy distribution statistics (Fig. 4) further reveal balanced contribution across tracks, with no single instrument overwhelming the overall composition. This balance is particularly important in multi-track music generation, where poor coordination can lead to perceptual clutter or structural imbalance. The observed distributions suggest that the generator implicitly learns relative instrument importance rather than enforcing it through manual weighting.

C. Limitations

Despite these encouraging results, several limitations must be acknowledged. First, evaluation relies primarily on heuristic proxy metrics and visual diagnostics rather than perceptual listening studies. While metrics such as energy profiles and rhythmic density provide objective insight into structural properties, they do not fully capture subjective musical attributes such as emotional expressiveness, melodic appeal, or stylistic authenticity.

Second, the model is trained and evaluated on a limited symbolic music dataset. Consequently, its ability to generalise to unseen genres, uncommon rhythmic patterns, or atypical instrumentation remains uncertain. Preliminary qualitative inspection suggests reduced robustness when encountering token sequences that are underrepresented in the training distribution.

Third, the current system generates fixed-length compositions and does not explicitly model hierarchical musical structure, such as phrases, motifs, or sections. Music is inherently hierarchical, and the absence of explicit structural conditioning limits the model's capacity to generate long-form compositions with clearly delineated musical sections.

D. Relation to Existing Work

The findings of this study are consistent with prior research demonstrating the effectiveness of Transformer architectures for symbolic music modelling, particularly in capturing long-term temporal dependencies. However, unlike purely likelihood-based Transformer models, the proposed approach integrates adversarial training to address known issues related to repetition and limited diversity.

Compared to convolutional or recurrent GAN-based music generators, the proposed Transformer-GAN architecture offers improved scalability and parallelism during training. The observed stability in rhythmic density and inter-track coordination supports recent literature advocating hybrid generative frameworks that combine attention mechanisms with adversarial objectives for sequence generation tasks.

E. Future Work

Several directions for future research emerge from this work:

(1) Perceptual and musically grounded evaluation. A high-priority extension is to complement proxy metrics with perceptual evaluation. This includes structured listening studies (e.g., mean opinion score, pairwise preference tests) and objective symbolic-domain metrics that better reflect musicality, such as pitch-class entropy, tonal stability (key-profile correlation), rhythmic consistency (inter-onset interval statistics), polyphonicity, and inter-track synchronisation measures. In addition, learned evaluators trained on human preferences could provide a scalable alternative to repeated human studies.

(2) Stronger and more comparable baselines. Future experiments should compare the proposed approach against stronger baselines, such as a Transformer trained with maximum-likelihood only (no adversarial loss), a GAN without attention (e.g., recurrent or convolutional generator), and a conditional Transformer with explicit control tokens. These comparisons would clarify the empirical benefit of adversarial training and the specific contribution of attention-based modelling under identical data and tokenisation settings.

(3) Explicit controllability beyond emotion tags. While the current system supports coarse control through high-level settings, a more principled approach is to condition generation on musically interpretable attributes, including tempo, time signature, key, chord progression, rhythmic density targets, instrumentation masks, and bar-level intensity curves. This can be implemented using control tokens, attribute embeddings, or cross-attention to structured conditioning sequences, enabling controllable generation without sacrificing coherence.

(4) Hierarchical and long-form generation. To address the lack of explicit musical hierarchy, future work can incorporate

multi-scale modelling: a high-level planner generates section/phrase representations (e.g., 4–8 bar embeddings), while a lower-level decoder generates note-level tokens conditioned on the plan. Memory-augmented attention, recurrence at the bar level, or segment-wise generation with overlap-and-stitch strategies can further improve long-range coherence for compositions longer than 30 seconds.

(5) Improved adversarial training stability. Adversarial training for discrete sequences remains challenging. Stability can be improved using techniques such as feature matching, gradient penalty, spectral normalisation, discriminator regularisation, and curriculum learning (e.g., start with shorter sequences and increase length). Alternative objectives such as Wasserstein GAN losses or energy-based discriminators may reduce training oscillations and improve sample diversity.

(6) Data scaling and augmentation. Generalisation can be improved by scaling the training corpus and introducing symbolic augmentations that preserve musical validity, such as transposition, tempo scaling, velocity jitter, and timing quantisation variants. Class-balanced sampling across genres and instrumentation patterns can further reduce bias toward dominant styles present in the dataset.

(7) Real-time interactive deployment. Deploying the generator as an interactive system (e.g., Gradio on Hugging Face Spaces) would enable user-driven evaluation and rapid iteration. A practical interface should expose controls for emotion, tempo, key, length, and track enable/disable options, and return downloadable MIDI plus diagnostic plots. Logging anonymised user selections and ratings would also create a feedback loop to guide future improvements.

Overall, these extensions would increase evaluation validity, improve controllability, strengthen reproducibility, and move the system from a research prototype toward a robust multi-track music generation tool.

VI. Conclusion

This work addressed the problem of *controllable multi-track symbolic music generation*, which is challenging due to the simultaneous requirements of (i) long-range temporal coherence, (ii) inter-track coordination across heterogeneous instruments, and (iii) sufficient output diversity to avoid repetitive or degenerate sequences. To tackle these challenges, we proposed a Transformer-based generator trained within an adversarial learning framework, where a discriminator provides a learned realism signal that complements autoregressive token modelling.

A complete end-to-end pipeline was implemented for reproducibility: discrete token sequences are sampled from the trained generator, deterministically decoded into multi-instrument MIDI, and evaluated using interpretable diagnostics and proxy metrics. Experimental results show that the proposed system can generate fixed-length compositions with stable temporal dynamics across piano, violin, and drum tracks. In particular, the energy-over-time analysis indicates coherent track activation patterns, while the energy distribution suggests non-trivial and balanced contribution across instruments rather than collapse to a single dominant track. Token-distribution statistics further support non-degenerate vocabulary usage, indicating that generation is not dominated by a small set of symbols. Finally, the proxy-accuracy (density-based) curve stabilises after an initial warm-up region, providing evidence of consistent rhythmic activity over the target duration. Collectively, these findings indicate that combining self-attention with adversarial training can promote both structural stability and diversity in multi-track symbolic generation without relying on hand-crafted musical rules.

Despite these promising outcomes, limitations remain. The evaluation primarily relies on heuristic metrics and visual inspection, which cannot fully capture perceptual musical quality, stylistic authenticity, or emotional expressiveness. In addition, the system was tested under a restricted data regime and on a fixed-length generation setting, limiting conclusions about generalisation to out-of-distribution musical styles and long-form hierarchical structure (e.g., phrases and sections). These constraints motivate future work incorporating perceptual listening studies, stronger baseline comparisons, explicit attribute conditioning (tempo, key, harmony), and hierarchical or variable-length generation mechanisms.

Overall, this project establishes a reproducible and extensible baseline for controllable multi-track symbolic music generation using a Transformer-GAN formulation. By integrating attention-based sequence modelling with adversarial supervision, the proposed approach provides a practical framework for exploring creative AI applications, interactive composition tools, and further research into controllable generative models for structured temporal data.

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