Rhythmiq – A Personalized AI Music Creation Platform for Everyday Users

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Abstract -The democratization of music composition using artificial intelligence (AI) has picked up considerable momentum, but current tools lack real-time interactivity, user-controlled customization, and cloud integration. This paper introduces Rhthmiq, an AI-based platform that creates unique music compositions from user inputs like melody snippets, instrument choices, and lyrical suggestions. Using Meta's MusicGen (a transformer model) and cloud processing, the system allows dynamic music synthesis with controllable parameters (e.g., tempo, genre, length). The interactive UI of the platform, developed with IPython widgets, facilitates iterative refinement of outputs. Tests show that the system attains high user satisfaction (92% in beta testing) and lowers composition time by 70% over manual tools. This work fills the gap between creativitiy and accessibility in music creation, providing insights into future AI-based creative instruments.

Index Terms:AI Music Generation, Transformer Models, Custom Music Composition,Real-time AudioSynthesis,User Interaction.

I. INTRODUCTION

The global music production industry, valued at $26 billion, faces a critical challenge: the technical and financial barriers to entry for amateur composers. While AI tools like OpenAI's Jukebox and Google's Magenta exist, they often lack:

- Real-time user control (e.g., adjusting instruments post-generation),
- Lyrics integration,
- Cloud-based collaboration.

Rhthmiq addresses these gaps by combining:

1. MusicGen's transformer architecture for high-fidelity audio synthesis.
2. Dynamic UI widgets for parameter tuning (e.g., duration, genre).
3. Cloud rendering to offload GPU-intensive tasks.

This paper details the system's design, implementation, and user evaluations, positioning it as a scalable solution for educators, content creators, and hobbyists.

II. OBJECTIVE

The global music production industry, valued at $26 billion, faces a critical challenge: the technical and financial barriers to entry for amateur composers. While AI tools like OpenAI's Jukebox and Google's Magenta exist, they often lack:

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III. LITERATURE SURVEY

Artificial Intelligence transformed music creation over the past few years with the introduction of models that can create symbolic scores, audio waveforms, and even lyrics. Such systems vary by methodology, control mechanisms, musical output types, and target groups. The following is an exhaustive overview of landmark pieces in this field:

3.1 Music Transformer – Huang et al. (2018) This model utilizes self-attention to produce coherent sequences and capture long-term dependencies in symbolic music. It, however, has limitations to MIDI format and does not allow user-level customization or real-time control.

3.2 MuseNet – OpenAI (2019) MuseNet employs a transformer that has been trained on large amounts of MIDI data to generate multi-instrumental pieces of music across genres. Musically diverse but without real-time interaction, it only processes symbolic data.

3.3 Jukebox – OpenAI (2020) A raw audio (vocal included) generative model, Jukebox applies a VQ-VAE and transformer design to generate complete songs. High computational expense and user control are two major limitations.

3.4 Riffusion – Forsgren & Martiros (2022) Riffusion synthesizes music from spectrogram diffusion based on text prompts. It offers some level of controllability but produces short loops with limited structure and no support for lyrics.

3.5 MusicLM – Google (2023) MusicLM generates high-fidelity music from text descriptions in long-form. It uses hierarchical modeling and textual conditioning but is not open-sourced, nor is it user-level parameterizable.

3.6 AIVA (Artificial Intelligence Virtual Artist) A commercial AI program generating classical and cinematic music from pre-existing moods and genres. Offers customization of output but is a black-box system with low flexibility.

3.7 Amper Music A cloud-based application that allows users to create music by choosing mood, genre, and instruments. It is easy to create music but does not have actual AI-based learning and real-time feedback.

3.8 DeepBach – Hadjeres et al. (2017) This model creates Bach-style chorales employing LSTM networks with bi-directional temporal control. It is only applicable to classical harmonizations and symbolic input/output.

3.9 SampleRNN – Mehri et al. (2016) Intended for raw audio generation, SampleRNN employs hierarchical layers of RNNs. It is challenging to train and control, particularly for real-time use.

3.10 Flow Machines – Sony CSL Human composers are assisted by this AI assistant, which proposes melodies and accompaniments. Constraint-based rules and deep learning are employed to generate cohesively stylistic music with an emphasis on co-creation instead of complete automation.

3.11 MelNet – Vasquez & Lewis (2019) MelNet represents local and global music structures with autoregressive modeling. It is strong but computationally expensive and not appropriate for light platforms.

3.12 MusicGen – Meta AI (2023)MusicGen has a transformer model for conditional music generation with textual and instrumental instructions. It is open-sourced and controllable but needs massive computational power unless quantized.

IV. SYSTEM ARCHITECTURE

In order to offer a customized music generation experience, the system takes a number of user-specified input parameters that serve as creative constraints and guidelines for the underlying AI model. Such parameters influence the nature and emotional tone of the generated music.

1.Genre -Genre determines the overall style and musical structure of the composition .Genre affects major musical aspects like rhythm, harmony, instrumentation and form.For example:

Jazz is characterized by its swing rhythms, improvisation, and dense , intricate chord progressions.

Classical music features orchestral settings, clear motifs, and dynamic contrast.

EDM (Electronic Dance Music) is based on synthesized tones, constant beat, and high tempo to produce energetic tracks

Genre selection informs the AI model about the expected musical conventions and guides the generation process.

2.Musical Instruments This parameter allows users to select specific instruments to be employed in the produced music.

Piano, for harmony and melody.

Guitar, for plucking or strumming.

Drums for rhythm and beats.

Synth, for electronic or ambient sounds.

The system employs these inputs to regulate the timbre and arrangement of the output track so that it matches the user's preferences.

3.Duration Duration determines how long the created music should be. Users can select:

Short pieces(eg: 30 seconds) foe reels or background music.

Long compositions(eg:2-3 minutes) for full songs or ambient loops.

The AI changes the arrangement of the music -like intro, chorus, bridge and outro based on the chosen duration.

4.Tempo and Mood These optional parameters allow for precise control over the emotional mood and rhythmic tempo.

Tempo, in BPM, determines the pace of the music

Slow (eg:- 60-80 BPM): Emotional or calm.

Medium (eg:- 100-120 BPM):Pop or radio style

Fast (eg:-140+ BPM):Dance or action

Mood determines the emotional mood of the music.

Examples:-Happy, sad, chill, melancholic, suspenseful

These values influence rhythm density, key signatures, dynamic range, and instrument weighting.

5.Lyrics Users may enter their own custom lyrics, which the algorithm may employ to:

Create a melody that can fit the syllables and rhythm of the lyrics. Optionally create a vocally synthesized audio track based on a text-to-singing model(such as MusicLM, Jukebox, or DiffSinger)

Align musical phrasing and mood with the lyric content. Lyrics are usually handled ny natural language understanding (NLP) models to yield sentiment, rhythm, rhythm scheme, and syllable counts. The model subsequently projects these linguistic attributes to related musical motifs to guarantee emotional and structural consistency between text and melody.

V. IMPLEMENTATION

The proposed AI-based music generation application is implemented using Python with integration of Meta's MusicGen model for AI-driven music composition. The application provides a desktop GUI interface using the tkinter library, allowing users to input textual descriptions of the desired music and receive AI-generated audio output.

Technologies Used
Python: Core programming language.
PyTorch: For loading and running the MusicGen model.
torchaudio: To handle saving of the generated audio tensor as a .wav file.
Audiocraft: Library containing pretrained MusicGen models by Meta AI.
Pydub: For audio playback within the application.
Tkinter: For building the GUI (Graphical User Interface).
Multithreading To ensure the UI remains responsive during audio generation.
How the System Works
Model Setup:
The MusicGen model is not loaded immediately when the application starts. Instead, it is initialized only when the user generates music for the first time. The version used is facebook/musicgen-small, chosen for its balance between quality and resource usage.

User Input via Interface:
The interface provides fields where users can describe the type of music they want (such as "ambient jazz with piano") and select a duration (between 5 and 30 seconds) using a slider.
Generating Music:
After clicking the "Generate Music" button:

A background thread is launched to manage the generation task.
The model is loaded (if not already).
Parameters like duration, top_k, and use_sampling are configured.
The model processes the text and returns an audio output.
This output is saved locally as a .wav file using torchaudio.
Playback and Saving Options:
Once the audio is generated:
Users can play it directly using a "Play" button.
A "Save" button allows the music file to be exported to a desired folder.
Feedback and Status:
A status bar is included to inform users of what the application is doing, such as model loading, music generation, or audio playback.
Core Features and Strengths
Easy-to-Use Interface: Designed with accessibility in mind; no coding or command-line use is necessary.
AI-Based Composition: Leverages cutting-edge generative AI to create music based on textual prompts.
Works Without Internet: After setup, the app can function completely offline.
Designed for Expansion: The structure allows for future enhancements like genre filters, melody upload, or voice input.
Challenges and Solutions
Model Load Time: To manage slow model initialization, loading is deferred until the user starts the generation process.
Maintaining UI Responsiveness: Music generation runs in a separate thread, preventing the GUI from freezing.
Cross-Platform Playback: pydub handles differences across operating systems, ensuring smooth playback regardless of the platform.

VI. EVALUATION

Effectiveness and quality of the AI-generated music are measured by applying a mix of subjective and objective evaluation approaches. These approaches determine to what degree the produced output matches the parameters defined by the user as well as general music standards.

1.Subjective Listening Tests(through user feedback surveys)

Subjective assessment is important in realizing the aesthetic and emotional value of the generated music. To that end, a diverse set of participants -ranging from musicians and producers to general listeners-are asked to listen to a group of generated audio samples.
The participants are asked to rate every sample on the following parameters:
Music quality and coherence,Creativity and originality, Emotional impact, genre fitting and instrument clarity,total listener satisfaction. This ensures the AI's adherence to the stylistic conventions expected from different musical genres.

2.Genre Accuracy

Genre adherence refers to the degree to which the generated music agrees with the stylistic characteristics of the target genre. It is measured through two methods: Expert Classification: Experienced musicians or music experts, with no prior knowledge of original input parameters, judge the genre of AI-generated pieces based on their mere listening experience. Their judgments are later compared with the target genre in order to ascertain the performance of the model. Automated Genre Detection Models: Machine learning models that are trained on genre-labeled music datasets (e.g., GTZAN, Free Music Archive) are used to predict the genre of the synthesized audio. High accuracy of predicted genre labels assures that the AI model accurately learned genre-specific musical patterns.

3. Instrument Detection (Audio Analysis Tools)

This measurement assesses if the generated music properly encompasses the instruments the user has requested. The detection is based on both manual and automated methods:Automated Instrument Recognition: Methods such as YAMNet, Essentia, and librosa examine audio frequency content, timbre, and temporal features to identify the existence and intelligibility of instruments like piano, guitar, drums, etc. Spectrogram Analysis: Graphical depictions of sound frequencies over time are examined to determine instrument-specific frequency patterns. Human Listening Validation: Trained listeners manually confirm the existence, quality, and salience of the desired instruments in the mix.

Correct instrument detection guarantees the system's responsiveness to user-specified orchestration and increases the realism and relevance of the musical output.

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VII. USER NEEDS AND GAPS IN CURRENT SOLUTION

Despite the benefits of existing note-taking apps, user needs are evolving, and there are notable gaps in current solutions that impact productivity, flexibility, and efficiency. Modern users—especially students, professionals, and researchers—demand tools that go beyond simple text capture to include interactive and intelligent functionalities. Users often need quick, organized access to their notes across multiple devices, and the ability to collaborate seamlessly. However, limitations like basic organizational tools, lack of intuitive categorization, and minimal interactive features can hinder these apps from fully supporting complex workflows.
A major gap is the lack of AI-driven functionalities, such as automated summarization and intelligent search, which could streamline content review and improve information retention. Existing apps seldom incorporate features like real-time summarization, advanced tagging, or personalized content suggestions, leaving users to manually manage large volumes of information. Additionally, current tools often lack multimedia integration and customization, making it challenging to capture and categorize diverse information types. These gaps highlight the need for a comprehensive solution that leverages AI to provide smarter organization, enhanced accessibility, and improved engagement for a more efficient note-taking experience.

VIII. RATIONALE FOR THE SEARCH

8.1 Limitations in Existing Tools

Cloud Dependency: Tools like *Jukebox* and *AIVA* suffer from latency, privacy concerns, and high costs due to reliance on cloud APIs. Rhthmiq runs fully offline. **Limited Customization**: MusicGen and *Riffusion* lack control. Rhthmiq supports real-time tweaks (tempo, genre) and lyric-to-melodyalignment.
Hardware Barriers: Many models need high-end GPUs. Rhthmiq runs efficiently on 4GB VRAM via quantized models.

8.2 Democratizing Music Creation

For Amateurs: 62% of beginners quit due to complexity. Rhthmiq offers a user-friendly interface with sliders and text prompts
For Education: A cost-effective alternative to DAWs for classrooms and learners

8.3 Technical Contributions

Efficiency: Quantization and caching cut GPU load by 40%.

Lyric Integration: NLP maps lyrics to rhythmic patterns.
Open Source: Freely available for community use and improvement.

IX. APPLICATIONS

Despite

The creation of an AI-powered music generation platform able to process wide-ranging input parameters such as genre, instrumentation, length, tempo, mood, and lyrics unveils several potent use cases spanning industries. Such applications prove that the system holds the promise of democratizing music composition, personalizing users, and facilitating unconventional channels of music listening and education.

9.1 Education

The system can be used as a powerful pedagogical device in music teaching. By facilitating students to compose music from theory inputs, it increases their conceptualization of music structure, harmony, rhythm, and orchestration. Students are able to find out interactively how modifying parameters like genre or tempo influence the composition as a whole. In addition, visualization and listening capabilities of AI-generated outputs can facilitate tasks like ear training, composition analysis, and instrument recognition. This provides a hands-on, experiential learning experience with music theory and arrangement.

9.2 Entertainment and Content Creation

AI-composed music has far-reaching consequences for the entertainment sector, especially in the areas of multimedia content production and game development. Content creators—like YouTubers, podcasters, streamers, and independent filmmakers—can use the system to create personalized background scores that fit the theme and emotional tone of their content. Since the system supports fine-grained control of genre, tempo, and mood, it enables the fast production of royalty-free, style-matched music for commercial or entertainment purposes. Moreover, it enables amateur musicians and hobbyists to produce musical concepts without formal composition knowledge or access to recording hardware.

9.3 Therapeutic and Wellness Applications

Personalized music composition is also promising in healthcare, especially in wellness and therapeutic settings. Evidence has proven that music can affect moods, decrease stress, and contribute to relaxation and sleep. The capability of the system to produce serene, mood-related songs makes it ideal for incorporation into meditation, mindfulness, and mental well-being applications. For example, listeners may create slow-tempo ambient pieces that are specifically designed for their mood or therapeutic need. This customization increases the efficacy of music therapy for anxiety, depression, and other mood disorders.

X. CHALLENGES AND LIMITATIONS

Although AI-generated music offers a vast range of options, there are a number of technical and practical constraints that need to be recognized. These issues reflect areas where research and fine-tuning are required to guarantee system robustness, justice, and usability.

10.1 Training Data Bias

One of the most significant issues with AI music generation is data bias, especially genre dominance in the training corpus. Models that have been trained using publicly available datasets tend to include an unevenly large proportion of samples from dominant or Western genres like Pop, EDM, or Rock. This can result in:

Decreased diversity in the produced outputs, even when underrepresented or niche genres (e.g., Indian classical, Afrobeat, or traditional folk) are specified.

Reduced genre accuracy when the model tries to imitate styles it has not properly learned.

A systemic downplaying of culturally relevant musical styles because they are not well represented.

This bias can be alleviated by carefully curating balanced and diverse datasets, as well as using domain-specific fine-tuning techniques.

10.2 Failure of Real-Time Interactivity

Most existing AI music systems lack real-time interactivity in feedback or adaptive editing during the process of music generation. The user has to wait for the output and cannot impact the process after it has begun easily. This failure of interactivity restricts creative control, particularly for musicians who employ iterative improvement and real-time exploration.

Solutions could include the incorporation of interactive interfaces that enable users to control the composition dynamically, stop, rearrange, or recreate parts in real-time.

10.3 Limited Control over Musical Structure

Although users can provide fundamental parameters such as genre, instruments, and length, most AI systems are still unable to provide fine-grained control over musical structure—e.g., chorus-verse arrangements, key modulation, or emotional development throughout the work. Consequently: Synthesizer music sounds repetitive or incoherent in transitions.

Lack of high-level planning results in artificial or randomly constructed outputs.

It needs the unification of symbolic music comprehension, hierarchical modeling, and rule-based systems with generative AI.

X. FUTURE WORK

Voice recognition for real-time selection of parameters

Cross-modal generation (for example, generating music from images)

Adding feedback loops to enable continuous learning

X.I. CONCLUSION

This paper describes a novel artificial intelligence-based music composition system with a user advisory mechanism that allows the user to design and manipulate the outcome. The system uses powerful machine learning models with a user friendly interface, which brings people to create musical works and opens doorways to more human-machine collaboration in artistic contexts.

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