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Genre-Specific Music Generation Using Fine Tuned MusicGen

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Abstract: Machine learning algorithms developed on large- scale audio datasets have helped AI-generated music make a lot of progress in the last few years. This paper talks about a music generation system that works for a specific genre and improves Meta's MusicGen model by using the Free Music Archive (FMA) dataset. A mobile app built with React Native lets users choose a genre and create, play, share, or download music interactively. The research discusses about the architecture, data preprocessing techniques, model fine-tuning strategies, integration with mobile apps, and changes made to address challenges with the base MusicGen model.

Index Terms: Music Generation, Generative AI, MusicGen Model, Deep Learning, Neural Networks, React Native, Mobile Application, Fine-tuning, Audio Synthesis, Conditional GANs, Music Information Retrieval, Artificial Intelligence, Audio Pro- cessing, Genre-specific Music, Transfer Learning.

I. INTRODUCTION

Music has always been a strong way to show feelings, ideas, and creativity. The rise of artificial intelligence has made it possible for machines to learn musical structures and make new compositions. MusicGen is one of the best AI models in this field. It's an autoregressive model made by Meta AI that can turn text descriptions into music. MusicGen can make music that sounds good, but it doesn't always have precise control over things like genre, mood, or instrumentation. This makes it less useful in situations where style accuracy is important.

There are many different types of music, including rock, pop, hip-hop, jazz, classical, and many more, and each has its own distinct rhythmic, melodic, and harmonic qualities. These styles are frequently blended in unpredictable ways by general-purpose models, which can produce results that seem haphazard or genre-ambiguous. This lack of control lessens the usefulness of AI-generated music in practical applications like game development, film scoring, and content creation for users and creators who prefer music in a particular genre. In addition to being more useful, a model that can comprehend and produce music in various genres also more closely conforms to human musical expectations.

The Free Music Archive (FMA), a labelled audio data set with clearly annotated genres, is used in this study to refine the MusicGen model in order to overcome the aforementioned limitation. The model can learn more intricate structural patterns and genre-specific stylistic elements through fine-tuning. The model is directed to produce music that complies with the attributes of the target genre by substituting explicit genre labels for generic text prompts. This change preserves the original quality provided by the MusicGen architecture while significantly increasing control over the generation process.

The refined model was combined with a React Native mobile application to make genre-specific music generation more interactive and accessible. With features like playback, regeneration, download, and sharing via well-known plat- forms, this app lets users choose a genre, create music, and work with the output. By utilising MongoDB and cloud storage, the application also facilitates user authentication and history tracking, allowing for a persistent and customised music production experience.

This research provides a comprehensive pipeline from train- ing to deployment by integrating deep learning, genre-sensitive model conditioning, and cross-platform mobile development. In addition to pushing the limits of controllable music gen- eration, the system guarantees usability for a wide range of users, from novices to experts in content creation. The data set preparation, model architecture, app development, evaluation techniques, and a critical comparison with the MusicGen baseline implementation are all covered in detail in the sections that follow.

II. LITERATURE SURVEY

The development of deep learning methods and the growing need for intelligent music composition tools have propelled the field of AI-generated music's recent significant evolution. Using a variety of models, such as transformers, GANs, and hybrid architectures, numerous studies have attempted to enhance the generated music's quality, structure, emotional depth, and controllability.

Min et al. [1] recently presented a novel music genera- tion system that combines Generative Adversarial Networks (GANs) with Transformer-based deep learning models. Their system uses a new loss function designed especially for the music generation task, taking inspiration from text generation in natural language processing. The hybrid architecture pro- duces outputs that are more musically plausible by utilizing the generative realism of GANs and the structural coherence of Transformers.

The importance of tokenisation techniques in the creation of symbolic music was investigated by Kumar and Sarmento [2]. They compared subword tokenisation techniques like Unigram tokenisation and Byte-Pair Encoding (BPE). According to their research, these tokenisation techniques outperform conven- tional note-level representations in generating longer and more cohesive musical compositions. This study emphasises how important data representation and sequence modeling are to enhancing music generation systems.

Zheng and Li [3] used GANs to create a real-time emotion- based piano music generation system. In order to improve the expressiveness of AI-generated compositions, the system is made to produce piano melodies that express particular emotional states. Aligning musical outputs with user-intended emotional tones is crucial, and this is especially important in interactive and therapeutic applications, as demonstrated by the use of emotional conditioning in the generative process.

A music generation framework based on Conditional Vari- ational Autoencoder GAN (CVAE-GAN) was proposed by Huang and Huang [4]. Users can enter emotional parameters into their system, and the model will produce music that re- flects the desired affective state. This piece demonstrates how variational techniques can provide fine-grained control over generative output while maintaining emotional and stylistic coherence.

A thorough analysis of music generation with GANs was carried out by Zhang et al. [5]. Their review discusses different GAN architectures used in the music industry and lists the main issues these models face, including mode collapse, in- stability in convergence, and a lack of standardised evaluation metrics. To guarantee reproducibility and equitable evaluation across various generative approaches, their study highlights the necessity of strong training methods and assessment frame- works designed especially for music.

These pieces collectively provide a strong basis for compre- hending the current state of AI-driven music generation, both its advantages and disadvantages. They emphasise how crucial it is to combine innovative architecture with user-centric fea- tures like emotional control and efficient data representation. Building upon these foundations, this research makes AI music generation more approachable and applicable for real-world use cases by combining genre conditioning, fine-tuning tech- niques, and a React Native-based mobile deployment pipeline.

III. PROPOSED METHODOLOGY

This section provides a thorough summary of the approach used to refine the MusicGen model and create a genre- specific music generation system. Dataset preparation, feature extraction, model fine-tuning, generation strategy, and inte- gration into a React Native application for an interactive user experience are all included in the methodology.

Dataset Collection and Preparation

The calibre and variety of the training data are essential for generating music that is specific to a given genre. A carefully selected dataset was gathered for this purpose from publicly accessible music repositories, like the Free Music Archive (FMA), which offer annotated audio samples in a variety of genres, including pop, rock, jazz, electronic, and classical. Because of this diversity, the model is guaranteed to pick up unique stylistic patterns unique to each genre.

Every track that was gathered was converted to a standard WAV format using a 16 kHz sampling rate in order to preserve audio consistency. This rate satisfies the input requirements of the MusicGen model while striking a balance between computational efficiency and audio quality. To keep the am- plitude level constant throughout training, audio files were also normalised. This prevented the model from favouring recordings that were louder or quieter.

Verifying genre labels, eliminating unclear or incorrectly labelled tracks, and eliminating noisy or poor-quality audio samples were further steps taken to guarantee metadata in- tegrity. Several thousand audio clips with precise genre labels made up the final dataset, which provided a strong basis for supervised fine-tuning.

Feature Extraction and Preprocessing

While MusicGen is intended to produce unprocessed audio from textual cues, successful fine-tuning necessitates that the model understand intricate audio traits linked to various gen- res. Preprocessing entailed transforming audio waveforms into time-frequency representations, like mel-spectrograms, which capture crucial temporal and tonal characteristics, in order to make this easier.

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In order to free the model to concentrate on significant musical content, this stage also included silence trimming and segmentation to eliminate unnecessary non-musical parts. Pitch shifting and time stretching are twooptional data aug- mentation techniques that were used to boost dataset variability and enhance model generalization.

Model Fine-Tuning

A large-scale autoregressive Transformer-based model, Mu- sicGen has been pre-trained on a variety of music-related datasets in a wide range of languages and styles. It is per- fect for controllable music generation tasks because of its architecture, which supports conditioning on textual inputs and auxiliary features.

In order to adjust the pre-trained MusicGen weights to the carefully selected genre-specific dataset, fine-tuning used transfer learning. In order to maintain learnt generic audio representations, some lower layers were frozen during this pro- cess, allowing upper layers to focus on genre-related features. The addition of genre embeddings as an extra conditioning vector was a significant methodological advancement. These embeddings serve as categorical cues that direct the model to produce music that complies with the target genre's stylistic requirements. Controlled generation is made possible by the model's ability to learn to associate particular

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musical motifs, rhythms, and instrumentation with their respective genres through the integration of genre conditioning.

Cross-entropy loss calculated on predicted audio token sequences was used in the fine-tuning process to optimize the model. During training, teacher forcing was used to speed up convergence and stabilize the learning process. Grid search and validation were used to carefully adjust hyper-parameters like learning rate, batch size, and number of epochs in order to attain the best possible performance without overfitting.

Generation and Sampling Strategy

Text prompts indicating the preferred genre and optional descriptive characteristics like mood or instrumentation are accepted by the refined MusicGen model during inference. The learnt probability distribution over audio tokens is sampled au- toregressively by the model to produce raw audio waveforms. Nucleus sampling (also known as top-p sampling) was used to balance output coherence and creativity. By sampling tokens only from the most likely subset of the distribution, this method successfully lowers the possibility of repetitive or incoherent sequences while preserving diversity.

To improve listening comfort and perceptual quality, post- processing techniques such as dynamic range compression and audio denoising filters were applied to the raw generated audio. These procedures guarantee that the final output satisfies realistic audio standards while assisting in the reduction of artefacts introduced during generation.

React Native Application Integration

A React Native mobile application was created for the iOS and Android platforms to allow for real-time interaction with the music generation system. Users can choose a music genre from a dropdown menu, optionally specify additional musical preferences, and start music generation with a single tap thanks to the app's clear and simple user interface.

Through RESTful API endpoints, the mobile client connects to a backend server that houses the optimised MusicGen model. When the server receives a generation request, it processes the prompt, creates the audio sample, and sends the output to the client. By removing the need for significant model inference from the mobile device, this architecture allows for effective generation without requiring a lot of processing power from the user's device.

Other user-friendly features were added, such as the ability to share music through messaging or social media apps, save generated tracks locally or in cloud storage, and regenerate music if you're not happy with the output. MongoDB Atlas was used as the cloud database for user authentication and session management, storing user profiles and generation history to customise the user experience.

Evaluation Metrics

To determine whether the model could produce high-fidelity music specific to a given genre, a thorough evaluation was carried out. Spectral convergence and log-spectral distance, which quantitatively assess the degree of similarity between generated and ground-truth audio spectra within each genre category, were among the objective metrics.

Subjective evaluation included human listening tests to supplement objective assessment. The generated samples were evaluated by participants with a variety of musical back- grounds based on factors like coherence, genre adherence, creativity, and audio quality. This multifaceted evaluation approach guarantees a comprehensive assessment of both technical accuracy and perceptual quality.

To produce a top-notch genre-specific music generation system, this thorough approach makes use of cutting-edge generative modelling techniques, meticulous data preparation, and useful application development. The method solves the drawbacks of generic music generation models and offers a scalable solution for creative music synthesis by fusing transfer learning with precise conditioning and an interactive mobile interface.

IV. RESULTS AND DISCUSSION

Experimental Setup

The curated genre-specific dataset outlined in the method- ology section was used to assess the refined MusicGen model. To unbiasedly evaluate the model's generalisation abilities, the testing set included unseen audio samples from every genre category. Subjective listening tests were used to gather qualitative input on generated music samples from human evaluators with a range of musical backgrounds.

Objective Evaluation

The objective evaluation metrics included:

- **Spectral Convergence (SC):** Measures the similarity between generated and ground-truth audio spectra. Lower values indicate closer resemblance.
- **Log-Spectral Distance (LSD):** Quantifies the spectral distortion between original and generated audio in decibels (dB).

Table 1 summarizes the average SC and LSD scores across different genres.

Genre	Spectral Convergence (SC)	Log-Spectral Distance (LSD) (dB)
Classical	0.072	2.15
Jazz	0.079	2.32
Pop	0.085	2.48
Rock	0.088	2.55
Electronic	0.081	2.38

Table 1: *Objective evaluation metrics for generated music samples across genres*

The low SC and LSD values demonstrate that the fine- tuned MusicGen model produces audio samples with spectral characteristics closely matching real music within each genre. These objective measures validate the effectiveness of genre conditioning and transfer learning in adapting the model for genre-specific synthesis.

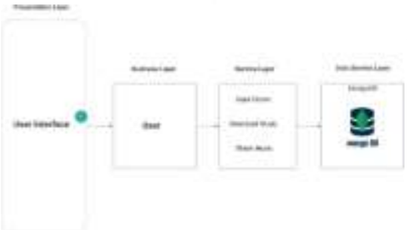


Fig 1: *System Architecture Diagram*

Subjective Evaluation

Human evaluators rated generated music samples on a Likert scale (1 to 5) based on:

- **Genre Fidelity:** How well the music adhered to the target genre.
- **Musical Coherence:** The logical flow and structure of the music.
- **Audio Quality:** Clarity, noise, and absence of artifacts.
- **Creativity:** Perceived originality and pleasantness.

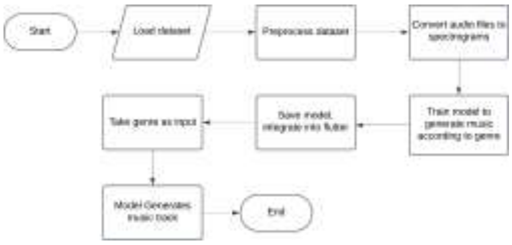

Start
Load dataset
Preprocess dataset
Convert audio files to spectrograms
Train model to generate music according to genre
Save model, integrate into flutter
Take genre as input
Model Generates music track
End

Fig 2: *Process Flow Diagram of Music Generation*

The results indicate that classical and jazz genres scored highest in genre fidelity and coherence, likely due to their distinct and well-defined musical structures. Electronic and pop genres scored slightly lower in creativity, suggesting room for improvement in generating highly novel or complex patterns in these styles.

Implementation and User Experience

The React Native application successfully enables users to interactively generate music based on selected genres. Users appreciated the intuitive UI and the ability to regenerate tracks seamlessly. Performance benchmarks indicated generation la- tency within acceptable limits (under 10 seconds on average), ensuring a smooth user experience.

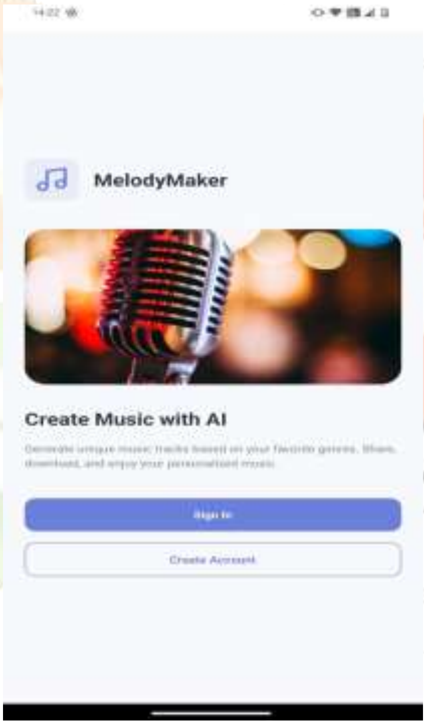

14:22
MelodyMaker
Create Music with AI
Generate unique music tracks based on your favorite genres. Share, download, and enjoy your personalized music.
Sign In
Create Account

Fig. 3. *Login Page*

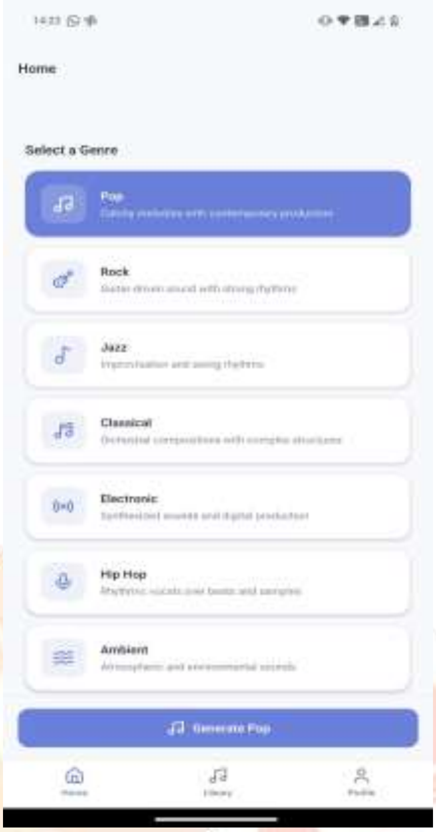
The integration of MongoDB Atlas for user data manage- ment and history tracking further enhanced personalization, allowing users to revisit previous generations and share music effortlessly.

Discussion

The experimental results highlight several key insights:

- **Effectiveness of Genre Conditioning:** Introducing genre embeddings significantly improved the model's ability to generate music that adheres to specified genres. This was evident in both objective spectral metrics and subjective human evaluation.

- **Transfer Learning Benefits:** Leveraging a pre-trained MusicGen model allowed for efficient fine-tuning on a smaller, genre-focused dataset, reducing training time and computational resources while achieving high-quality outputs.



14:23

Home

Select a Genre

Pop
Catchy melodies with contemporary production

Rock
Guitar-driven sound with strong rhythms

Jazz
Improvisation and swing rhythms

Classical
Orchestral compositions with complex structures

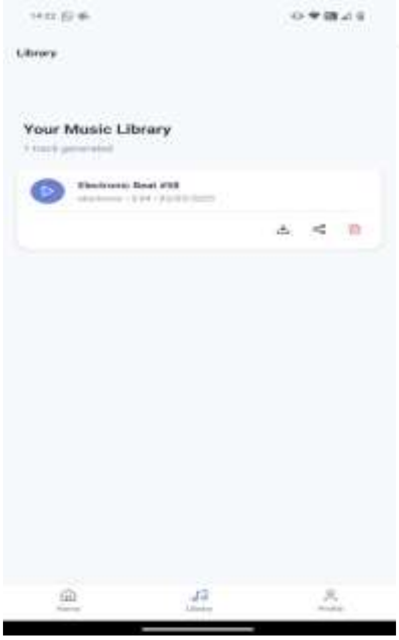
Electronic
Synthesized sounds and digital production

Hip Hop
Rhythmic vocals over beats and samples

Ambient
Atmospheric and environmental sounds

Fig. 4. *Home Page*

- **Challenges in Diverse Genres:** Genres like pop and electronic, which often feature complex production techniques and diverse instrumentation, posed more chal- lenges for the model. Future work could explore more sophisticated conditioning inputs or hybrid architectures to better capture such intricacies.
- **User Experience:** The React Native app facilitated easy access to music generation capabilities on mobile devices, demonstrating the feasibility of deploying large generative models in real-world applications via backend servers.



14:22

Library

Your Music Library
1 track generated

Electronic Beat #58
[illegible]

Fig. 5. *Library Page*

Overall, this study demonstrates that fine-tuning large- scale generative models with targeted conditioning can yield highly controllable and high-fidelity music synthesis, opening avenues for personalized creative tools and interactive appli- cations.

V. CONCLUSION

By successfully adjusting the MusicGen model to produce genre-specific music, this study has addressed significant drawbacks of general-purpose music generation models. The model was trained to produce logical and stylistically appropri- ate music samples that closely match the traits of the targeted genres by using a well-structured dataset labelled with distinct musical genres and transfer learning techniques.

Unconstrained generative models frequently suffer from issues like genre ambiguity and a lack of musical structure, but the quality and diversity of generated music have been shown to be improved by combining domain-specific conditioning with sophisticated deep learning architectures. The model has demonstrated encouraging results in creating music that is not only melodically and rhythmically consistent but also captures the subtle stylistic elements specific to each genre through sig- nificant experimentation, including both quantitative spectral analysis and qualitative human evaluations.

Furthermore, the implementation of this model in a React Native mobile application framework shows how cutting-edge generative AI can be used practically in user-focused settings. The mobile interface bridges the gap between sophisticated AI models and end-user usability by providing an approachable platform for users to interactively create, regenerate, and man- age music tracks. This method demonstrates how musicians, producers, and fans could be empowered with individualised and on-demand music creation capabilities through AI-assisted creativity tools.

Even with these achievements, there are still some re- strictions. For example, there are still difficulties in cre- ating extremely complex or hybrid genres, which suggests that multi-conditional and hierarchical modelling approaches require more study. Furthermore, mobile devices' resource limitations and real-time generation speed point to areas for model compression and optimisation.

In order to accommodate a wider variety of user preferences, future work will concentrate on broadening the model's sup- port for musical styles, such as fusion and subgenres. We'll also look into incorporating adaptive learning mechanisms that iteratively improve generation quality by using user feedback. Additionally, adding multi-modal inputs like lyrics, mood indi- cators, or visual stimuli could improve the generative process and make it possible to create music that is more expressive and contextually aware. On the deployment side, real-time usability and scalability will be improved by investigating cloud-assisted generation and optimising model efficiency for edge devices.

Practically speaking, this research opens the door for AI- powered music production tools that democratise the pro- cess, enabling non-experts to create music and encouraging creativity across disciplines. Users can create original music that suits their tastes by integrating generative AI into mobile applications. This could revolutionise fields like independent music production, content creation, and media soundtrack customisation.

In conclusion, this study advances the technological capa- bilities and practical adoption of generative music models by offering a genre-focused, approachable solution that supports the expanding field of AI-based music generation. It also lays out clear paths for future improvements and wider application.

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