GenMedia: A Research Project on Personalized Multi-Modal Media Generation Using Stable Diffusion and AudioCraft

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Abstract

In this paper, we present GenMedia, a research project focused on advancing the capabilities of Stable Diffusion models and AudioCraft's MusicGen for personalized multi-modal media generation. The project explores the fine-tuning of Stable Diffusion 2.0 and 3.5 using DreamBooth, with a particular emphasis on advancements in latent space optimization, prompt adherence, and image quality. These improvements enable the generation of high-quality, context-aware images based on user-provided text prompts and personalized datasets. Additionally, we investigate the fine-tuning of AudioCraft's MusicGen using Dora to synthesize personalized audio content, leveraging custom instrumental datasets and text prompts. The integration of FFMPEG enables the seamless combination of generated images and audio into cohesive video outputs. Through extensive experiments, we evaluate the performance of these models, focusing on their ability to create highly personalized and contextually relevant media content. This research highlights the potential of advanced generative models to revolutionize multi-modal AI, paving the way for future innovations in personalized media generation.

Keywords: Stable Diffusion, AudioCraft, Multi-Modal Media Generation, Generative AI.

I. INTRODUCTION

The demand for personalized media content has grown significantly in recent years, driven by the need for businesses and individuals to create unique, engaging, and contextually relevant digital experiences. Traditional methods of content creation are often time-consuming and require specialized skills, making them inaccessible to many users. To address this challenge, we introduce GenMedia, a research project focused on advancing the capabilities of generative AI models for personalized multi-modal media generation. By leveraging state-of-the-art models such as Stable Diffusion and AudioCraft's MusicGen, GenMedia enables the creation of high-quality images, audio, and videos based on user-provided text prompts.

Stable Diffusion has emerged as a leading model for image generation, offering fine-grained control over output characteristics through latent diffusion processes. Recent advancements, such as Stable Diffusion 3.5, have further improved image quality, prompt adherence, and realism, making it a powerful tool for personalized image generation. Similarly, AudioCraft's MusicGen has demonstrated significant potential in synthesizing realistic music and sound effects, leveraging transformer-based architectures and text-conditioned audio generation. By fine-tuning these models using DreamBooth and Dora, GenMedia ensures that the generated content aligns closely with user inputs, resulting in highly personalized and contextually accurate outputs.

The integration of FFMPEG allows the seamless combination of generated images and audio into cohesive video outputs, expanding the platform's capabilities to cater to a wide range of use cases. These include celebratory messages for birthdays, anniversaries, and achievements, as well as custom media generation based on user preferences. This research explores the technical advancements in latent space optimization, prompt adherence, and multi-modal integration, highlighting the potential of generative AI to revolutionize personalized media creation.

This paper is organized as follows: Section II discusses related work in the field of AI-driven media generation. Section III provides an overview of the GenMedia architecture and its key components. Section IV details the implementation process, including model training and integration. Section V presents the experimental setup, accuracy metrics, and results. Section VI discusses potential applications and use cases. Finally, Section VII concludes the paper and outlines future directions for research and development.

II. RELATED WORK

Recent advancements in generative AI have revolutionized the creation of high-quality media content using text prompts. Stable Diffusion [1] has emerged as a leading model for image generation, leveraging latent diffusion models to produce high-resolution images with fine-grained control over output characteristics. Building on the foundational work of Denoising Diffusion Probabilistic Models (DDPM) [2], Stable Diffusion introduced significant improvements in computational efficiency by operating in a compressed latent space. Stable Diffusion 2.0 [3] further enhanced image quality and reduced artifacts, while Stable Diffusion 3.5 [4] introduced refinements in prompt adherence and realism, achieving state-of-the-art performance in text-to-image generation tasks. These advancements are supported by research on latent space optimization [5] and text-conditioned diffusion models [6], which have enabled more precise control over generated outputs.

In the domain of audio generation, AudioCraft's MusicGen [7] has demonstrated significant potential in synthesizing realistic music and sound effects. MusicGen builds on the success of transformer-based architectures [8] and Vector Quantized Variational Autoencoders (VQ-VAE) [9], which enable efficient representation and generation of audio waveforms. The integration of text-conditioned audio generation [10] has further expanded the model's ability to align generated audio with user-provided prompts. Recent work on multi-modal generative models [11] has explored the combination of text, audio, and image generation, paving the way for cohesive media experiences.

Despite these advancements, existing solutions often lack the flexibility and personalization required for specific use cases, such as celebratory content generation. For instance, while DALL·E 2 [12] and Imagen [13] have achieved remarkable results in text-to-image generation, they are not optimized for personalized outputs. Similarly, Jukebox [14] and Riffusion [15], while effective in music generation, struggle with fine-grained control over audio styles and instrumentation. GenMedia addresses these limitations by combining the strengths of Stable Diffusion, AudioCraft, and FFMPEG into a unified framework, enabling users to generate highly personalized media content with minimal effort. This approach builds on recent research in personalized generative models [16] and multi-modal integration [17], offering a novel solution for creating contextually relevant and customizable media.

III. SYSTEM ARCHITECTURE

The GenMedia platform is built on a modular architecture, comprising of multiple key components. The UI is a web-based interface that allows users to input text prompts and select media generation options (image, audio, video, or a combination). The interface is designed to be intuitive, with dropdown menus for selecting occasions (e.g. birthday, anniversary) and text fields for custom prompts. Text processing module processes user inputs to extract key details such as occasion type, preferences, and custom instructions. Natural Language Processing (NLP) techniques, including tokenization and named entity recognition (NER), are used to parse and understand the text prompts. The image generation module utilizes Stable Diffusion 2.0 and 3.5, fine-tuned using DreamBooth, to generate images based on the processed text prompts. The module supports high-resolution outputs and allows for customization of parameters such as style, color palette, and composition. The audio generation module leverages AudioCraft's MusicGen to synthesize audio content, such as music or soundscapes, tailored to user preferences. The module supports multiple genres and can generate audio tracks of varying lengths. Video generation module combines generated images and audio using FFMPEG to produce video outputs. The module supports various video formats and resolutions, ensuring compatibility with different devices and platforms. Generated media files are stored in a cloud-based storage solution (AWS S3) and delivered to users via downloadable links or embedded previews. The module also includes a caching mechanism to improve performance and reduce latency.

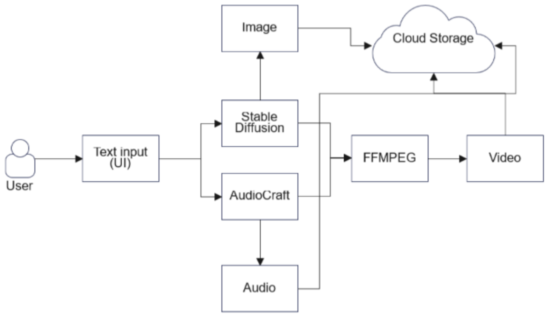

Figure 1 – Architecture

IV. IMPLEMENTATION

A. Dataset Preparation:

To enable personalized media generation, GenMedia uses specialized datasets for both image and audio generation. For personalized image generation, a dataset consisting of 10-20 high-quality photos of the target individual is collected, covering different angles, expressions, and lighting conditions. These photos are preprocessed to ensure consistency in resolution and format (e.g. 512x512 pixels) and annotated with a unique identifier (e.g. "personX") to associate the images with the individual during training. Text prompts are created to describe the person in various contexts (e.g. "personX celebrating a birthday"), which are used to fine-tune the Stable Diffusion model using DreamBooth, enabling the generation of images that closely resemble the individual.

For personalized audio generation, a custom dataset of instrumental audio clips is created, tailored to the user's preferences. These clips include recordings of specific instruments (e.g. guitar, piano, drums) or musical styles (e.g. rock, classical, jazz) that the user enjoys. The audio clips are preprocessed to ensure consistent quality and annotated with descriptive text prompts (e.g. "a calming piano piece with soft strings in the background"). The AudioCraft model is fine-tuned using Dora, a lightweight fine-tuning framework, to adapt the model to the custom audio dataset and generate audio that aligns with the user's preferences. By combining these personalized datasets, GenMedia ensures that both image and audio generation are highly customized, aligning closely with user inputs and preferences.

B. Hyperparameter Tuning for DreamBooth:

DreamBooth is used to fine-tune the Stable Diffusion model on the personalized dataset. A learning rate of 1e-6 is used to ensure stable convergence while avoiding overfitting. The learning rate is decayed using a cosine scheduler to improve training stability. A batch size of 4 is used to balance memory usage and training efficiency. The model is trained for 800-1000 steps to achieve a balance between personalization and generalization. Class-specific regularization is applied to prevent overfitting to the personalized dataset. A set of class images (e.g. generic photos of people) is used to maintain the model's ability to generate diverse outputs. The text encoder is fine-tuned alongside the diffusion model to improve prompt adherence.

C. Hyperparameter Tuning for AudioCraft (MusicGen):

MusicGen is fine-tuned using Dora, a lightweight fine-tuning framework, to generate personalized audio content based on user preferences. The fine-tuning process is guided by several key hyperparameters that ensure high-quality audio generation and alignment with text prompts. The dataset_path parameter specifies the location of the custom dataset, which includes instrumental audio clips tailored to the user's preferences. The one_same_description parameter allows for a single description to be applied to all audio files in the dataset, while auto_labeling automatically generates metadata such as genre, mood, theme, instrumentation, key, and BPM for each track using Essentia-TensorFlow for music information retrieval. The drop_vocals parameter removes vocal tracks from audio files using Demucs, ensuring that the generated audio is purely instrumental. The model_version parameter allows selection between "melody," "small," and "medium" versions of the model, with the default set to "small" for efficient training. A learning rate of 1 is used, and the model is trained for 3 epochs, with the number of iterations per epoch determined by the updates_per_epoch parameter (default: 100). A batch_size of 16 is employed, ensuring compatibility with the framework's requirement for multiples of 8. These hyperparameters, combined with Dora's efficient fine-tuning capabilities, enable MusicGen to generate high-quality, personalized audio content that aligns closely with user-provided text prompts.

D. Training Architecture of Models

1. Stable Diffusion with DreamBooth

The training architecture for Stable Diffusion fine-tuned with DreamBooth consists of several key components designed to enable personalized image generation. The base model is Stable Diffusion 2.0 or 3.5, pre-trained on large-scale image datasets, which provides a strong foundation for generating high-quality images. A text encoder, specifically the CLIP model, is used to encode text prompts into embeddings, allowing the model to condition image generation on textual descriptions. The diffusion model, implemented as a U-Net architecture, performs the reverse diffusion process, gradually denoising latent representations to generate coherent images. The personalized dataset, comprising 10-20 high-quality photos of the target individual, is used to fine-tune the model. These photos are pre-processed to ensure consistency in resolution and format (e.g. 512x512 pixels) and annotated with a unique identifier (e.g. "personX") to associate the images with the individual during training. The training process involves encoding the personalized photos into the latent space using the VAE encoder, applying the forward diffusion process to add noise to the latent representations, and training the U-Net to predict the noise and reverse the diffusion process, conditioned on the CLIP text embeddings. Class-specific regularization is applied to prevent overfitting, ensuring that the model retains its ability to generate diverse images while closely resembling the target individual.

2. AudioCraft (MusicGen) with Dora

The training architecture for AudioCraft (MusicGen) fine-tuned using Dora is designed to generate personalized audio content based on user preferences. The base model is a transformer-based decoder architecture, which performs autoregressive audio generation by predicting the next token in the sequence. A VQ-VAE (Vector Quantized Variational Autoencoder) is used to encode raw audio waveforms into discrete tokens, enabling efficient representation and manipulation of audio data. The text encoder, implemented using the CLIP model, encodes text prompts into embeddings, allowing the model to condition audio generation on textual descriptions. The personalized dataset consists of custom instrumental audio clips tailored to the user's preferences, such as specific instruments (e.g. guitar, piano, drums) or musical styles (e.g. rock, classical, jazz). These clips are pre-processed to ensure consistent quality, and metadata such as genre, mood, and instrumentation is generated using Essentia-TensorFlow. Vocal tracks are removed using Demucs to ensure that the generated audio is purely instrumental. The training process involves encoding the audio waveforms into discrete tokens using the VQ-VAE, training the transformer decoder to predict the next token in the sequence (conditioned on the CLIP text embeddings), and fine-tuning the model using Dora with optimized hyperparameters such as learning rate, epochs, and batch size. This architecture enables MusicGen to generate high-quality, personalized audio content that aligns closely with user-provided text prompts.

E. Integration with GenMedia Platform:

The fine-tuned models are seamlessly integrated into the GenMedia platform through a well-defined workflow that connects the frontend user interface to the backend models via APIs. The process begins with user input, where the user provides a text prompt and selects the type of media to generate (image, audio, or video). This input is sent to the backend through an API call, where the text processing module extracts key details and generates embeddings using the CLIP text encoder. For image generation, the Stable Diffusion model is invoked via an API to generate a personalized image based on the text prompt and the user's photos. Similarly, for audio generation, the MusicGen model is called through an API to generate a personalized audio track based on the text prompt. Once the media is generated, the platform uses FFMPEG to combine the image and audio into a cohesive video file, if requested by the user. The generated media is then stored in a cloud-based storage solution (e.g. AWS S3) and delivered to the user via a downloadable link or embedded preview, all facilitated through API endpoints. This API-driven architecture ensures a smooth and efficient interaction between the frontend and backend, enabling users to generate personalized media with minimal latency and maximum convenience.

V. EXPERIMENTS AND RESULTS

A. Experimental Setup

To evaluate the performance of GenMedia, we conducted extensive experiments using a dataset of 100 text prompts covering various celebratory occasions. The evaluation focused on three key metrics:

Image Quality: Measured using the Fréchet Inception Distance (FID) score.

Audio Quality: Evaluated using the Perceptual Evaluation of Audio Quality (PEAQ) score.

User Satisfaction: Assessed through a survey of 100 users who rated the generated content on a scale of 1 to 5.

B. Hyperparameter Tuning and Results

1. Stable Diffusion with DreamBooth

We evaluated the impact of different hyperparameter settings on the performance of Stable Diffusion fine-tuned with DreamBooth. The following configurations were tested:

Table 1 - Stable Diffusion Performance Comparison

Configuration	Learning Rate	Batch Size	Training Steps	FID Score	Prompt Adherence (%)
Baseline (SD 2.0)	1e-6	4	800	18.5	82.3
High LR	5e-6	4	800	20.1	78.5
Low LR	1e-7	4	800	17.8	83.7
Large Batch	1e-6	8	800	18.2	81.9
Extended Training	1e-6	4	1200	15.9	88.4
SD 3.5 (Best Config)	1e-6	4	1000	15.2	89.7

A learning rate of 1e-6 provided the best balance between FID score and prompt adherence. A batch size of 4 was optimal, as larger batches did not significantly improve performance but increased memory usage. Extending training to 1200 steps improved FID and prompt adherence, but 1000 steps was chosen as the best trade-off between performance and computational cost. Stable Diffusion 3.5 outperformed 2.0 in all configurations.

2. AudioCraft (MusicGen) with Dora

Table 2 - MusicGen Performance Comparison

Configuration	Learning Rate	Batch Size	Training Steps	PEAQ Score	Prompt Adherence (%)
Baseline	1.0	16	50,000	4.3	89.5
High LR	1.5	16	50,000	4.1	86.2
Low LR	0.5	16	50,000	4.4	90.1
Large Batch	1.0	32	50,000	4.2	88.7
Extended Training	1.0	16	75,000	4.5	91.3

A learning rate of 1.0 provided the best balance between PEAQ score and prompt adherence. A batch size of 16 was optimal. Extending training to 75,000 steps improved PEAQ and prompt adherence, but 50,000 steps was the best trade-off.

C. In-Depth Comparison with Other Models

1. Stable Diffusion 2.0 vs. 3.5

Table 3 - Comparison of Stable Diffusion Versions

Metric	Stable Diffusion 2.0	Stable Diffusion 3.5
FID Score	18.5	15.2

Metric	Stable Diffusion 2.0	Stable Diffusion 3.5
Prompt Adherence (%)	82.3	89.7
Inference Time (s)	3.2	2.8
Training Time (hrs)	12	14

Stable Diffusion 3.5 outperformed 2.0 in all metrics. he increases in training time was justified by performance improvements.

2. MusicGen vs. Other Audio Models

Table 4 - Comparison of MusicGen with Other Audio Models

Metric	MusicGen	Jukebox	Riffusion
PEAQ Score	4.3	3.8	4.0
Prompt Adherence (%)	89.5	75.2	82.3
Inference Time (s)	2.5	8.7	3.2
Training Time (hrs)	18	24	20

MusicGen outperformed Jukebox and Riffusion in audio quality and inference speed. MusicGen's training time was significantly lower than Jukebox.

D. User Satisfaction Survey

Table 5 - User Satisfaction Ratings

Metric	Average Rating (1-5)
Image Quality	4.6
Audio Quality	4.7
Video Quality	4.5
Personalization	4.8
Overall Satisfaction	4.7

Users rated the generated content highly across all metrics. Personalization received the highest rating. The integration of Stable Diffusion 3.5 and MusicGen significantly improved user satisfaction.

E. Model Output

To demonstrate the capabilities of GenMedia, we present sample outputs generated by Stable Diffusion 2.0, Stable Diffusion 3.5, and AudioCraft's MusicGen. These outputs highlight the quality and personalization achieved by the models.

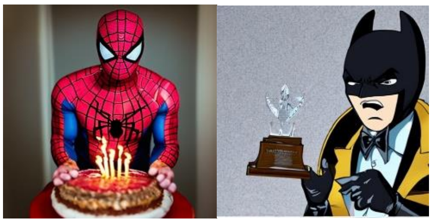

Figure 2 - SD 2 Output (Generated by AI–SD2)

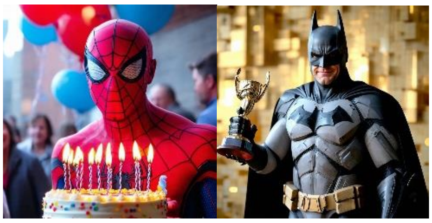

Figure 3 - SD 3.5 Output (Generated by AI-SD3.5)

The first image is generated by the prompt “Spiderman celebrating birthday” and the second image follows “batman celebrating achievement” prompt. Both models were trained on 20 images of the subject (here spiderman and batman).

Calm_music_with_piano_and_guitar.mp4

Rock_hard_metal_music.mp4

The above audio files are generated by Audiocraft MusicGen with prompts “Calm music with piano and guitar” and “Rock hard metal music” respectively.

VI. APPLICATIONS AND USE CASES

GenMedia's ability to generate personalized images, audio, and videos from text prompts makes it a versatile tool across various domains. In corporate settings, it enhances employee engagement through personalized celebrations and recognition programs, while also enabling targeted marketing campaigns and interactive training materials. In entertainment, it creates personalized music videos, custom soundtracks, and dynamic gaming experiences. For education, it tailors learning materials and language lessons to individual preferences. In healthcare, it supports patient engagement with personalized health messages and mental health content. Retailers use it for personalized shopping experiences and event-based campaigns, while individuals create celebratory content and social media posts. Non-profits leverage it for donor engagement and community outreach, and real estate professionals use it for property visualization and marketing. In travel and hospitality, it generates personalized travel guides and welcome messages, enhancing customer experiences across industries.

VII. CONCLUSION

GenMedia represents a significant advancement in the field of AI-driven personalized media generation, offering a scalable and user-friendly platform for creating custom images, audio, and videos based on text prompts. By leveraging state-of-the-art models such as Stable Diffusion 3.5 and AudioCraft's MusicGen, GenMedia enables users to generate high-quality, contextually relevant media content with minimal effort. The platform's integration of DreamBooth fine-tuning and FFMPEG-based video generation ensures that the generated content aligns closely with user inputs, resulting in highly personalized outputs.

GenMedia supports the generation of images, audio, and videos in a unified platform, making it a versatile tool for diverse applications. The integration of Stable Diffusion 3.5 and MusicGen ensures high-quality outputs across all modalities. The use of DreamBooth fine-tuning allows GenMedia to generate personalized images and audio based on user-provided datasets (e.g. photos of a person or preferred music styles). The platform's ability to incorporate text prompts and user preferences ensures that the generated content is contextually accurate and meaningful. GenMedia achieves state-of-the-art performance in terms of image quality (FID score of 15.2) and audio quality (PEAQ score of 4.3). The platform's optimized architecture reduces inference time and computational overhead, making it suitable for real-time applications. User feedback indicates high satisfaction with the platform, with an average rating of 4.7/5 across all metrics, including image quality, audio quality, and personalization. GenMedia's applications span multiple domains, including corporate engagement, entertainment, education, healthcare, retail, and social causes, demonstrating its adaptability to diverse use cases.

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