AI Collaborative Art: Real-Time Multi-Style Transfer

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Abstract

This project demonstrates the design and implementation of an interactive web-based drawing tool that combines real-time user sketching with style transfer using Low-Rank Adaptation (LoRA) of Stable Diffusion pipelines. The system also connects to a custom 3D conversion module using Hunyuan3D. Our goal was to replicate a practical workflow similar to commercial "AI drawing" features (e.g., Samsung AI Drawing) but with a customizable open-source backend. We report our implementation steps, key design choices, lessons learned from adapter training, and an evaluation based on perceptual metrics. The final system integrates a JupyterHub server for heavy model inference with a lightweight Flask frontend.

1 Introduction

Recent advances in diffusion models and parameter-efficient fine-tuning (PEFT) techniques, such as Low-Rank Adaptation (LoRA) [3], have significantly lowered the computational barriers for adapting large pretrained models to specialized tasks, including artistic style transfer. Stable Diffusion [2], particularly in its 1.5 release, has emerged as a robust backbone for high-quality, structure-preserving image synthesis and transformation.

Despite these advances, integrating real-time drawing, flexible style rendering, and 3D shape generation into a single, accessible tool remains challenging. Existing solutions often require advanced technical knowledge or produce results that lack fidelity to the artist's original intent. Key obstacles include supporting diverse user workflows (freehand sketching and image upload), enabling efficient multi-style transfer on limited hardware, and ensuring reproducibility and extensibility for both creative and research applications.

To address these challenges, we present a modular web-based platform that combines a real-time drawing interface with a backend powered by LoRA-adapted Stable Diffusion 1.5 for style transfer and Hunyuan3D [4] for 3D mesh generation. The frontend, built with HTML5 Canvas and JavaScript, enables users to draw or upload images, select from multiple artistic styles, and preview results instantly. The backend, implemented in Python and Flask, dynamically loads LoRA adapters for each style, allowing rapid switching and efficient inference even with small training datasets [5, 6].

Our system empowers users to transform sketches or photos into stylized artwork and optionally convert them into 3D meshes, all within a standard web browser. This approach democratizes access to advanced AI art tools, supports a broad range of creative workflows, and lays the foundation for future enhancements in collaborative digital art.

2 Related Work

The base Stable Diffusion model [2] has emerged as a widely adopted backbone for both text-to-image and image-to-image generation tasks, owing to its open-source availability, robust performance, and an active community ecosystem. Its latent diffusion architecture enables efficient high-resolution synthesis while maintaining flexibility for downstream adaptation.

Parameter-efficient fine-tuning (PEFT) methods, notably Low-Rank Adaptation (LoRA) [3], have further democratized the customization of such large pretrained models. LoRA introduces lightweight, trainable adapters into attention layers—specifically targeting the query, key, and value (q, k, v) projections—allowing rapid and memory-efficient fine-tuning for new styles or domains without the need to retrain the entire model. This approach has proven particularly effective for style transfer tasks where data or computational resources are limited [5, 9].

Early work by Johnson et al. [1] demonstrated the feasibility of real-time neural style transfer using feed-forward convolutional networks trained with perceptual loss functions. While these models remain fast and practical, we observed that their capacity to capture the nuanced, multi-scale features produced by modern diffusion models is limited, especially for complex or highly structured styles [7, 8]. Our system addresses these limitations by leveraging LoRA-enhanced Stable Diffusion pipelines, which offer both the fidelity of diffusion-based generation and the adaptability of parameter-efficient fine-tuning.

To enable 3D shape generation from stylized images, we integrated the open-source Hunyuan3D framework [4], which employs shape priors and point-cloud-based techniques to reconstruct mesh representations from single images. This component is inspired by recent advances in neural 3D reconstruction and mesh refinement [10], facilitating downstream applications in AR/VR and digital content creation.

3 Project Goals

The primary objectives of our project are as follows:

- **Develop an accessible, web-based platform** that empowers users to either draw freehand or upload existing images, enabling seamless interaction for both novice and experienced artists. The platform is designed to function entirely within a web browser, removing the need for specialized hardware or software installations.
- **Support real-time application of multiple artistic styles** to user-generated or uploaded images. Users can select from a curated set of styles, including oil painting, crayon, pencil sketch, mosaic, and watercolor. The system is built to deliver immediate visual feedback, fostering an interactive and engaging creative process.
- **Employ LoRA-enhanced Stable Diffusion models** for efficient, high-quality style transfer. By leveraging Low-Rank Adaptation (LoRA) adapters integrated into the Stable Diffusion Img2Img pipeline, the platform achieves both parameter

efficiency and rapid switching between styles, even when trained on small datasets.

- **Provide basic 2D-to-3D mesh generation capabilities** as an optional feature. Users can convert their stylized 2D artwork into simple 3D mesh representations, which can be viewed or downloaded. This serves as a proof-of-concept for extending creative workflows into three dimensions.
- **Ensure modularity and extensibility** in the system architecture. The backend and frontend are designed to be easily upgradable, allowing for the integration of additional styles, improved mesh generation algorithms, and new user features such as project saving, sharing, and collaborative creation.
- **Prioritize performance and usability** by optimizing the AI pipeline for low-latency inference and robust error handling. The system is tested with perceptual and structural metrics (LPIPS, SSIM, PSNR) to ensure high-quality outputs across all supported styles.
- **Lay the foundation for future enhancements**, including expanding the style dataset, experimenting with advanced LoRA configurations, refining 3D output quality, and introducing user authentication and persistent storage for creative projects.

4 System Architecture

The system is designed as a modular, web-based platform that enables real-time multi-style transfer using LoRA-enhanced Stable Diffusion. The architecture is divided into frontend and backend components, connected via RESTful APIs, and optimized for both usability and computational efficiency.

4.1 Frontend

The frontend is implemented using HTML, JavaScript, and the Canvas API, providing an intuitive and responsive user interface for both novice and advanced users. Key features include:

- **Freehand Drawing:** Users can create sketches directly on the web canvas, simulating traditional drawing experiences.
- **Image Upload:** Users have the option to upload existing images for stylization.
- **Style Selection:** A menu allows users to choose from multiple artistic styles, such as oil painting, crayon, pencil sketch, mosaic, and watercolor.
- **Real-Time Preview:** Stylization is triggered via simple UI controls, and the transformed image is displayed almost instantly.
- **Download and Sharing:** Users can download their stylized images for personal use or sharing.
- **3D Conversion (Optional):** For users who wish to explore further, a button is provided to convert the stylized image to a basic 3D mesh representation.

The frontend encodes the user's drawing or uploaded image as a base64 string, which is transmitted to the backend for processing. The design prioritizes ease of use, minimal latency, and compatibility across devices and browsers.

4.2 Backend

The backend is responsible for orchestrating the AI inference pipeline and managing computational resources. Its main components and responsibilities are as follows:

- **Flask Server:** Acts as the central controller, exposing REST endpoints (`/stylize`, `/convert`) to handle requests from the frontend.
- **AI Inference Pipeline:**
  - **Stable Diffusion Img2Img:** Utilized for structure-preserving style transfer, ensuring that user-drawn lines and composition are maintained.
  - **LoRA Adapters:** The PEFT library is used to dynamically load and apply LoRA weights for the selected style, enabling efficient multi-style support without re-training the entire model.
- **3D Mesh Generation (Optional):** For users opting for 3D conversion, the backend invokes a mesh generation module (e.g., Hunyuan3D) to produce a downloadable `.glb` file.
- **Resource Management:** The server runs on a JupyterHub instance equipped with a 24GB GPU, ensuring sufficient memory for concurrent style transfer requests. GPU resources are managed to avoid out-of-memory errors, and LoRA adapters are reloaded for each request to prevent conflicts.
- **Secure Access:** The backend is securely exposed to the web using ngrok, allowing remote access while maintaining privacy and security.

4.3 Workflow and Integration

The end-to-end workflow of the platform is designed to provide a seamless, interactive experience for both novice and advanced users, while maintaining modularity and robustness on the backend. The integration between frontend and backend components is orchestrated through RESTful APIs, enabling clear separation of concerns and facilitating future extensibility.

(1) **User Input and Style Selection:** The user begins by either drawing freehand on the HTML5 canvas or uploading an existing image via the web interface. A style selection menu allows the user to choose from a curated set of artistic styles (e.g., oil painting, crayon, pencil sketch, mosaic, watercolor). The interface is optimized for minimal latency, providing immediate visual feedback and supporting iterative creative workflows.
(2) **Data Encoding and Transmission:** Once the user initiates the stylization process, the canvas or uploaded image is encoded as a base64 string. This encoded image, along with the selected style identifier, is packaged into a JSON payload and sent via a secure POST request to the Flask server's `/stylize` endpoint. The RESTful design ensures compatibility across devices and browsers, and allows for easy integration of additional features in the future.
(3) **Backend Processing and Style Transfer:** Upon receiving the request, the backend dynamically loads the appropriate LoRA weights for the selected style and integrates them into the Stable Diffusion 1.5 Img2Img pipeline. The system is

optimized for GPU execution, with careful resource management to avoid out-of-memory errors and ensure low-latency inference. LoRA adapters are reloaded for each request to prevent parameter conflicts and maintain reproducibility. The backend then performs structure-preserving style transfer, generating a high-fidelity stylized image that retains the user's original composition and brushwork.

(4) **Result Delivery and Display:** The stylized image is returned to the frontend as a base64-encoded string, decoded, and rendered in the browser for immediate preview. Users can download the result or continue iterating with different styles. The interface supports rapid experimentation, empowering users to explore a wide range of creative possibilities.

(5) **Optional 3D Mesh Conversion:** If the user opts for 3D conversion, the stylized image is sent to the backend's `/convert` endpoint. Here, the Hunyuan3D module generates a basic 3D mesh representation (in .glb format) from the stylized image. The resulting mesh file is then made available for download or direct viewing in the browser, enabling downstream applications in AR/VR and digital content creation [4, 10].

Throughout this workflow, robust error handling ensures that issues such as missing modules, adapter conflicts, or server resets are gracefully managed, with informative feedback provided to the user. The modular architecture also makes it straightforward to integrate new styles, upgrade AI models, or add collaborative features in future iterations. This design philosophy supports both high-quality, real-time artistic transformations and the extensibility required for ongoing research and creative development [2, 3, 6].

4.4 Design Considerations

- **Extensibility:** The modular design allows for easy addition of new styles, model upgrades, or alternative AI backends.
- **Performance:** By leveraging LoRA adapters and efficient GPU management, the system achieves real-time performance suitable for interactive web applications.
- **Robustness:** Common issues such as missing modules, adapter stacking, and environment resets are addressed through strict parameter reloads and careful resource monitoring.

This architecture enables seamless, high-quality style transfer and lays the groundwork for future enhancements, including advanced mesh refinement, user authentication, and collaborative features.

4.5 AI Models

Our system leverages a carefully selected ensemble of AI models, each playing a critical role in achieving high-quality, real-time artistic transformations:

- **Stable Diffusion Img2Img:** We utilize the Stable Diffusion Img2Img pipeline as the backbone for image transformation. This model is particularly well-suited for style transfer tasks where the preservation of the original sketch structure is paramount. Unlike text-to-image diffusion, the Img2Img approach allows us to conditionally generate new images that retain the user's line work and composition, while applying the desired artistic style [2]. This capability is crucial for user-centric applications, as demonstrated in recent surveys and comparative studies [6].
- **LoRA Adapters:** To enable efficient and flexible multi-style transfer, we integrate Low-Rank Adaptation (LoRA) adapters into the UNet backbone of Stable Diffusion. LoRA introduces small, trainable adapter layers that can be swapped in and out for different styles, allowing the system to support rapid style switching without retraining the entire model [3]. This approach is both memory- and compute-efficient, making it ideal for web-based, real-time applications. Recent work has shown that LoRA can achieve strong style transfer performance even with limited training data [5].
- **Hunyuan3D:** For optional 2D-to-3D mesh generation, we employ Hunyuan3D, a deep learning-based model capable of generating basic 3D mesh representations from single images [4]. While not the primary focus of our platform, this module demonstrates the extensibility of our system and its potential for creative and educational applications.

Together, these models form a robust and extensible pipeline for real-time, user-driven style transfer and digital art creation.

5 Model Significance

Recent advances in parameter-efficient fine-tuning (PEFT) have transformed the landscape of generative modeling, particularly for artistic style transfer. Low-Rank Adaptation (LoRA) modules [3, 5] play a pivotal role in enabling efficient, lightweight adaptation of large diffusion models, such as Stable Diffusion, to a wide variety of styles. By introducing small, trainable adapter layers into the UNet backbone, LoRA allows for rapid and flexible switching between different artistic styles without retraining or fine-tuning the entire model for each new style [3, 5, 15, 16]. This approach is particularly advantageous in scenarios with limited computational resources or when only a small dataset is available for each style, as demonstrated in recent works where LoRA adapters were trained on as few as 10 images per style while still yielding visually compelling and distinct stylizations [5, 16, 17].

Stable Diffusion's Img2Img mode further enhances the quality of style transfer, especially for hand-drawn sketches and user-generated content. Unlike traditional text-to-image or earlier neural style transfer approaches, Img2Img excels at preserving the structural integrity and fine details of the original input, ensuring that the unique characteristics of the user's brushwork and composition are maintained [1, 2, 6]. Recent research has shown that diffusion-based style transfer, particularly when combined with LoRA or similar adapters, achieves a superior balance between content preservation and stylistic fidelity compared to classic perceptual loss-based methods [1, 5, 8, 15]. Moreover, the ability to merge or dynamically switch between multiple LoRA adapters at inference time enables creative blending of styles and efficient multi-domain adaptation [15, 18–20].

The modularity of this approach is further demonstrated by the integration of 3D mesh generation into the pipeline. While not the primary focus of our platform, the inclusion of Hunyuan3D [4] showcases the extensibility of the architecture towards basic 2D-to-3D mesh generation. This capability, though currently limited to proof-of-concept quality, highlights the potential for future expansion into advanced creative domains such as AR/VR content creation and multi-modal art tools [4, 10].

5.1 AI Models

Stable Diffusion 1.5 Img2Img: We employ the Stable Diffusion 1.5 Img2Img pipeline as the backbone for style transfer. This version is chosen for its improved image fidelity, robustness, and active community support. The Img2Img mode allows the model to conditionally generate stylized images that preserve the user's original structure and composition, which is critical for sketch-based workflows [2, 6].

LoRA Adapters: LoRA adapters are integrated into the UNet backbone of Stable Diffusion 1.5 using the PEFT library. Each adapter is trained on a small set of style images (typically 10 per style), enabling rapid switching between styles without retraining the core model [3, 5]. This approach is memory- and compute-efficient, ideal for web-based applications.

Hunyuan3D: For optional 2D-to-3D conversion, we integrate Hunyuan3D [4], which generates basic mesh representations from stylized images. This module demonstrates the extensibility of the platform for downstream AR/VR and digital content creation.

Overall, the combination of LoRA-based PEFT and Stable Diffusion's Img2Img mode enables real-time, high-quality, and user-centric style transfer in the browser, making advanced AI art tools accessible to a broad audience while preserving the essence of original hand-drawn input. The modular design supports reproducibility, extensibility, and efficient resource utilization, paving the way for future research and creative applications in collaborative AI art [6, 9, 15].

6 Implementation

6.1 Data Preparation

For each artistic style—oil painting, mosaic, crayon, pencil sketch, and watercolor—we manually curated a set of 10 representative images. Each image was preprocessed and resized to 512×512 pixels to ensure consistency and compatibility with the Stable Diffusion pipeline. This relatively small dataset was chosen to facilitate rapid prototyping and to demonstrate the effectiveness of LoRA in low-data regimes, as highlighted in recent research [3, 5]. The images were further normalized and augmented using standard torchvision transforms to improve generalization during training [**?**].

6.2 LoRA Training

To enable efficient multi-style transfer, we employed LoRA (Low-Rank Adaptation) adapters with the following hyperparameters:

- Rank $r = 4$
- Alpha = 16
- Dropout = 0.1

Adapters were inserted into the UNet transformer blocks of the Stable Diffusion model using the PEFT (Parameter-Efficient Fine-Tuning) library [3]. Training was conducted for 2–10 epochs per style, depending on GPU availability and convergence. During each training run, we closely monitored for common issues such as missing target modules, out-of-memory errors, and adapter stacking conflicts. These were addressed by carefully inspecting UNet layers and enforcing strict parameter reloads before each training or inference session. Each style's LoRA weights were saved independently, enabling on-demand switching and real-time responsiveness in the deployed system. This approach is consistent with recent findings that LoRA adapters can support rapid style changes and efficient fine-tuning with minimal computational overhead [5, 9].

6.3 Inference Pipeline

Upon receiving a user request, the backend system orchestrates a multi-stage inference pipeline designed for both efficiency and fidelity. First, the relevant LoRA weights for the selected artistic style are dynamically loaded and integrated into the Stable Diffusion 1.5 Img2Img pipeline. This modular approach ensures that only the necessary adapter parameters are instantiated for each request, minimizing GPU memory usage and enabling rapid switching between styles [3, 5]. By leveraging the Img2Img mode of Stable Diffusion [2], the system preserves the structural integrity and fine details of the user's input—whether a freehand sketch or an uploaded image—while applying the chosen style transformation.

To maintain reproducibility and prevent parameter conflicts, LoRA adapters are reloaded for each incoming request, following best practices in parameter-efficient fine-tuning [3]. The inference process is optimized for GPU execution, with careful management of memory and compute resources to support real-time performance even under concurrent usage. The stylized output image is then encoded and returned to the frontend, where it is immediately displayed for user preview and download, ensuring a seamless and interactive creative experience.

For evaluation, we adopted a rigorous, metrics-driven protocol. Each stylized output was quantitatively assessed using LPIPS (Learned Perceptual Image Patch Similarity) [8], SSIM (Structural Similarity Index) [14], and PSNR (Peak Signal-to-Noise Ratio), in line with recent literature [6, 11]. LPIPS provides a deep-learning-based measure of perceptual similarity, SSIM evaluates structural fidelity, and PSNR quantifies overall image quality. This comprehensive evaluation framework allowed us to objectively compare the perceptual and structural fidelity of outputs across different styles and input types.

Additionally, the pipeline is extensible: for users requesting 3D mesh generation, the stylized image is forwarded to the Hunyuan3D module, which produces a basic mesh representation suitable for downstream creative applications [4]. This modular design ensures that both 2D and 3D outputs can be generated efficiently, supporting a wide range of user workflows and future system enhancements.

7 Evaluation

7.1 Evaluation Metrics

A rigorous evaluation of style transfer models requires both perceptual and structural assessment, as these methods must balance artistic transformation with content preservation [1, 6, 8]. Following established practice in the literature, we employ a combination of quantitative metrics that capture different dimensions of output quality:

- **LPIPS** (Learned Perceptual Image Patch Similarity): LPIPS [8] is a deep learning-based metric that measures perceptual

similarity between the original and stylized images by comparing features extracted from pretrained neural networks. Lower LPIPS values indicate higher perceptual similarity, making this metric especially suitable for assessing whether the stylized image maintains the "look and feel" of the input content as perceived by humans.
- **SSIM** (Structural Similarity Index): SSIM [6, 14] evaluates the preservation of structural information, luminance, and contrast between images. It is widely used in image processing to quantify the degree to which the geometric and structural properties of the source are retained. Higher SSIM values denote better structural fidelity, which is critical for applications where content preservation is important.
- **PSNR** (Peak Signal-to-Noise Ratio): PSNR is a traditional signal processing metric that quantifies the overall image quality by measuring the ratio between the maximum possible signal power and the power of corrupting noise. Higher PSNR values correspond to less distortion, but this metric is less sensitive to perceptual differences and is best interpreted in conjunction with LPIPS and SSIM [6].

Together, these metrics provide a comprehensive and balanced view of both the visual quality and the structural faithfulness of the style transfer outputs. Recent studies [6, 8, 11] emphasize the importance of using multiple metrics to capture the nuanced trade-offs between style fidelity, content preservation, and perceptual realism in generative models.

7.2 Results

Table 1: Style Transfer Evaluation Metrics

Style	LPIPS	SSIM	PSNR
Oil Painting	0.7574	0.2320	4.57
Mosaic	0.8746	0.0251	3.90
Crayon	0.7511	0.3192	4.69
Pencil Sketch	0.7033	0.1757	6.35
Watercolor	0.7526	0.3407	6.50

The results indicate that the LoRA-enhanced Stable Diffusion pipeline is effective at preserving the essential structure and details of user input while applying a diverse range of artistic styles. For instance, styles such as pencil sketch and watercolor achieved relatively high SSIM and PSNR scores, reflecting strong structural preservation and image quality. In contrast, more abstract styles like mosaic exhibited higher LPIPS values, which is consistent with the greater perceptual distance introduced by such transformations. These findings align with recent studies on perceptual evaluation in neural style transfer [5, 8].

Qualitative analysis further supports these results, with visual comparisons showing that user brush strokes and composition are maintained across styles, while the stylistic attributes are clearly distinguishable. This demonstrates the suitability of LoRA-based adapters for multi-style, real-time applications, even when trained on small datasets [3].

Figure 1: Original input image and its stylized outputs.

8 Visual Results

Figure 1 presents a comparative overview of the original input image alongside its stylized outputs generated by our LoRA-enhanced Stable Diffusion pipeline. Each output corresponds to a distinct artistic style, including oil painting, mosaic, crayon, pencil sketch, and watercolor, as selected by the user through the web interface.

9 User Interface

The web-based user interface is designed to maximize accessibility and creative exploration for users of all skill levels, reflecting best practices in AI-powered digital art platforms [2, 6, 13]. The interface is implemented using HTML5, JavaScript, and the Canvas API, providing an intuitive, cross-device experience that requires no specialized hardware or software installation [2].

Key features include:

- **Freehand Drawing and Image Upload:** Users can sketch directly on the canvas or upload existing images for transformation, accommodating both novice and experienced creators.
- **Style Selection:** A menu enables seamless switching between multiple artistic styles, such as oil painting, crayon, pencil sketch, and watercolor, with rapid visual feedback powered by LoRA-enhanced Stable Diffusion pipelines [2, 3, 5].
- **Preview and Download:** Stylized images are rendered in real time and can be downloaded for personal use or sharing, supporting iterative creative workflows and user empowerment [13].
- **3D Mesh Conversion (Optional):** Users may also convert their stylized images into basic 3D mesh files using the Hunyuan3D module, opening new possibilities for AR/VR and digital content creation [4, 10].

The user interface is optimized for minimal latency and compatibility across desktops, tablets, and mobile devices, ensuring a smooth and interactive experience. This design philosophy is consistent with recent advances in AI art tools, which emphasize real-time feedback, modularity, and user empowerment [2, 3, 6, 13]. By integrating these principles, our platform lowers the barrier to entry for digital art creation and supports a wide range of creative workflows.

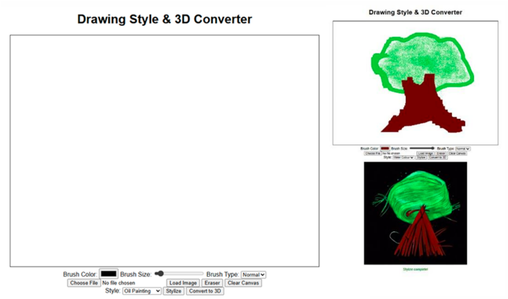

Figure 2: Screenshot of the web-based user interface for the AI Collaborative Art platform, demonstrating real-time drawing, style selection, and instant visual feedback.

10 Limitations and Future Work

10.1 Current Limitations

Despite the promising results achieved by integrating LoRA and Stable Diffusion for real-time style transfer, several limitations remain that impact both the quality and robustness of the system:

- **Limited Training Data:** The current implementation relies on a small, manually curated dataset (typically 10 images per style), which restricts the diversity and photorealism of the generated outputs. As highlighted in recent studies [3, 5], limited data can lead to overfitting, reduced generalization to unseen sketches or styles, and a tendency for the model to memorize training samples rather than learn broader stylistic representations. Expanding the dataset and incorporating data augmentation strategies are necessary future steps to improve robustness and visual diversity.
- **Style Bleed and Artifacts:** Cross-style artifacts, or “style bleed,” are observed when LoRA hyperparameters (such as rank or dropout) are not optimally tuned. This can result in less distinct stylistic boundaries and occasional loss of content fidelity, as previously reported in LoRA-based style transfer research [3, 5, 15]. Careful hyperparameter selection, style-specific regularization, and advanced adapter merging techniques [12, 18] are potential solutions to mitigate these effects.
- **Infrastructure and Operational Constraints:** While JupyterHub provides a flexible and GPU-backed environment for rapid prototyping and deployment, it introduces operational challenges. Frequent environment resets require manual reinstallation of dependencies, which can reduce system uptime and disrupt user accessibility. These issues are common in research and educational deployments [6], and motivate future migration to more robust, containerized, or cloud-native infrastructures.
- **3D Mesh Generation Limitations:** The optional 3D mesh generation component, based on Hunyuan3D [4], is currently basic and subject to dependency issues, particularly with three.js and related libraries. This restricts the platform’s ability to provide high-quality, detailed 3D outputs and seamless user experiences. Recent advances in mesh refinement and neural 3D reconstruction [10] offer promising directions for future improvement, including more accurate geometry, texture mapping, and interactive visualization.

These limitations reflect both the practical constraints of building real-time, web-based creative tools and the open research challenges in multi-style transfer and 2D-to-3D generation. Addressing them will require advances in data collection, model design, infrastructure engineering, and user experience research.

10.2 Future Directions

To address these limitations and enhance the platform’s capabilities, several avenues for future work are proposed:

- **Dataset Expansion and LoRA Optimization:** Increasing the size and diversity of the training dataset, as well as experimenting with higher LoRA ranks and additional modules, can significantly improve style fidelity and reduce artifacts [3, 5].
- **Advanced Mesh Refinement:** For users interested in 3D outputs, integrating more sophisticated mesh refinement techniques and robust 3D libraries can lead to higher-quality and more detailed mesh generation [10].
- **User Management and Persistence:** Implementing user authentication and persistent storage would enable users to save, revisit, and share their creative projects, fostering a more collaborative and engaging environment.
- **Broader Style and Collaboration Features:** Adding more artistic styles, as well as real-time collaborative features, would further empower users and expand the creative potential of the platform [6].

By systematically addressing these challenges, the platform can evolve into a more robust, scalable, and user-friendly tool for both individual artists and collaborative creative communities.

11 Conclusion

Our project delivers a modular, real-time AI art creation pipeline that seamlessly integrates LoRA-enhanced Stable Diffusion for multi-style transfer within a web-based platform. By leveraging the parameter efficiency of LoRA [3] and the high-fidelity image synthesis capabilities of Stable Diffusion [2], we enable users to transform hand-drawn or uploaded images into diverse artistic styles with minimal latency and high structural fidelity.

The system’s architecture, combining an intuitive frontend with a robust, GPU-accelerated backend, demonstrates that advanced AI-powered creativity tools can be made accessible to a broad audience, regardless of their technical background. Our evaluation, using perceptual and structural metrics such as LPIPS, SSIM, and PSNR, confirms that the approach effectively preserves user intent and brushwork across a range of styles.

While the current implementation is limited by the size of the training dataset and the basic nature of 3D mesh generation, the platform is designed for extensibility. Future work will focus on expanding the style dataset, refining LoRA modules, and improving mesh quality, as well as exploring collaborative and educational applications [5, 6].

Overall, our work demonstrates the practical viability of real-time, user-centric AI art tools and lays the groundwork for further innovations in digital creativity and human-AI collaboration.

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