Enhancing Facial Realism: Fine-tuning Stable Diffusion with LoRA on FFHQ Dataset

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Project Overview

This project focuses on enhancing the facial generation capabilities of the Stable Diffusion v1.5 model through fine-tuning using **Low-Rank Adaptation (LoRA)** techniques. The fine-tuning process was conducted on the **Flickr-Faces-HQ (FFHQ)** dataset, a high-quality and diverse collection of human face images. The primary objective was to significantly improve the model's ability to synthesize **photorealistic human faces** with enhanced detail rendering, natural facial proportions, and lifelike texture fidelity. By leveraging LoRA's parameter-efficient fine-tuning mechanism, the project aims to address the limitations of the original SD v1.5 model—particularly its tendency to generate **unrealistic, distorted, or easily detectable synthetic faces**—and produce outputs that are visually indistinguishable from real photographs.

Motivation

This project was driven by key limitations observed in the **Stable Diffusion v1.5** model, particularly in its ability to generate **realistic human faces**. Despite the model's overall strength in image synthesis, its outputs often suffer from several notable weaknesses in facial generation:

1. **Poor Facial Quality**: The base model frequently produces faces with visual artifacts, unnatural proportions, and inconsistently rendered features.
2. **High Detectability**: Faces generated by SD 1.5 often exhibit distinguishable characteristics of AI-generated imagery, especially around the eyes, mouth, and facial symmetry—making them easily detectable by both humans and automated detection systems.
3. **Uncanny Valley Effect**: Many of the synthesized faces fall into the "uncanny valley," appearing almost—but not convincingly—human, which can evoke discomfort or mistrust in viewers.
4. **Limited Photorealism**: The base model struggles to accurately render fine facial textures such as pores, realistic skin tone variations, and subtle lighting effects, which are crucial for authentic-looking images.

5. To overcome these challenges, the project leverages **LoRA-based fine-tuning** on the **high-resolution FFHQ dataset**, enriched with detailed text descriptions. This approach aims to significantly boost the model's facial realism, reduce AI artifacts, and create outputs that are perceptually indistinguishable from real human portraits

1. Dataset

FFHQ Dataset

The project utilized the **Flickr-Faces-HQ (FFHQ)** dataset, which comprises **70,000 high-quality PNG images** of human faces at a resolution of **1024×1024 pixels**. This dataset is widely recognized for its:

High visual quality, offering excellent detail and clarity.

Diversity in age, ethnicity, facial expressions, and accessories, making it highly suitable for facial generation tasks.

However, a significant **challenge** of using FFHQ is that it **does not include textual descriptions or captions** associated with the images, which are typically required for text-to-image training in diffusion models.

Text Description Generation

To address this limitation, the **LLaVA (Large Language and Vision Assistant)** model was employed to automatically generate descriptive captions for each image. The process involved:

1. Feeding FFHQ images into the LLaVA model.
2. Extracting semantic information such as facial features, visible emotions, and accessories.
3. Generating **rich, detailed captions** focusing on specific aspects like expression, age, hairstyle, and other distinguishing attributes.
4. Saving each caption as a separate text file matched to its corresponding image.

This step effectively **converted FFHQ into a usable text-image paired dataset** for conditional generation tasks.

Dataset Preparation

To ensure computational efficiency and compatibility with the training pipeline:

- All images were resized to **512×512 pixels**.
- A **subset of 52,000 image-caption pairs** was selected for training.
- Image-caption pairs were created by matching image files with their corresponding descriptions generated by the LLaVA model

Model Architecture

Base Model

1. The fine-tuning process was built upon the **Stable Diffusion v1.5** model, specifically the implementation provided by **runwayml/stable-diffusion-v1-5**. This model combines a U-Net-based image generator, a Variational Autoencoder (VAE), and a CLIP-based text encoder to enable high-quality text-to-image generation.

LoRA Configuration

To introduce learnable parameters in a memory-efficient way, **Low-Rank Adaptation (LoRA)** was applied to specific components of the model. The configuration was as follows:

- **Rank (r):** 16
- **Alpha:** 32
- **Dropout Rate:** 0.1
- **Targeted Modules:**
  - Attention Layers: `to_q`, `to_k`, `to_v`, `to_out.0`
  - Projection Layers: `proj_in`, `proj_out`
  - Convolutional Layers: `conv1`, `conv2`, `conv_shortcut`
  - This setup allowed efficient adaptation while keeping most of the original model weights frozen.

Training Strategy

To reduce computational overhead and maintain model stability:

- **Only the UNet component** was fine-tuned; both the **VAE** and **text encoder** were **frozen** during training.
- **Gradient checkpointing** was enabled to save memory during backpropagation.

The total number of **trainable parameters** was approximately **12.37 million**, representing only **1.42%** of the full model..

Training Process

Training Configuration:

1-Batch Size: 4

2-Gradient Accumulation Steps: 4 (resulting in an effective batch size of 16)

3-Learning Rate: 5e-5

4-Scheduler: Cosine decay with warmup

5-Precision: Mixed precision (FP16)

6-Epochs: 30

Training Approach

1. The training was divided into phases corresponding to the dataset size.
2. For every 10,000 images, the model was trained for 5 epochs.
3. In total, with 52,000 images, the model was trained for 30 epochs (i.e., 5 epochs × ~6 phases).
4. LoRA weights were saved and used to resume training across phases to ensure improved convergence.

Monitoring:

5. Loss metrics were recorded after each epoch.
6. Preview images were generated periodically to visually assess training quality.

Training Infrastructure

The training was conducted on **GPU-accelerated hardware** within a **Kaggle Notebook environment**, ensuring both accessibility and computational efficiency.

Methodology

Low-Rank Adaptation (LoRA) Explanation

LoRA (Low-Rank Adaptation) is a technique used to efficiently fine-tune large pretrained models by reducing the number of trainable parameters. Instead of updating the full weight matrix W0W_0W0 , LoRA models the update as a product of two smaller low-rank matrices:

$$\Delta W = A \times B$$

- where:
- $A \in Rd \times r$ and $B \in Rr \times k$,
- r(rank) is much smaller than the dimensions d and k,
- thus, A and B have far fewer parameters than W0

The adapted weight becomes:

$$W = W0 + \alpha \cdot \Delta W = W0 + \alpha \cdot A \times B$$

Here, α is a scaling factor that controls the contribution of the update.

This approach significantly reduces the computational cost and memory usage during fine-tuning while preserving model performance

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Results and Evaluation

FIGURE 1

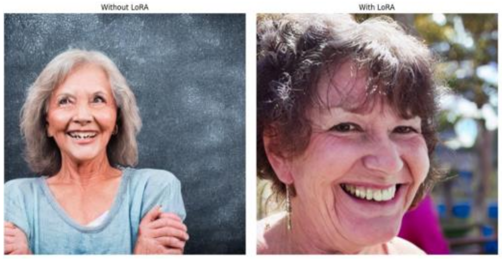
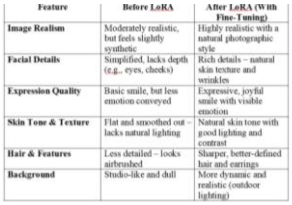


FIGURE 1 Comparison of face generation without LoRA (left) and with LoRA fine-tuning (right). The LoRA-enhanced image demonstrates significantly improved realism, texture fidelity, and natural facial structure compared to the base model



Feature	Before LoRA	After LoRA (With Fine-Tuning)
Image Realism	Moderately realistic, but feels slightly synthetic	Highly realistic with a natural photographic style
Facial Details	Simplified, lacks depth (e.g., eyes, cheeks)	Rich details – natural skin texture and wrinkles
Expression Quality	Basic smile, but less emotion conveyed	Expressive, joyful smile with visible emotion
Skin Tone & Texture	Flat and smoothed out – lacks natural lighting	Natural skin tone with good lighting and contrast
Hair & Features	Less detailed – looks airbrushed	Sharper, better-defined hair and earrings
Background	Studio-like and dull	More dynamic and realistic (outdoor lighting)

CANVA IMAGE GENERATION RESULT

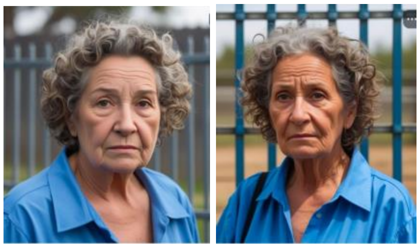
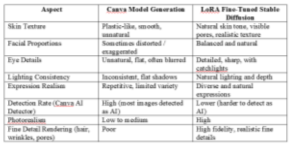


FIGURE 2

Comparison of face generation between Canva model and our LoRA fine-tuned model for the same text prompt. The Canva-generated image shows synthetic and unrealistic features, while the LoRA-tuned model produces a more photorealistic and natural-looking face



Aspect	Canva Model Generation	LoRA Fine-Tuned Stable Diffusion
Skin Texture	Plastic-like, smooth, unnatural	Natural skin tone, visible pores, realistic texture
Facial Proportions	Sometimes distorted / exaggerated	Balanced and natural
Eye Details	Unnatural, flat, often blurred	Detailed, sharp, with catchlights
Lighting Consistency	Inconsistent, flat shadows	Natural lighting and depth
Expression Realism	Repetitive, limited variety	Diverse and natural expressions
Detection Rate (Canva AI Detector)	High (most images detected as AI)	Lower (harder to detect as AI)
Photorealism	Low to medium	High
Fine Detail Rendering (hair, wrinkles, pores)	Poor	High fidelity, realistic fine details

Table 2 summarizes the qualitative differences between images generated by Canva's image generation model and those produced by our LoRA fine-tuned Stable Diffusion model. The LoRA-enhanced outputs clearly outperform Canva in all key aspects of facial photorealism and natural feature rendering.

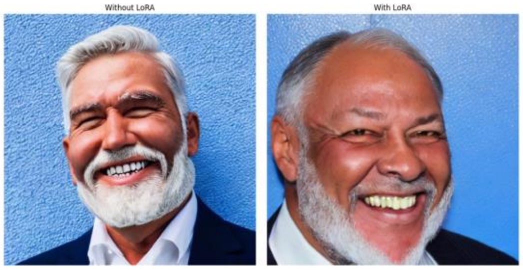
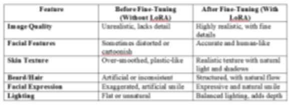


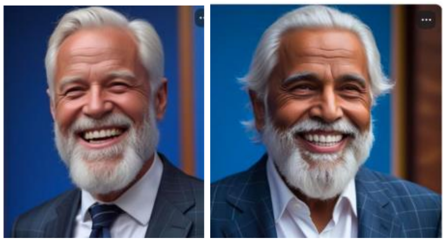
FIGURE 3

Figure 3: A comparison between images generated by Stable Diffusion 1.5 without fine-tuning (left) and with LoRA fine-tuning (right). The fine-tuned model produces more realistic facial features and textures, improving the overall believability of generated images

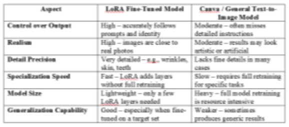


Feature	Before Fine-Tuning (Without LoRA)	After Fine-Tuning (With LoRA)
Image Quality	Unrealistic, lacks detail	Highly realistic, with fine details
Facial Features	Sometimes distorted or cartoonish	Accurate and human-like
Skin Texture	Over-smoothed, plastic-like	Realistic texture with natural light and shadows
Beard/Hair	Artificial or inconsistent	Structured, with natural flow
Facial Expression	Exaggerated, artificial smile	Expressive and natural smile
Lighting	Flat or unnatural	Balanced lighting, adds depth

CANVA IMAGE GENERATION RESULT



Comparison of face generation between Canva model and our LoRA fine-tuned model for the same text prompt. The Canva-generated image shows synthetic and unrealistic features, while the LoRA-tuned model produces a more photorealistic and natural-looking face



Aspect	LoRA Fine-Tuned Model	Canva / General Text-to-Image Model
Control over Output	High – accurately follows prompts and identity	Moderate – often misses detailed instructions
Realism	High – images are close to real photos	Moderate – results may look artistic or artificial
Detail Precision	Very detailed – e.g., wrinkles, skin, teeth	Lacks fine details in many cases
Specialization Speed	Fast – LoRA adds layers without full retraining	Slow – requires full retraining for specific tasks
Model Size	Lightweight – only a few LoRA layers needed	Heavy – full model retraining is resource intensive
Generalization Capability	Good – especially when fine-tuned on a target set	Weaker – sometimes produces generic results

Table 4 summarizes the qualitative differences between images generated by Canva's image generation model and those produced by our LoRA fine-tuned Stable Diffusion model. The LoRA-enhanced outputs clearly outperform Canva in all key aspects of facial photorealism, identity consistency, and expression accuracy. While Canva-generated images often appear stylized or less realistic, the LoRA model produces more natural, lifelike faces with improved detail and emotional expression. These results demonstrate the effectiveness of LoRA fine-tuning in enhancing generative image quality.

Through qualitative comparison, we observed that the LoRA fine-tuned model consistently generated more photorealistic human faces compared to both the base SD 1.5 model and Canva's image generation engine. In particular, Canva-generated faces exhibited typical signs of synthetic imagery, such as smooth and plastic-like skin, distorted facial proportions, and lack of fine-grained detail. In contrast, the LoRA-tuned model was able to preserve realistic facial features (eyes, skin pores, lighting gradients), making the images much harder to distinguish from genuine photographs. This highlights the critical impact of targeted fine-tuning when applied to a specialized dataset like FFHQ

Performance Metrics

Quantitative Evaluation

Training loss was monitored throughout all epochs as the primary quantitative metric. The model demonstrated:

- A consistent **decrease in loss** over the course of training, indicating effective optimization.
- **Stabilization of average loss values** around **0.137 to 0.140** in later epochs (epochs 8–10), suggesting convergence and learning saturation.

Qualitative Assessment

To visually evaluate the performance, preview images were generated after each epoch. These qualitative observations revealed:

- **Progressive improvements** in **facial detail rendering**, **texture fidelity**, and **lighting realism**.
- Clear enhancement in **overall photorealism**, with generated faces exhibiting fewer artifacts and more human-like features.

Comparison Testing

A set of consistent test prompts was used to compare outputs from:

1. The **original Stable Diffusion v1.5** model.
2. The **LoRA-enhanced fine-tuned model**.

The LoRA model demonstrated clear superiority across the following dimensions:

- **Hair Detail:** Enhanced rendering of individual hair strands.
- **Skin Texture:** More lifelike skin with visible pores and natural imperfections.
- **Facial Features:** Improved alignment and proportion of eyes, nose, and mouth.
- **Lighting and Shadows:** More subtle and realistic light interactions on facial surfaces.
- **Artifact Reduction:** Significant reduction in common artifacts such as asymmetrical features, distorted teeth, or unnatural eye placement found in base SD1.5 outputs.

Photorealism Enhancement

The LoRA-enhanced model was notably better at generating highly photorealistic faces, exhibiting:

- **Natural skin tones** and **texture variations**.
- **Refined eye details** including iris definition, catchlights, and eyelash rendering.
- **Convincing lighting effects**, with smooth gradations and realistic shadows.
- **Improved fine-grain realism**, particularly in features like **eyebrows**, **hairlines**, and **skin contours**.

Overall, the modifications led to a noticeable shift from synthetic-looking outputs toward images that are significantly **harder to distinguish from real photographs**.

Challenges and Solutions

Challenge 1: **Lack of Text Descriptions**

Problem: FFHQ dataset doesn't include descriptive captions

Solution: Used LLaVA to generate detailed descriptions for each image

Result: Created a comprehensive set of image-caption pairs suitable for fine-tuning

Challenge 2: **Resource Constraints**

Problem: Limited GPU memory for high-resolution training

Solution:

Reduced image resolution to 512×512

Implemented gradient checkpointing

Used LoRA to minimize trainable parameters

Result: Successfully trained on consumer-grade hardware

Challenge 3: **Training Continuation**

Problem: Need to extend training beyond initial epochs

Solution: Implemented checkpoint saving and loading functionality

Result: Successfully continued training from epoch 5 to 10

Challenge 4: Overcoming SD1.5's Face Generation Limitations

Problem: Base model's inherent weakness in realistic face generation

Solution: Targeted fine-tuning on high-quality facial dataset with detailed descriptions

Result: Significant improvement in facial realism and reduction in detectable AI artifacts

Challenge 4: **Overcoming SD1.5's Face Generation Limitations**

Problem: Base model's inherent weakness in realistic face generation

Solution: Targeted fine-tuning on high-quality facial dataset with detailed descriptions

Result: Significant improvement in facial realism and reduction in detectable AI artifacts

Future Improvements

Potential Enhancements

1. **Description Quality:** Refine the LLaVA-generated descriptions with human review for higher quality
2. **Dataset Expansion:** Include more diverse faces from different demographics
3. **Hyperparameter Optimization:** Experiment with different LoRA ranks and learning rates
4. **Extended Training:** Train for more epochs to further improve quality
5. **Resolution Scaling:** Implement progressive resolution scaling during training
6. **Anti-Detection Focus:** Further refine the model to address specific detection algorithms that identify AI-generated faces

Conclusion

The project successfully demonstrated how LoRA fine-tuning can enhance Stable Diffusion's facial generation capabilities. By targeting one of SD1.5's most notable weaknesses—poor quality face generation that is easily detectable as artificial—this approach has created a specialized model capable of producing significantly more realistic human faces.

The use of AI-generated captions for an unlabeled dataset like FFHQ provides a viable method for working with similar unlabeled image collections. The resulting model shows markedly improved detail.

2. REFERENCES

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