Fine-Tuning Stable Diffusion XL for Naruto-Style Image Generation with DreamBooth and LoRA

1. Project Overview

This project aims to generate high-quality Naruto-themed anime images from natural language prompts (e.g., "Naruto fighting in the rain") using Stable Diffusion XL (SDXL). By fine-tuning SDXL with DreamBooth and Low-Rank Adaptation (LoRA), we adapt the model to produce Naruto-style visuals. The process leverages the Hugging Face diffusers library and a custom Naruto dataset.

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2. Background and Key Concepts

2.1 Diffusion Models

Diffusion models generate images by iteratively denoising random noise into meaningful visuals. Stable Diffusion, a latent diffusion model, operates in a compressed latent space to reduce computational costs.

- **How It Works**:
  - A forward process adds Gaussian noise to an image.
  - A reverse process, powered by a U-Net, predicts and removes noise to reconstruct the image.
  - A Variational Autoencoder (VAE) encodes images into latent space and decodes them back to pixels.
  - Text conditioning is achieved via a frozen CLIP text encoder, enabling classifier-free guidance.
- **Components**:
  - VAE (encoder/decoder)
  - U-Net (diffusion model)
  - CLIP text encoder
- **Advantages**:
  - High-fidelity image generation
  - Fine-grained text conditioning

2.2 Stable Diffusion XL (SDXL)

SDXL is an advanced version of Stable Diffusion with enhanced capabilities.

- **Key Features**:
  - 3.5 billion parameters
  - Larger U-Net (~3× compared to SD2.x)
  - Dual text encoders: OpenCLIP ViT-bigG/14 and original CLIP
  - Size-and-crop conditioning
  - Two-stage pipeline (base + refiner model)
  - Outputs high-resolution images (e.g., 1024×1024) with photorealistic details

2.3 DreamBooth

DreamBooth personalizes diffusion models for specific subjects or styles using 3–5 images.

- **Core Idea**:
  - Introduces a new token (e.g., [V]) associated with the target subject/style.
  - Enables prompts like “[V] in a forest” to generate context-specific images.
- **Training**:
  - Uses a prompt template (e.g., “a photo of a [V] dog”).
  - Employs prior-preservation loss with class images to prevent overfitting.
  - Phases: Low-resolution token binding, high-resolution refinement.

2.4 Low-Rank Adaptation (LoRA)

LoRA is a lightweight fine-tuning method that modifies a small subset of model parameters.

- **How It Works**:
  - Freezes original weights (W).
  - Adds trainable low-rank matrices (A, B) such that $W' = W + B \times A$.
  - Targets cross-attention layers for text-image alignment.
- **Benefits**:
  - Reduces VRAM usage
  - Speeds up training
  - Maintains full fine-tuning quality
  - Simplifies deployment

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3. Dataset

3.1 Description

We used the lambdalabs/naruto-blip-captions dataset from Hugging Face:

- **Content**: 1,221 Naruto-style anime images (~501 MB) with BLIP-generated captions.
- **Format**: Each entry includes a JPEG image and a text caption (e.g., “Naruto Uzumaki with orange background”).
- **Source**: Images from Narutopedia, captioned using BLIP.

3.2 Preprocessing

- **Images**:
    - Resized to 256×256 and center-cropped if needed.
    - Converted to RGB and normalized to the SDXL latent space.
    - No augmentations applied to preserve identity learning.
- **Captions**:
    - Used directly as prompts without cleaning.
    - Tokenized with SDXL’s CLIP tokenizer.
    - Appended to a fixed instance prompt: “a naruto anime character.”
- **Special Tokens**:
    - No new tokens introduced; the class prompt “a naruto anime character” was used.
- **Splitting**:
    - All images used for training (no validation split) due to the small dataset size.
    - DreamBooth’s regularization mitigates overfitting.

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4. Fine-Tuning Setup

4.1 Model Architecture

Component	Details
Base Model	stabilityai/stable-diffusion-xl-base-1.0
VAE	madebyollin/sdxl-vae-fp16-fix
Text Encoder	Dual CLIP encoders (OpenCLIP + original)
Scheduler	DDIM with multi-step denoising
Fine-Tuning Method	DreamBooth + LoRA (attention layers only)

4.2 Training Configuration

Parameter	Value
Pretrained Model	stabilityai/stable-diffusion-xl-base-1.0
VAE Model	madebyollin/sdxl-vae-fp16-fix
Dataset	lambdalabs/naruto-blip-captions
Instance Prompt	“a naruto anime character”
Resolution	256×256
Train Batch Size	1
Gradient Accumulation	4 (effective batch size = 4)
Learning Rate	1.0 (with Prodigy optimizer)
Text Encoder LR	1.0
Optimizer	Prodigy
SNR Gamma	5.0
LR Scheduler	Constant
Max Train Steps	500
Gradient Checkpointing	Enabled
Mixed Precision	fp16
LoRA Rank	4

Push to Hub	Enabled

4.3 Training Process

- **Hardware**: Single Tesla T4 GPU.
- **Duration**: ~1 hour with mixed precision.
- **Steps**:
  - Installed dependencies (diffusers, transformers, peft, accelerate, prodigyopt).
  - Downloaded Hugging Face's train_dreambooth_lora_sdxl_advanced.py script.
  - Configured accelerate for GPU and fp16.
  - Authenticated with Hugging Face Hub using a token.
  - Launched training with accelerate launch, specifying hyperparameters.
  - Trained for 500 diffusion steps, updating LoRA parameters in U-Net's cross-attention layers.
  - Pushed LoRA weights to Hugging Face Hub.
- **Training Dynamics**:
  - U-Net processes batches of latents + noise and text embeddings.
  - Computes MSE loss on predicted noise.
  - Prodigy optimizer updates LoRA matrices.
  - SNR weighting (γ=5.0) emphasizes low-noise timesteps.
  - Gradient checkpointing reduces VRAM usage.

4.4 Attention Mechanisms

- **SDXL's Cross-Attention**:
  - Aligns image latents (queries) with text embeddings (keys/values) from dual CLIP encoders.
  - Enables spatial feature binding to prompt words (e.g., "Naruto" → orange hair).
- **LoRA's Role**:
  - Adds low-rank matrices (A, B) to query/value projections in cross-attention layers.
  - Rank-4 updates perturb weights minimally, capturing Naruto-style features.
  - Post-training, LoRA matrices are fused into U-Net weights for efficient inference.

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5. Code Walkthrough

The fine-tuning was implemented in a Jupyter notebook:

1. **Setup**:
   - Installed libraries and downloaded the training script.
   - Configured accelerate and authenticated with Hugging Face.

2. **Training**:
    - Executed !accelerate launch with parameters (see Section 4.2).
    - Script loaded SDXL, applied LoRA, and processed the dataset with the instance prompt.
3. **Post-Training**:
    - Cleared GPU memory.
    - Loaded the fine-tuned pipeline with StableDiffusionXLPipeline and fused LoRA weights.

Inference Example:
python
Copy
```python
prompt = "a naruto anime character with red hair and green eyes"
negative_prompt = "low quality, worst quality, bad anatomy, bad composition"
image = pipe(
    prompt=prompt,
    negative_prompt=negative_prompt,
    guidance_scale=7.5,
    num_inference_steps=30
```

4. `).images[0]`

    - Generated a 1024×1024 Naruto-style image for visual inspection.

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6. Evaluation

6.1 Qualitative Results

- **Prompts Tested**:
    - “Naruto fighting in the forest”
    - “A Naruto anime-style portrait”
    - “Sasuke Uchiha with red Sharingan”
- **Observations**:
    - Images exhibit Naruto’s anime aesthetic (bright colors, sharp outlines, ninja headbands).
    - Negative prompts reduce artifacts like bad anatomy.

6.2 Quantitative Metrics

- **Fréchet Inception Distance (FID)**: Measures similarity between generated and real Naruto images (lower is better).

- **CLIP Score**: Evaluates text-image alignment via cosine similarity of CLIP embeddings (higher is better).
- **Limitations**: Metrics may be less reliable for narrow styles; human judgment is critical.

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7. MLOps Considerations

To productionize the pipeline:

Tool	Purpose
MLflow	Track experiments, parameters, checkpoints
TensorBoard	Monitor loss and learning rate
Hugging Face Hub	Version and deploy models
Docker	Ensure reproducible environments
FastAPI	Create a prompt-to-image web API

- **CI/CD**: Use GitHub Actions for automated testing and small-scale training.
- **Serving**: Deploy via Docker/Kubernetes with NVIDIA Triton or Hugging Face Inference API.
- **Monitoring**: Track latency, throughput, and output quality.
- **Data Management**: Version datasets with DVC or Delta tables.

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8. Challenges and Limitations

- **Overfitting**: Small dataset (~1.2K images) risks memorization. Mitigated by DreamBooth's prior-preservation and limited steps.
- **Caption Noise**: BLIP captions may be inconsistent (e.g., unrelated scenes).
- **Generalization**: Prompts outside the Naruto domain (e.g., "Naruto in space") may yield poor results.
- **Memory**: LoRA reduces VRAM needs, but SDXL is still resource-intensive.

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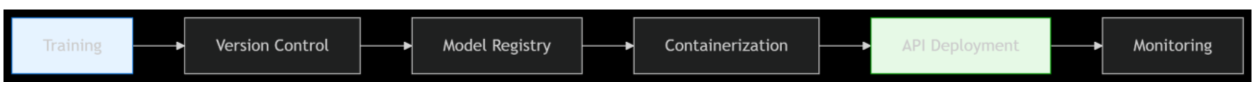
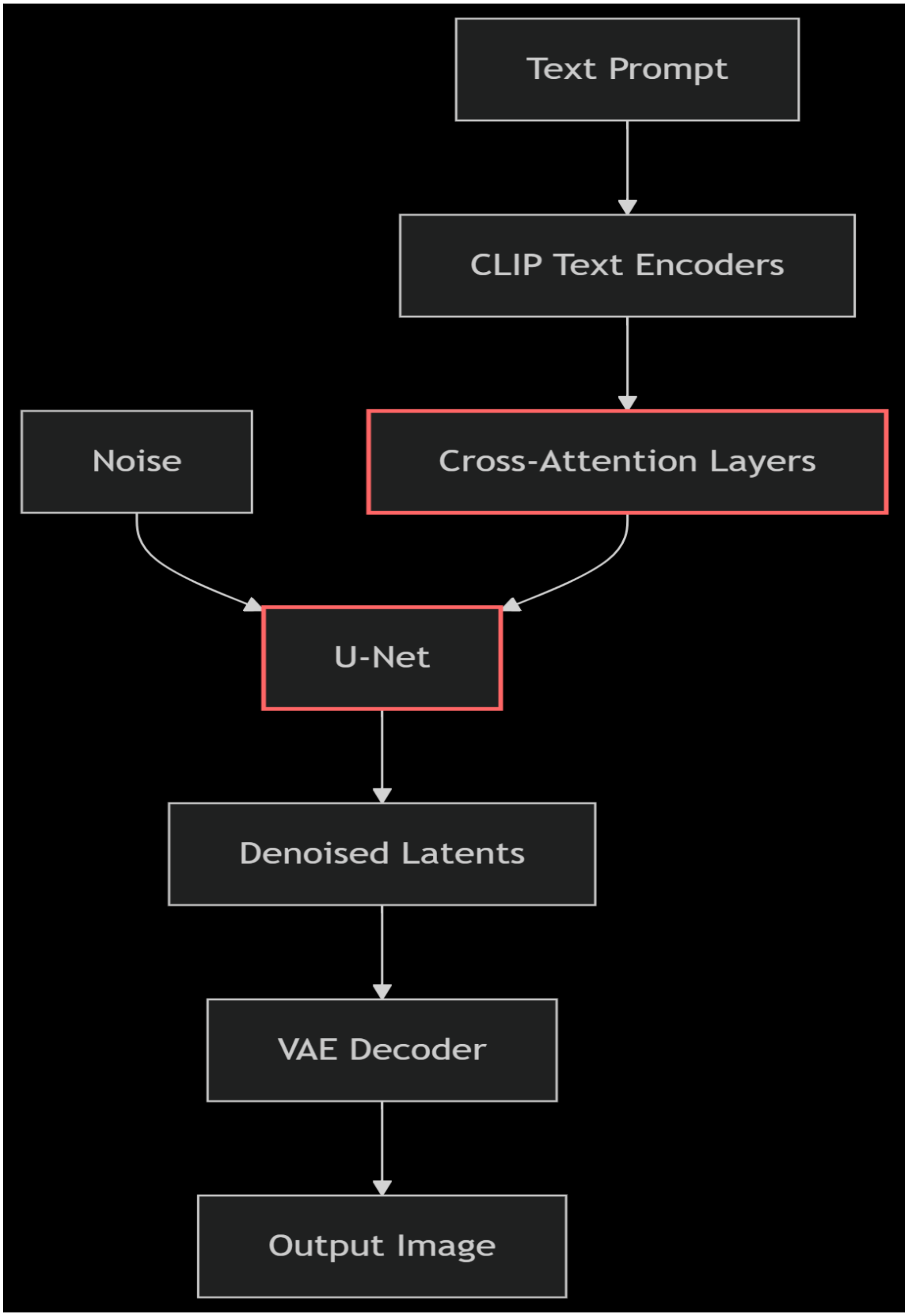
9. Future Work

- **Dataset Expansion**:
  - Curate cleaner captions or re-caption with specialized models.
  - Include multi-character images for complex prompts (e.g., “Naruto and Sasuke”).
- **Prompt Engineering**:
  - Introduce unique tokens via textual inversion (e.g., <naruto-style>).
  - Combine LoRA with textual inversion for finer control.
- **Multi-Style Training**:
  - Extend to other anime styles (e.g., One Piece) using multi-token or multi-head LoRA.
- **Advanced Techniques**:
  - Apply dropout, weight decay, or augmentations to reduce overfitting.
  - Explore gradual unfreezing or style transfer objectives.

10.MLOps Pipeline



11.Model Architecture


Text Prompt
CLIP Text Encoders
Noise
Cross-Attention Layers
U-Net
Denoised Latents
VAE Decoder
Output Image

12. Conclusion

This project successfully fine-tuned Stable Diffusion XL to generate Naruto-style anime images using DreamBooth and LoRA. Key achievements:

- Efficient fine-tuning with minimal parameters via LoRA.
- High-quality Naruto-themed outputs aligned with input prompts.
- Practical MLOps strategies for production deployment.

The approach is extensible to other styles and demonstrates the power of combining advanced diffusion models with lightweight fine-tuning techniques.