Neural Networks and Deep Learning - CSCI 6366

Project Deliverable I

Project Title: Photo Restoration Using LoRA Fine-Tuned Diffusion Models

We are developing an AI-based tool that automatically restores damaged photographs. Many ancient family photos have scratches, water stains, or fading, and professional restoration services typically cost between $50-$200 per photo, making them unaffordable for most people.

Our system uses LoRA (Low-Rank Adaptation) to fine-tune a Stable Diffusion model specifically for photo restoration. This enables the model to effectively remove visual damage and revive the original appearance of old or degraded photos.

We plan to collect approximately 100-50 clean photos and artificially introduce realistic damage (e.g., scratches, tears, fading) to generate our training dataset. The model will then learn to reverse this damage through fine-tuning.

We will evaluate success based on both quantitative and qualitative criteria:

- PSNR (Peak Signal-to-Noise Ratio): Above 25 dB
- SSIM (Structural Similarity Index): Above 0.85
- Visual Quality: Restored photos should look natural and appealing to human observers.

Team Members

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Research Sources

I. LoRA Paper

Source: ″LoRA: Low-Rank Adaptation of Large Language Models″ by Hu et al., 2021
Link: https://arxiv.org/abs/2106.09685

Value & Application: This paper introduced the LoRA technique, which enables fine-tuning large-scale AI models efficiently without requiring expensive hardware. This is ideal for our setup since we will be using free Google Colab GPUs. The methodology outlined in this paper will guide our approach to training the photo restoration model.

II. Hugging Face Diffusers Documentation

Source: Stable Diffusion Inpainting Guide
Link: https://huggingface.co/docs/diffusers/using-diffusers/inpaint

Value & Application: This provides step-by-step guidance on implementing diffusion-based inpainting. It explains how to load pre-trained models, configure the inpainting pipeline, and prepare inputs correctly (i.e., the damaged image and the corresponding damage mask). It will serve as our main reference for implementation.

III. PEFT Library

Source: Hugging Face PEFT Repository
Link: https://github.com/huggingface/peft

Value & Application: The PEFT (Parameter-Efficient Fine-Tuning) library contains built-in implementations of LoRA and examples for fine-tuning Stable Diffusion models. We will adapt their codebase to train our model for photo restoration tasks, allowing for faster experimentation and efficient training.

IV. Microsoft's Photo Restoration Project

Source: Bringing Old Photos Back to Life - GitHub
Link: https://github.com/microsoft/Bringing-Old-Photos-Back-to-Life

Value & Application: This project demonstrates realistic techniques for artificially damaging images and evaluating restoration quality. Although it utilizes GANs rather than diffusion models, the synthetic damage generation methods and evaluation metrics are highly relevant to our dataset creation process. We will also use this project as a performance benchmark.

V. Text-to-Image Diffusion Models Paper

Source: ″Text-to-Image Diffusion Models in Generative AI: A Survey″ - Brunel University
Link: https://bura.brunel.ac.uk/bitstream/2438/30634/1/FullText.pdf

Value & Application: This paper provides a comprehensive overview of how diffusion models generate images from text prompts. Since our model will use prompt-based conditioning (e.g.,“restore damaged photo”), understanding the text-to-image mechanism will help us design more effective prompts to produce cleaner and more accurate restorations.