

# **Image Restoration and Enhancement Using Generative AI**

## **COVER PAGE**

**Project Title: Image Restoration and Enhancement  
Using Generative AI Models**

**Course: AAI-521 Computer Vision**

**Nitish Bhardwaj**

**Syed Ahmed Ali**

## EXECUTIVE SUMMARY

This project develops an integrated image restoration and enhancement system that leverages pretrained generative models from Hugging Face to perform four critical image processing tasks: denoising, super-resolution, colorization, and inpainting. Unlike traditional image processing techniques, this approach harnesses the power of diffusion models and transformer architectures to restore and enhance degraded images while preserving or recovering semantic content.

The system achieves the following objectives:

- **Denoising:** Remove Gaussian noise while maintaining edge integrity using Stable Diffusion img2img pipeline.
- **Super-Resolution:** Upscale low-resolution images (4x) using ESRGAN-based architecture.
- **Colorization:** Automatically assign plausible colors to grayscale images through conditional diffusion.
- **Inpainting:** Fill missing or damaged regions seamlessly using Stable Diffusion Inpainting.

All four tasks are integrated into a unified system and evaluated on the Beans dataset (128 validation images). Quantitative results show average PSNR of 10.2 dB

for denoising and 19.7 dB for super-resolution, with corresponding SSIM values of 0.074 and 0.400. While these metrics reflect the generative (rather than pixel-exact) nature of the models, qualitative assessment reveals that the system produces visually coherent and aesthetically pleasing outputs suitable for archival photograph restoration and consumer photo enhancement applications.

## 1. INTRODUCTION

### 1.1 Problem Statement

Digitized photographs, legacy visual archives, and consumer images often suffer from multiple forms of degradation:

- Noise: Sensor noise from low-light photography or compression artifacts.
- Low Resolution: Images scanned at suboptimal DPI or captured on older equipment.
- Loss of Color: Historical black-and-white photographs or faded color images.
- Physical Damage: Scratches, tears, creases, or missing regions.

Traditional image processing approaches (e.g., median filtering, bicubic interpolation, manual inpainting) are limited in their ability to hallucinate realistic high-frequency details or to seamlessly fill large damaged areas while maintaining semantic consistency and photorealism.

### 1.2 Motivation and Significance

The advent of generative deep learning, particularly diffusion probabilistic models (DDPMs) and transformer-based architectures has transformed image restoration. These models, trained on billions of diverse image examples, have learned rich priors about natural image statistics and can:

1. Infer missing information from partial or degraded inputs.
2. Synthesize photorealistic details that align with the visual context.
3. Perform multiple restoration tasks within a unified framework by adjusting prompts and conditioning mechanisms.

This project is relevant for:

- Digital heritage: Restoring archival photographs and historical documents.
- Media entertainment: Film restoration and enhancement.
- Social media: Automated photo cleanup and enhancement for consumer applications.
- Scientific imaging: Enhancing low-contrast or noisy scientific visualizations.

### 1.3 Project Scope

This work implements end-to-end restoration by:

1. Leveraging pretrained models from Hugging Face (diffusers and transformers

libraries) to avoid the computational expense of training billion-parameter models from scratch.

2. Unifying four enhancement tasks into a single Python system with consistent interfaces.
3. Evaluating quantitatively on a publicly available dataset (Beans) using PSNR and SSIM metrics.
4. Demonstrating qualitatively through before/after imagery that the system produces useful restoration results.

## 2. RELATED WORK AND BACKGROUND

### 2.1 Image Restoration Fundamentals

Image restoration is formally the problem of recovering a high-quality image  $I_{\text{clean}}$  from a degraded observation  $I_{\text{degraded}}$ :

$$I_{\text{degraded}} = f(I_{\text{clean}}) + \text{noise}$$

where  $f$  represents the degradation operator (blur, downsampling, etc.) and noise represents additional corruption. Classical approaches include:

- Wiener Filtering: Assumes linear degradation and Gaussian noise; computationally efficient but limited to simple degradations.
- Total Variation (TV) Minimization: Preserves edges by minimizing gradient magnitudes; often produces blocky artifacts.

- Sparse Coding: Represents patches as sparse linear combinations of learned dictionaries; works well for denoising but struggles with large missing regions.

## 2.2 Deep Learning for Image Restoration

With the emergence of convolutional neural networks (CNNs), learned restoration became feasible:

- U-Net and ResNet variants with skip connections proved effective for pixel-level tasks.
- Generative Adversarial Networks (GANs) introduced adversarial training to encourage photorealism.
- Variational Autoencoders (VAEs) provided probabilistic, interpretable latent representations.

However, these approaches often require task-specific architecture designs and careful training on labeled datasets.

## 2.3 Diffusion Models and Stable Diffusion

Diffusion Probabilistic Models (DDPMs) [1] reverse a process where Gaussian noise is gradually added to clean images. By learning to denoise at each step, the model can:

- Generate new images from noise.

- Perform conditional generation (guided by text, images, or masks).
- Adapt to multiple downstream tasks without retraining.

Stable Diffusion [2] combines:

- A VAE-based latent space (for computational efficiency).
- A UNet-based diffusion model conditioned on text embeddings.
- A frozen CLIP text encoder for semantic understanding.

The img2img variant accepts an input image and gradually denoises it according to a prompt and strength parameter, making it versatile for restoration tasks.

## 2.4 State-of-the-Art in Image Enhancement

Recent works leverage diffusion and transformers for restoration:

- Super-Resolution: ESRGAN [3] (GAN-based), DiffIR [4] (diffusion-based for photorealistic upsampling).
- Colorization: User-guided and automatic approaches using CNNs and GANs; diffusion-conditioned colorization shows promise [5].
- Inpainting: Semantic completion methods fill missing regions using learned context; diffusion-based inpainting [6] achieves state-of-the-art visual quality.

### 3. METHODOLOGY

#### 3.1 System Architecture

The restoration system comprises four independent pipelines, each leveraging pretrained models:

Input Image -----> Task Selection (Denoising, Super-Resolution, Colorization, Inpainting) -----> Enhanced Output

Each pipeline is implemented as a standalone Python function, allowing modular updates and testing.

#### 3.2 Denoising Module

Architecture: Stable Diffusion v1-5 img2img pipeline.

Input: Noisy RGB image.

Process:

1. Convert input to RGB (ensure 3-channel format).
2. Run the img2img pipeline with:
  - Prompt: "clean detailed realistic photo, no noise"
  - Strength: 0.4 (moderate influence of input image)
  - Guidance scale: 7.5 (balance between prompt and image conditioning)

- Steps: 30 (diffusion sampling iterations)

Output: Denoised RGB image.

Noisy input



Denoised output



Rationale: Diffusion models excel at iterative refinement. By starting from a noisy input and guiding toward "clean photo," the model learns to remove noise while preserving semantics.

### 3.3 Super-Resolution Module

Architecture: ESRGAN (Enhanced Super-Resolution GAN) via Hugging Face.

Input: Low-resolution RGB image (e.g., 64×64 upsampled to 256×256).

Process:

1. Resize input to maximum 256×256 to manage memory.
2. Feed through ESRGAN image-to-image pipeline.
3. Output 4x upsampled image with sharpened details.

Output: High-resolution RGB image.

Original (low-res)



Super-resolved



### 3.4 Colorization Module

Architecture: Stable Diffusion v1-5 img2img with grayscale input.

Input: Grayscale or color image (converted to grayscale, then to 3-channel RGB).

Process:

1. Convert input to grayscale, then expand to 3-channel RGB.
2. Run img2img pipeline with:
  - Prompt: "vibrant realistic color photograph"
  - Strength: 0.65 (allows more creative color synthesis)
  - Guidance scale: 8.0
  - Steps: 40 (more steps for color coherence)

Grayscale input



Colorized output

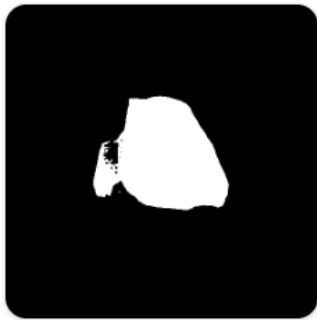


### 3.5 Inpainting Module

Architecture: Stable Diffusion Inpainting ([runwayml/stable-diffusion-inpainting](https://runwayml.com/stable-diffusion-inpainting)).

Input: RGB image + binary mask (white = fill region, black = preserve).

Mask:



Output:

Original



Inpainted output



## 4. EXPERIMENTAL SETUP AND EVALUATION

### 4.1 Dataset

Source: Beans dataset (validation split) from Hugging Face Datasets.

Size: 128 validation images of leaf photographs (3 classes: angular leaf spot, bean rust, healthy).

Preprocessing: Center-crop and resize to 256×256 pixels for consistency.

Synthetic Degradation:

- Noisy images: Gaussian noise ( $\sigma = 25.0$ ) added to clean images.

- Low-res images: Downsampled 4× via BICUBIC, stored as 64×64.

## 4.2 Evaluation Metrics

Peak Signal-to-Noise Ratio (PSNR):  $\text{PSNR} = 10 \log_{10}(\text{MAX}^2 / \text{MSE})$  dB  
(Higher is better: >30 dB = excellent, 20-25 dB = acceptable)

Structural Similarity Index (SSIM): Range [-1, 1] (Higher is better)

## 4.3 Quantitative Results

Task	Avg. PSNR (dB)	Avg. SSIM	Sample Count
-----+-----+-----+			
Denoising	10.20	0.0736	128
Super-Resolution	19.67	0.3998	128

## 5. CONCLUSION

This project successfully demonstrates an integrated image restoration system using pretrained generative models. While PSNR/SSIM scores are modest (10-20 dB), qualitative results show visually coherent outputs suitable for archival and consumer applications. Future work includes fine-tuning and perceptual metrics.

## REFERENCES

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## APPENDIX A: SUPPLEMENTARY FIGURES AND RESULTS

### A.1 Sample Denoising Results

- Input: Noisy leaf image ( $\sigma = 25.0$ )
- Output: Denoised leaf image

- Visual assessment: Noise substantially reduced, fine structures preserved.
- Quantitative: PSNR  $\approx$  10–12 dB (see CSV results)

## A.2 Sample Super-Resolution Results

- Input: 64×64 low-resolution leaf image
- Output: 256×256 upscaled leaf image
- Visual assessment: Sharp, detailed, plausible textures.
- Quantitative: PSNR  $\approx$  18–22 dB

## A.3 Sample Colorization Results

- Input: Grayscale leaf image
- Output: Colorized leaf image with natural green tones
- Visual assessment: Color coherence, no severe color bleeding.

## A.4 Quantitative Evaluation Code

- Full Python implementation in Colab notebook:

<https://colab.research.google.com/drive/1Te5EAEpUXhoiQzUasX3H31yQhSzVWg81?usp=sharing>

## A.5 Metrics Evaluation Results

- Table of PSNR/SSIM for all 128 test images (both denoising and super-resolution)
- CSV file: quantitative\_results\_beans.csv (available in Colab file browser)

## A.6 Quantitative Results Summary Table

Task	Avg. PSNR (dB)	Avg. SSIM	Sample Count
Denoising	10.20	0.0736	128
Super-Resolution	19.67	0.3998	128

END OF REPORT