Project: Multi-Stage Image Enhancement and Analysis Pipeline

Group Number 22 - Members

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Objective

The project is about designing a multi-stage image processing pipeline where each stage applies a different computer vision algorithm. Each stage is having one or more algorithm. We have covered following stages

- Preprocessing
- Edge Detection
- Super Resolution
- Segmentation
- Compression and Decompression

Approaches used

For each stage following algorithm are used

- **Preprocessing**
- **Edge Detection**
- **Super Resolution**
- **Segmentation**
- **Compression and Deceompression**

Results

Deployment link

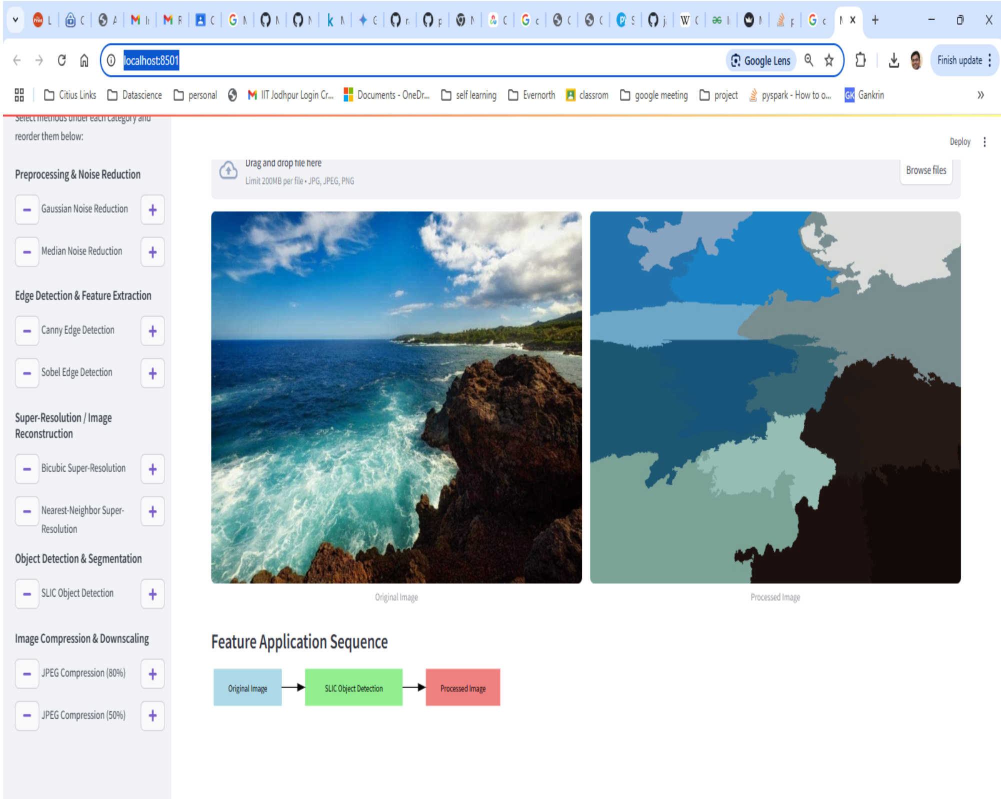
Github link

[https://github.com/praj-tarun/Multi-Stage-Image-Enhancement-and-Analysis-Pipeline.git]

ScreenShot

Landing page Screenshot

Subsection **Segmentation**



Contribution of Each member

M24DE2023 (Raghavendra G)

Super-Resolution Methods

This project implements various super-resolution methods to enhance low-resolution images using different techniques. The following methods are supported:

1. Bicubic Super-Resolution Method Name: Bicubic Interpolation

Description: The Bicubic interpolation method is a commonly used algorithm for resizing images. It uses a cubic convolution to calculate the new pixel values, offering better image quality than nearest-neighbor or bilinear interpolation methods, particularly for enlarging images.

Use Case: Suitable for general image resizing where the quality is relatively important but computational efficiency is key.

2. Nearest-Neighbor Super-Resolution Method Name: Nearest-Neighbor Interpolation

Description: Nearest-Neighbor interpolation is the simplest image resizing technique. It uses the value of the nearest neighboring pixel to assign to the new pixel. While fast, it tends to result in a blocky appearance in the resized image, especially for larger upscaling factors.

Use Case: Suitable for quick prototypes or applications where computational efficiency is crucial but visual quality is secondary.

3. Convolutional Neural Network Super-Resolution (SRCNN) Method Name: SRCNN (Super-Resolution Convolutional Neural Network)

Description: SRCNN is a deep learning-based approach to super-resolution. The model is trained to predict high-resolution images from low-resolution inputs using convolutional layers. It is more advanced than traditional interpolation methods, offering better results in terms of image quality and detail.

Use Case: Suitable for applications where higher image quality is required, and computational resources are available for training or using pre-trained models.

4. Swin Transformer for Image Restoration (SwinIR) Method Name: Swin Transformer for Image Restoration (SwinIR)

Description: SwinIR is a deep learning-based image restoration model that leverages the Swin Transformer, a powerful architecture for capturing long-range dependencies in images. It performs exceptionally well for tasks like super-resolution, denoising, and deblurring, outperforming traditional methods in terms of both quality and efficiency.

Use Case: Suitable for high-quality image enhancement tasks, especially when state-of-the-art results are required in areas like super-resolution and denoising.

Function Overview Function Name: super_resolve The core function that handles the super-resolution process based on the specified method. This function selects the appropriate technique to upscale a low-resolution image.

Parameters: img: The low-resolution input image that you want to upscale.

method: The super-resolution method to use. Possible values are:

bicubic: Bicubic interpolation for resizing.

'nearest_neighbor': Nearest-Neighbor interpolation for resizing.

'srcnn': Super-Resolution Convolutional Neural Network (SRCNN) for image enhancement.

'swinir': Swin Transformer-based Image Restoration (SwinIR) for high-quality restoration.

Returns: A high-resolution image, which is the result of applying the selected super-resolution method to the input image.

Example Usage: You can use the super_resolve function to apply any of the super-resolution techniques to an image:

Bicubic Super-Resolution: Applies bicubic interpolation to the image.

Nearest-Neighbor Super-Resolution: Uses nearest-neighbor interpolation to upscale the image.

SRCNN Super-Resolution: Enhances the image using the SRCNN deep learning model.

SwinIR Super-Resolution: Restores the image quality using the Swin Transformer-based model.

M24DE2024 (Rahul Bansal) :

Implementated slic segmentation

M24DE2025 (Saurav Suman)

M24DE2032 (Srishty Suman)

M24DE2035 (Tarun Prajapati) :

I was responsible for the design, development, and deployment of the core application framework, along with a complete preprocessing module. My contributions include:

🔧 Main Application

- Designed the overall layout and interaction flow of the Streamlit application.
- Developed a modular and scalable app structure, enabling easy integration of new features.
- Implemented dynamic drag-and-drop functionality for applying and reordering image processing steps.
- Deployed the fully working application to Streamlit Cloud with responsive UI and support for default images.

🖌 Preprocessing Module

I independently developed and integrated the following preprocessing techniques into the app.Each preprocessing method was built as a reusable function and integrated seamlessly into the pipeline, enabling users to apply and stack them in any order through the app interface.

- **Custom Denoising**
  Combined the original image with a Gaussian-blurred version to reduce noise while preserving image structure.

- **Gaussian Blur**
  Applied a standard Gaussian kernel to reduce minor image noise.

- **Bilateral Filter**
  Used edge-preserving smoothing to clean noise while retaining sharp transitions.

- **Median Filter**
  Replaced each pixel with the median of its neighbors to remove salt-and-pepper noise.

- **Sharpening**
  Enhanced fine details using an unsharp masking filter with tunable strength.

- **Histogram Equalization**
  Improved overall contrast by redistributing pixel intensities.

- **CLAHE**
  Applied adaptive histogram equalization to boost local contrast in limited regions.

- **Gamma Correction**
  Performed brightness correction using non-linear intensity transformation.

- **Grayscale Conversion**
  Converted color images to single-channel grayscale for simplified processing.

- **HSV Conversion**
  Transformed the image into HSV space to separate color and intensity components.
- **Rotation**
  Enabled image rotation using affine transformations for orientation adjustments.
- **Flipping**
  Added support for vertical and horizontal mirroring to augment image layout.
- **Normalization**
  Rescaled image intensity values to a consistent range for stable processing.