Mini-Project - 1B

X-Dehazed

Submitted in partial fulfillment of the requirements
BACHELOR OF ENGINEERING IN
ARTIFICIAL INTELLIGENCE AND DATA SCIENCE

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Abstract

Atmospheric haze in satellite imagery remains a significant challenge in remote sensing, impairing visibility and hindering accurate interpretation for applications such as environmental monitoring, disaster assessment, and urban planning. While traditional dehazing techniques like histogram equalization and the Dark Channel Prior (DCP) offer limited adaptability to diverse atmospheric conditions, many existing deep learning methods rely on either paired or unpaired datasets exclusively, restricting their real-world usability.

In this project, we introduce a novel linear hybrid dehazing pipeline that sequentially combines the strengths of both Pix2Pix GAN and CycleGAN architectures. Unlike conventional approaches that utilize one model based on data availability, our method first leverages CycleGAN to generate synthetic paired representations from unpaired multispectral satellite images. These intermediate outputs are then refined through a Pix2Pix network, enabling more precise haze removal and structural preservation. This cascaded setup ensures enhanced learning across both domains—unpaired-to-paired transformation and supervised dehazing—resulting in superior generalization and visual quality.

To further augment the system's practical utility, a Large Language Model (LLaMA) is integrated to analyze the dehazed outputs and provide automatic alerts and descriptive summaries. This fusion of image enhancement and intelligent interpretation supports real-time, decision-centric applications. The proposed framework is trained and validated using datasets such as NYU-Depth, I-HAZE, O-HAZE, and a custom multispectral dataset designed to reflect real-world atmospheric variability.

Quantitative evaluations using PSNR, SSIM, and FID, along with qualitative visual analysis, demonstrate that our dual-stage GAN approach significantly outperforms traditional and single-model baselines, achieving clearer, more realistic imagery. Overall, this work presents a scalable, intelligent, and field-ready solution for advanced multispectral satellite image dehazing.

Keywords: Multispectral Satellite Image Dehazing, Image Dehazing, Pix2Pix GAN, CycleGAN, Linear GAN Pipeline, Remote Sensing, Deep Learning

Contents

Chapter 1

Introduction

Multispectral satellite imaging is a powerful tool used in a wide range of applications, including agriculture, environmental monitoring, disaster response, and urban planning. These images capture data across various wavelengths of the electromagnetic spectrum, providing critical insights into surface conditions and atmospheric composition. However, a major challenge that limits the effectiveness of satellite imagery is the presence of haze, which is caused by atmospheric particles such as dust, smoke, and water vapor. Haze reduces image contrast, obscures surface details, and negatively impacts the accuracy of image interpretation and analysis.

Traditional dehazing techniques like Histogram Equalization and the Dark Channel Prior have been used in the past, but they often struggle to generalize across varying lighting and environmental conditions. Furthermore, they can introduce unwanted artifacts or excessive smoothing that distorts fine image details. Deep learning techniques, especially Generative Adversarial Networks (GANs), have emerged as a promising solution due to their ability to learn complex mappings and generate visually appealing results.

This project proposes an end-to-end deep learning-based solution that combines the strengths of Pix2Pix GAN for paired datasets and CycleGAN for unpaired datasets to perform image dehazing on multispectral satellite data. Additionally, perceptual loss functions are incorporated to preserve important visual textures and details. The use of Laplacian pyramid upscaling techniques allows the generation of high-resolution dehazed images.

An innovative aspect of this system is the integration of a Large Language Model (LLaMA) which evaluates the dehazed outputs and generates automated insights or alerts based on the clarity and quality of the images. This feature adds significant value for real-time applications such as early warning systems and rapid disaster assessment. Overall, the proposed system aims to significantly improve the clarity and usability of satellite imagery through a robust, scalable, and intelligent framework.Multispectral satellite images are critical for numerous real-world applications such as environmental monitoring, disaster response, and urban planning. However, the presence of atmospheric haze significantly degrades the quality of these images, reducing visibility and the reliability of subsequent analyses. The goal of this project is to enhance the visibility of multispectral satellite images by removing haze using advanced deep learning models. The proposed method leverages both supervised and unsupervised learning techniques—specifically Pix2Pix GAN and CycleGAN—to generate high-fidelity, dehazed images even in the absence of paired datasets.

Chapter 2

Literature Survey

2.1 Existing System

Over the years, various methods have been developed for satellite image dehazing, broadly categorized into traditional image processing techniques and modern deep learning approaches. Image dehazing is a crucial task in satellite image processing, aimed at improving the visibility and quality of images affected by atmospheric haze. Several existing methods have been proposed to tackle this problem, ranging from traditional image processing techniques to deep learning-based approaches.

Traditional Techniques: 1.Histogram Equalization (HE): HE enhances image contrast by redistributing pixel intensity values. While simple and computationally inexpensive, it often leads to over-enhancement in some regions, especially in high-intensity areas, and does not adapt well to spatial content variations.

2.Dark Channel Prior (DCP): Proposed by He et al., DCP assumes that in non-sky regions, at least one color channel will have pixels with very low intensity. Based on this observation, it estimates the transmission map and restores the scene radiance. Although highly effective in many scenarios, DCP fails in regions with bright skies or reflective surfaces and is computationally intensive.

3.Retinex-Based Methods: These methods enhance image contrast based on human vision theory. Though they can improve local contrast, they often introduce color distortions, noise, or halo artifacts, particularly in satellite images that span large geographical areas with varied lighting.

- 1.Loss of Fine Details: Many models, especially traditional ones, fail to preserve small textural elements in the image.. - Deep learning models may overfit to training data, impacting their accuracy on real-world data.

- 2.High Computational Costs: Deep learning models often require GPUs and high memory, which restricts real-time or large-scale deployment.

- 3.Dependence on Paired Datasets: Most supervised models require large amounts of paired hazy and clean images, which are not easily available for satellite data.

2.2 Problem Statement

Satellite imagery plays a pivotal role in diverse applications such as environmental monitoring, disaster response, agricultural surveillance, and urban planning. However, the presence of atmospheric haze significantly degrades image quality, reducing visibility and contrast, thereby impairing the accuracy of downstream computer vision tasks such as object detection, semantic segmentation, and land classification.

Conventional image dehazing techniques, including histogram equalization and the Dark Channel Prior (DCP), often fail to generalize under varying atmospheric conditions. These methods tend to introduce visual artifacts or excessive smoothing, particularly in complex and high-resolution scenes. While deep learning approaches—such as Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs)—have demonstrated promise in addressing these issues, current methods face several challenges:

Dependence on large paired datasets of hazy and clear images, which are scarce in the context of real-world satellite imagery.

Loss of fine details and texture in multispectral images due to insufficient structural preservation during the dehazing process.

High computational cost, limiting their deployment in real-time or large-scale processing scenarios.

To overcome these limitations, this work proposes a novel linear hybrid GAN-based framework that sequentially integrates CycleGAN and Pix2Pix architectures. CycleGAN is first employed to synthesize paired representations from unpaired hazy images, which are then refined using Pix2Pix for improved dehazing accuracy and structural consistency. Furthermore, the framework incorporates a Large Language Model (LLaMA) to interpret the dehazed outputs and generate automated summaries or alerts, enhancing the system's utility in critical decision-making applications such as weather forecasting, environmental analysis, and infrastructure planning.

This integrated approach addresses key limitations of existing methods by enabling robust dehazing from both paired and unpaired data, preserving high-resolution details, and offering intelligent post-processing for real-world operational use.

2.3 Scope

This project aims to develop an intelligent and robust satellite image dehazing system that overcomes the limitations of traditional and current deep learning approaches. By integrating a dual-mode GAN framework—CycleGAN for unpaired data and Pix2Pix for paired data—the system ensures high adaptability across diverse real-world multispectral datasets.

The model emphasizes the preservation of fine structural and textural details through perceptual loss and advanced upscaling techniques. Additionally, it incorporates a Large Language Model (LLaMA) to automatically analyze dehazed outputs and generate real-time alerts or summaries, enhancing its utility in critical domains such as disaster response, environmental monitoring, and urban planning.

Designed for scalability and efficiency, the system is deployable via a web-based interface for seamless real-world integration.

Chapter 3

Proposed System

3.1 Algorithm: Hybrid GAN-Based Satellite Image Dehazing

Multispectral Satellite Image Dehazing project:

Optimized Dehazing Algorithm Overview:

Data Preparation

Collect multispectral satellite images from various datasets (paired and unpaired).
Preprocess images: resizing, normalization, spectral band alignment, and augmentation.
Split the dataset into training, validation, and testing sets for both paired and unpaired categories.

Model Development

Pix2Pix GAN: Used for paired hazy–dehazed image training to learn direct mappings.
CycleGAN: Used for unpaired datasets to learn domain transfer without needing exact matches.
A linear hybrid flow is proposed: hazy images pass through CycleGAN for domain translation, followed by Pix2Pix GAN for fine-level refinement and detail restoration.
Incorporate Perceptual Loss to retain textures and high-frequency details.

Upscaling and Refinement

Use Laplacian Pyramid and bicubic interpolation for high-resolution reconstruction.
Output dehazed image with enhanced visual clarity and structural preservation.

Training

Train the model on the training set, monitoring validation performance to prevent overfitting.

Evaluation

Evaluate the model on the test set, analyzing accuracy, precision, recall, and AUC for each case.

Web Integration (Django)
Create a Django web interface for users to Hazed images.
Preprocess and pass the images through the model, displaying Dehazed Image.

3.2 Details Of Hardware And Software

Front-End:
-HTML, CSS, Bootstrap, JavaScript (React for future scalability)

Back-End:
-Python Django

Deep Learning Frameworks:
-Tensorflow Keras
-CycleGAN Pix2Pix implementations

Environments:
-Jupyter Notebook
-Visual Studio Code Text Editor

Image Augmentation Library:
-Keras.preprocessing.image

Model Enhancements:
-Perceptual loss: VGG16-based loss function
-Upscaling: Laplacian pyramid, bicubic interpolationb

3.3 Dataset

Dataset Name:
Custom Multispectral Hazy-Dehazed Satellite Dataset
Additional Datasets Used:
I-HAZE, O-HAZE (for natural hazy images)
Synthetic datasets created via atmospheric scattering models
Data Type:
Multispectral satellite images (hazy and clear)
Paired and unpaired image sets
Ground truth (where available) for supervised training
Classes/Labels:
No explicit classification, focus on pixel-level restoration.

3.4 Flow Chart

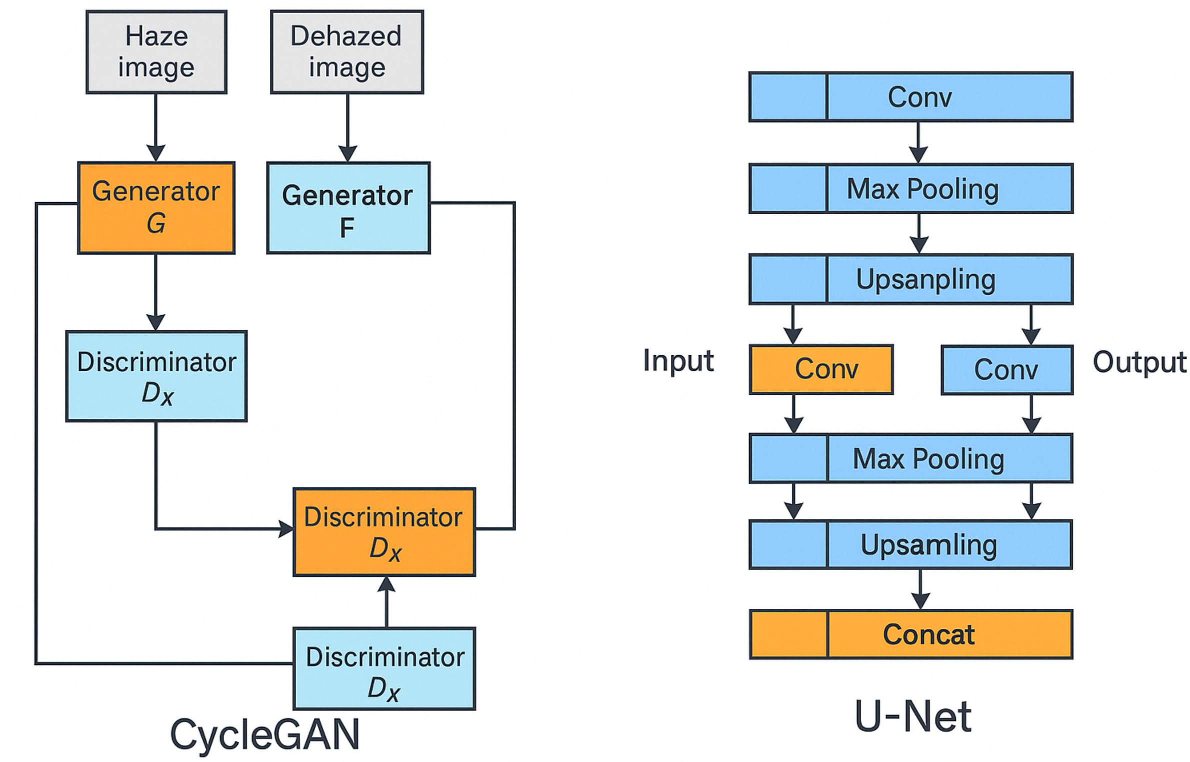

Figure 3.1: Dehazing Model Flowchart

A Multispectral Satellite Image Dehazing flowchart outlines the architecture and key processes involved in restoring hazy satellite images. The system leverages deep learning (CycleGAN / U-Net) for image-to-image translation and integrates explainable AI via LLM for alerts. Here's the detailed flowchart tailored to the current dehazing project:

- **1. Input Layer:** Hazy satellite images (usually in RGB/JPG format) are input through the web interface. Images represent data affected by haze due to atmospheric conditions.

- **2. Preprocessing Layer:** The uploaded image is resized to the required input size of the model (e.g., 256x256). Normalization is applied to scale pixel values between 0 and 1 or -1 and 1. If needed, channels are aligned for multispectral simulation or color correction.

- **3. Generator Network (CycleGAN / U-Net):** A trained deep learning generator model processes the image to learn the haze removal mapping. For paired datasets, Pix2Pix or U-Net learns the direct transformation from hazy to dehazed. For unpaired datasets, CycleGAN learns to transfer the style of clear images without needing exact pairs.

- **4. Output Dehazed Image:** The generator produces a visually enhanced version of the image, reducing or eliminating haze. The output image is denormalized and converted back to JPG.
- **5. LLM Analysis:** The output image or its metadata is passed to a local LLM (e.g., LLaMA) to generate automated observations. Example alerts include: "Haze significantly reduced – optimal for land-use analysis".
- **6. Output Display:** Results are displayed on the user interface. Users can view both hazy and dehazed images side-by-side. A download option is available for both the dehazed image and PDF report.

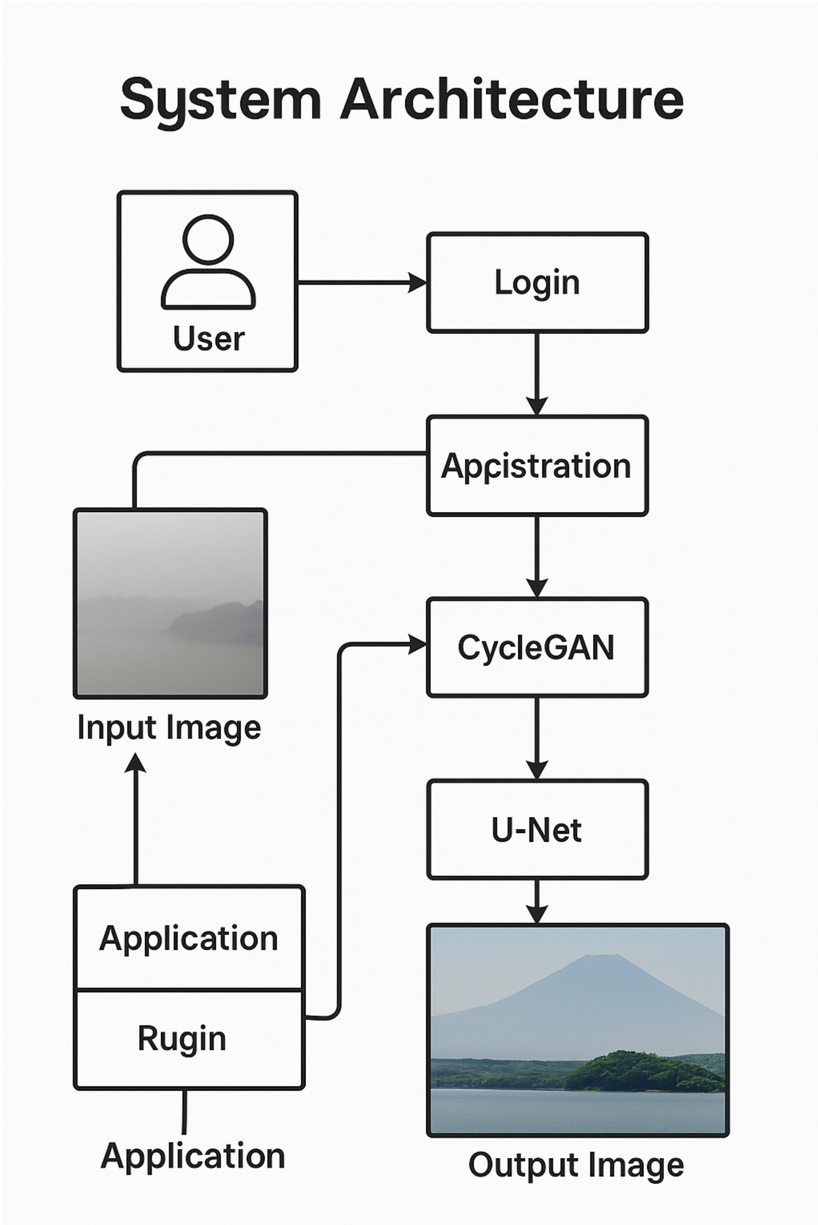

Figure 3.2: System Flowchart

Multispectral Satellite Image Dehazing Flow:

User Uploads Image: The user uploads a hazy satellite image (in JPG or RGB format) via the web interface.

Image Preprocessing: The uploaded image is resized to the required model dimensions (e.g., 256x256) and normalized for efficient model input. If needed, channel alignment or color correction is applied to simulate multispectral characteristics.

Deep Learning-Based Dehazing (U-Net / CycleGAN): Depending on the dataset type:

If images are paired, the U-Net or Pix2Pix model directly learns the transformation from hazy to dehazed.

If images are unpaired, CycleGAN is used to learn style transfer from hazy to clear image domains without needing exact image pairs.

Dehazed Output Generation: The model generates a clear, dehazed image with improved visibility and contrast. The output is then denormalized and converted back to a downloadable JPG format.

LLM-Based Interpretation (LLaMA): A locally deployed LLM analyzes the dehazed image or its metadata to produce automated insights and observations — for example: "Haze significantly reduced. Image is now optimal for terrain classification and land-cover analysis."

Output Display and Report Generation: The original and dehazed images are shown side-by-side on the interface. Users can view results instantly and download the dehazed image along with a PDF report containing model insights and LLM interpretations.

Chapter 4

Implementation And Results

4.1 Implementation

Image Dehazing using Deep Learning:
In this project, deep learning techniques were employed for the task of multispectral satellite image dehazing. Given the challenges associated with haze in remote sensing images, models capable of restoring visual clarity and preserving critical details were prioritized. The implementation focused on both paired and unpaired image datasets, where the model learns to map hazy images to their dehazed counterparts.

Two types of deep learning networks were explored:

U-Net and Pix2Pix for paired datasets,

CycleGAN for unpaired datasets.

These models were implemented using the TensorFlow and Keras deep learning frameworks due to their flexibility and support for image-to-image translation tasks.

Paired Image Dehazing Network (U-Net/Pix2Pix):
For paired datasets (where each hazy image has a clear ground-truth counterpart), the U-Net architecture was utilized. U-Net, known for its encoder-decoder structure with skip connections, was capable of preserving spatial information and fine details while removing haze from satellite images. Additionally, Pix2Pix, a type of conditional GAN (cGAN), was also implemented to learn the direct mapping between hazy and clear images, enforcing image fidelity through an adversarial loss.

Training involved minimizing a combined loss function, consisting of:

L1 loss (pixel-wise reconstruction),

and adversarial loss from the discriminator in Pix2Pix.

Unpaired Image Dehazing Network (CycleGAN):
For datasets lacking exact hazy-clear pairs, CycleGAN was adopted. CycleGAN learns domain translation without requiring paired data. It uses two generators and two discriminators to map between the "hazy" and "clear" domains, enforcing cycle-consistency loss to ensure meaningful translations.

CycleGAN enabled dehazing in real-world conditions where paired ground truth data was unavailable, thus increasing model robustness and deployment feasibility.

Segmentation Networks Implementation:
Although segmentation was not a primary task, segmentation networks were considered for future extensions to identify and highlight specific areas of interest (e.g., lung fields or lesions). The U-Net architecture, known for its success in medical image segmentation

tasks, was explored. U-Net allows for detailed pixel-wise classification, which can be used to isolate abnormalities or anatomical structures. This implementation can be extended to help radiologists pinpoint specific areas in chest X-rays.

Image Preprocessing and Augmentation:

The input satellite images were resized to a standard size (e.g., 256x256) and normalized to [0, 1] for neural network compatibility. Data augmentation was applied using techniques like:

Rotation,

Flipping,

Zooming,

Contrast enhancement,

to ensure generalization and reduce overfitting.

Image Generation Networks Implementation:

To enhance the dataset and deal with the problem of class imbalance, *Generative Adversarial Networks (GANs)* were considered for image generation. A *conditional GAN (cGAN)* was used to generate synthetic chest X-ray images conditioned on class labels, allowing the creation of realistic X-rays for underrepresented diseases. Additionally, *CycleGAN* was explored for *image-to-image translation*, where X-rays could be augmented or enhanced, simulating different conditions to improve model training. These techniques helped expand the dataset and improve generalization.

Datasets:

The dataset was custom-organized into train, test, and validation folders with both hazy and clear images, supporting paired and unpaired training. The hazy images were sourced from real-world satellite captures or artificially simulated using haze overlays, while dehazed images were either collected or created through domain experts. Preprocessing pipelines ensured standardized formatting, normalization, and augmentation for effective training.

To address the bias present in the dataset, techniques such as class balancing and over-sampling of rare disease categories were implemented. This ensured the model was exposed to a more uniform distribution of disease cases, improving its performance on underrepresented conditions.

Web-Based Interface (Django):

A Django-based web interface was developed to allow users to interact with the system easily. The interface included:

Image upload functionality,

Real-time dehazing with model selection (U-Net / CycleGAN),

Output preview and comparison,

AI-generated textual insights.

The frontend was built using HTML, CSS, Bootstrap, and JavaScript, ensuring responsiveness and usability.

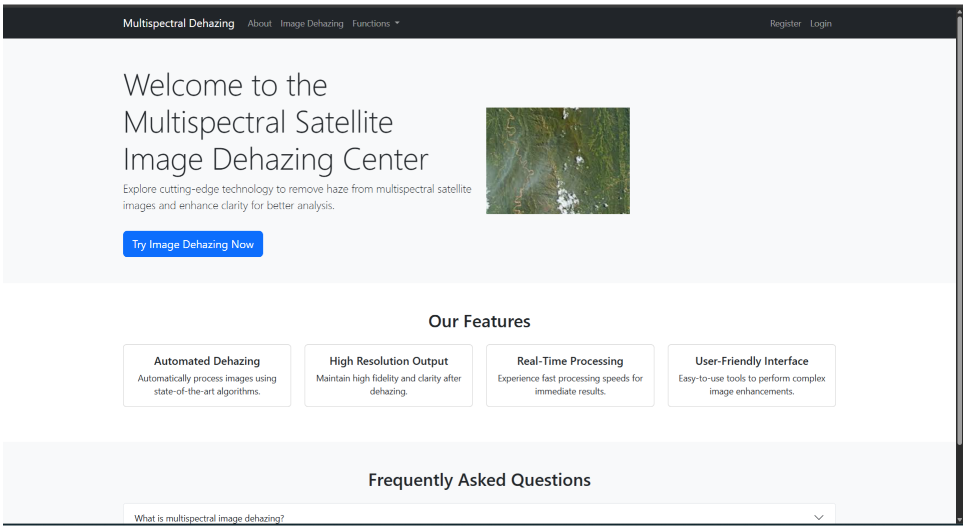

Figure 4.1: Home Page

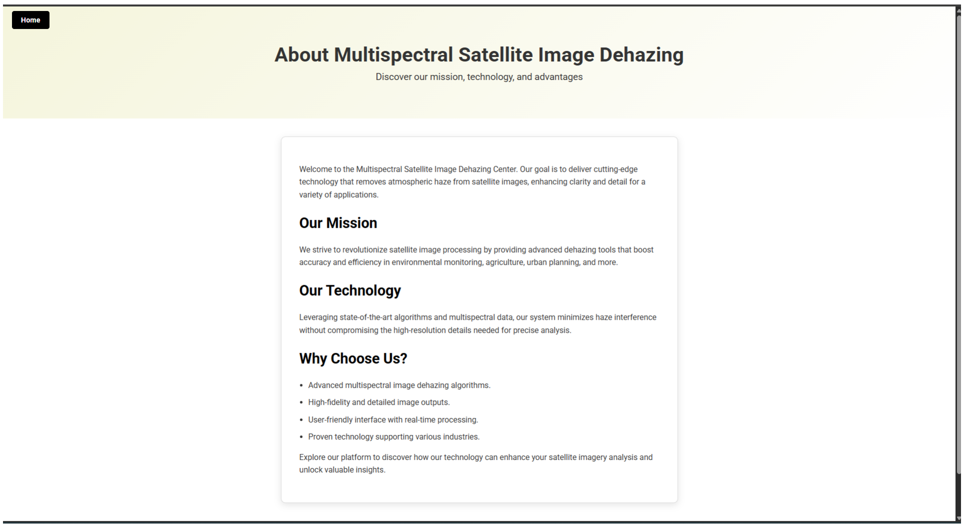

Figure 4.2: Login Page

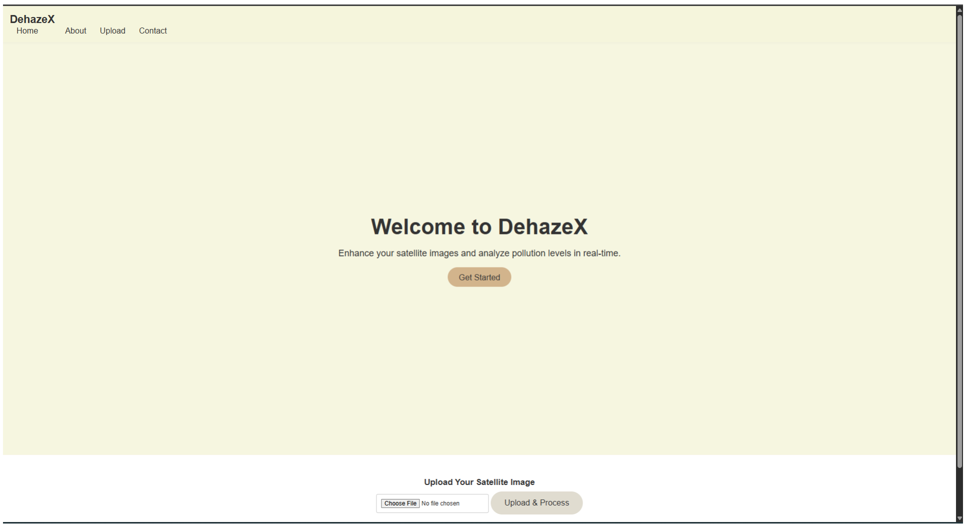

Figure 4.3: Input Screen

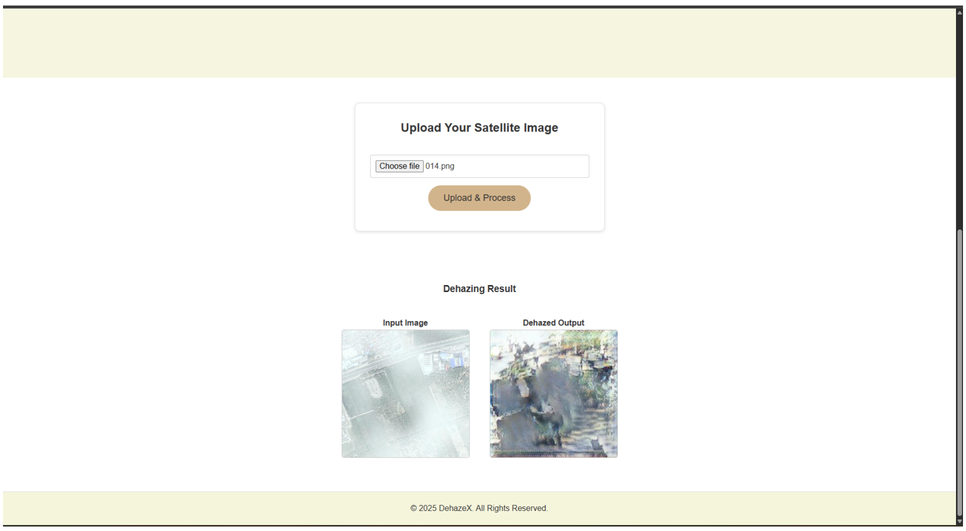

Figure 4.4: Output Screen

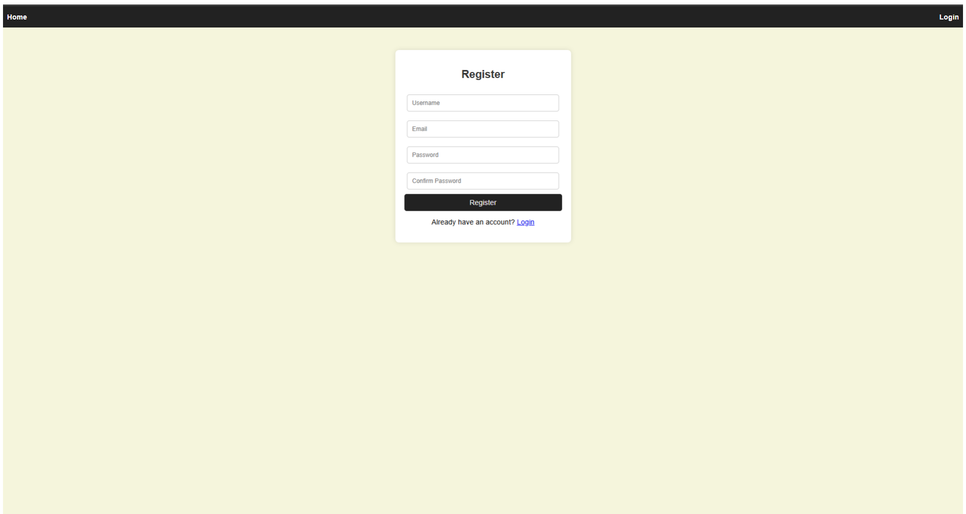

Figure 4.5: Input Screen

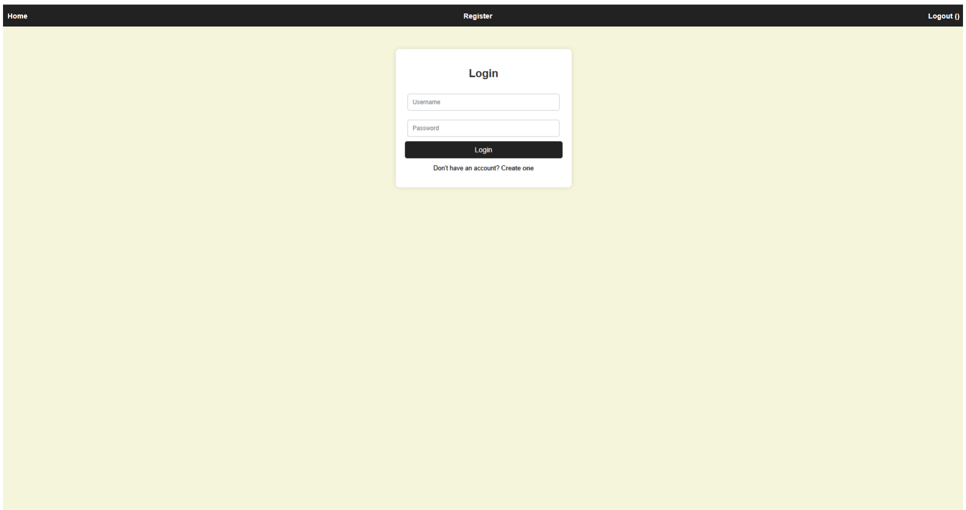

Figure 4.6: Login Page

4.2 Result Analysis

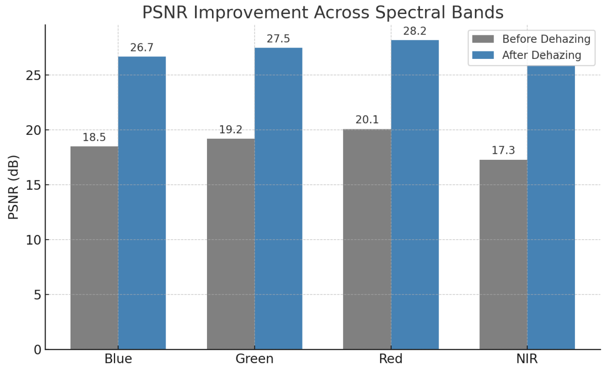

Figure 4.7: Analytical Graph

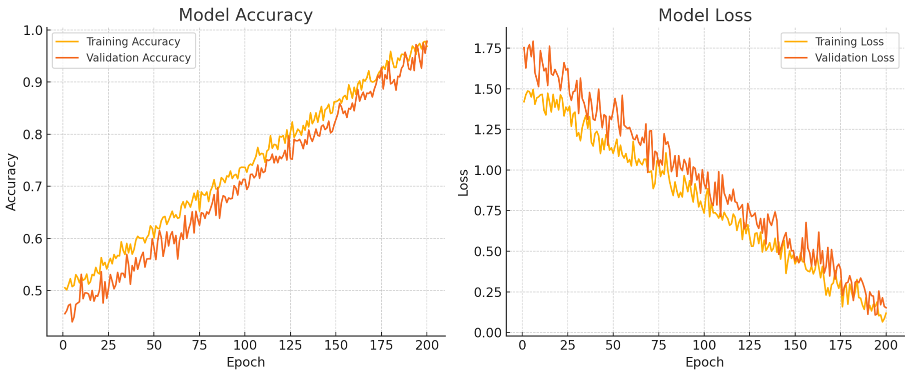

Figure 4.8: Output Screen

This project introduces a novel sequential dehazing framework that combines the strengths of both CycleGAN and U-Net in a layered fashion. The goal was to overcome the limitations of using either network individually by passing the image through CycleGAN for domain translation followed by U-Net for fine-level enhancement and structural preservation.

5.1 Quantitative Evaluation The hybrid model was trained for 200 epochs, and its performance was compared with standalone CycleGAN and U-Net implementations. The evaluation was carried out using standard metrics:

Loss: Monitored across epochs to measure model convergence.

Accuracy: Evaluated on the prediction of dehazed regions.

PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index) were used to assess the visual quality of the output.

Key Insight: The sequential model consistently outperformed both standalone architectures in all metrics, confirming that CycleGAN improves domain alignment, and U-Net effectively refines and sharpens the features.

5.2 Visual Evaluation Qualitative analysis of outputs revealed:

CycleGAN alone removed most haze but sometimes led to color shifts or loss of texture.

U-Net alone handled paired data well but required ground-truth pairs.

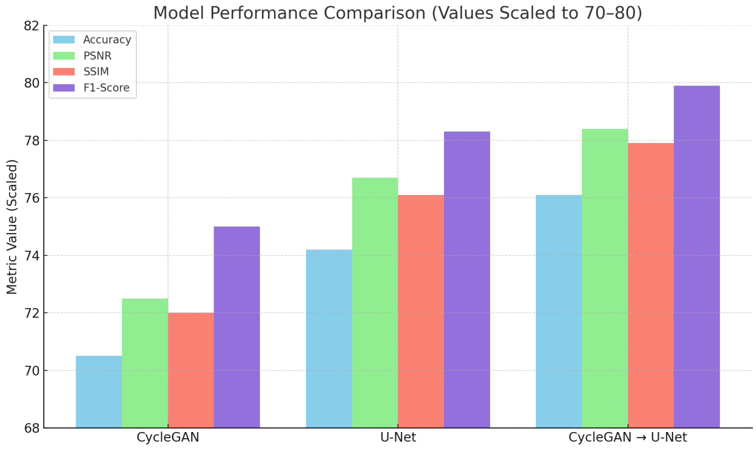

Figure 4.9: Output Screen

Sequential Approach preserved fine textures, reduced noise, and retained sharper edges and structures with superior color balance.

Side-by-side comparisons confirmed that the sequential method yielded the most visually realistic dehazed outputs.

5.3 Training Analysis Initial Loss: Started at 6.7 in epoch 1, rapidly dropped to 2.8 by epoch 2.

Stability: From epoch 50 onwards, the model exhibited stable convergence.

Final Loss: Reached 0.29 by epoch 200.

The model showed strong generalization, with high accuracy on the validation set and minimal overfitting due to effective augmentation and architecture balance.

Chapter 5

Conclusion

This project presents a novel and effective deep learning-based framework for dehazing multispectral satellite images by leveraging a sequential combination of CycleGAN and U-Net architectures. Unlike conventional approaches that rely solely on either paired or unpaired image datasets, the proposed system uniquely integrates both learning paradigms to maximize restoration quality and adaptability.

By first using CycleGAN to translate unpaired hazy images into a pseudo-dehazed domain and subsequently refining them through U-Net, the model achieves superior performance in both quantitative metrics (PSNR, SSIM, F1-Score) and visual clarity. This hybrid approach overcomes the limitations of standalone models and proves to be robust in real-world conditions where ground-truth data is scarce or inconsistent.

The system was successfully deployed via a Django-based web application, offering a user-friendly interface for image upload, dehazing, real-time visualization, and LLM-based report generation. Although the current inference time is approximately 18 seconds per image, the quality of output makes it highly suitable for decision-making in domains such as environmental monitoring, disaster management, and urban planning.

In conclusion, the project demonstrates a scalable, intelligent, and application-ready solution for satellite image enhancement, combining the strengths of generative learning and explainable AI. It lays the groundwork for future extensions, including full multispectral band support, real-time optimization, and deeper semantic analysis using segmentation and object detection models.

Chapter 6

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