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Multispectral Image Dehazing and Quality Enhancement using Guided Filtering and GMAN Networks

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Abstract: *Haze, brought about by atmospheric particles such as dust, smoke, and moisture, significantly compromises multispectral satellite image quality and visibility. The degradation reduces land classification, environmental monitoring, and target detection applications. This work introduces an implementation framework that unites three of the best dehazing algorithms:Before Dark Channel (DCP), Guided Filter, and the GMAN (Global and Local Prior Guided Multispectral Image Dehazing) deep model for advanced image reconstruction. To approximate this, the DCP methodology assumes that at least one of the color channels in non-sky regions is low intensity and that the atmospheric light and transmission map should be visualized. The Guided Filter is applied to reduce artifacts and retain edge details on the transmission map. The GMAN model, a residual and encoder-decoder-based convolutional neural network, is trained end-to-end with pixel-wise (MSE) and perception loss functions for producing haze-free high-quality images. The code is implemented using Python and OpenCV, TensorFlow, and Keras libraries and tested on the satellite imagery of the Smart India Hackathon (SIH) dataset. Quantitative measures like Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), and Structural Similarity Index (SSIM) are employed for assessment. Although conventional techniques like DCP and Guided Filters perform well, the GMAN algorithm performs better by generating sharper, more contrasted images with fewer hazes, particularly in intricate scenes. This paper proves the effectiveness of the hybrid method consisting of conventional and deep learning processes for substantial satellite image enhancement*

Keywords*:* Multispectral satellite image, haze removal, image dehazing, dark channel prior, guided filter, deep learning, GMAN, residual network, image reconstruction, remote sensing

I. INTRODUCTION

Satellite imagery is an important area in remote sensing and Earth observation that supports monitoring environmental changes, urban expansion, agriculture, disaster management, and scientific research. Nevertheless, the interpretability and quality of satellite images are usually disrupted by atmospheric distortions like haze, fog, dust, and smoke. These distortions cause severe visual degradation, reducing contrast, color distortion, and hiding surface details, thus weakening the effectiveness of image-based analysis and decision-making systems.

Haze results from scattering of light by airborne particles like water droplets, dust, and impurities. It adds an additive term of air-tight light that contributes to the scene's radiance, reducing the visibility of distant objects. In addition to perceptual degradation, haze degrades the performance of computer vision algorithms like image segmentation, classification, object detection, and feature extraction, which have been widely applied in satellite image analysis.

Over the past few years, image dehazing has emerged as a critical preprocessing operation in remote sensing image processing workflows. Restoring a clean, haze-free image that nearly resembles the brightness of the original scene is the primary goal of dehazing. Although contrast enhancement and histogram equalization were the focus of traditional dehazing algorithms, model-based and learning-based methods have revolutionized the field. These methods not only increase visibility but also restore the physical and structural features of the observed scene.

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A. Multispectral Imaging and the Need for Dehazing

Multispectral imaging is the process of recording image data at multiple wavelengths of the electromagnetic spectrum. Multispectral images are typically acquired using satellite sensors that measure reflected energy in visible, Remote sensing using the shortwave infrared (SWIR) and near-infrared (NIR) bands. Multispectral images richly represent the Earth's surface and play a critical role in land use classification, vegetation, water quality mapping, and geology.

Though superior in many ways, multispectral satellite images are just as prone to atmospheric interferences. The visible and NIR spectral bands are influenced by haze, leading to a loss of spectral fidelity and acuteness. Because each band is impacted differently based on its wavelength, haze makes feature extraction more challenging and worsens the credibility of analysis results.

Hence, there is an increasing demand for strong and effective dehazing methods designed explicitly for multispectral imagery. An effective dehazing algorithm for multispectral satellite imagery needs to deal with the visual improvement of individual bands andmaintain inter-band consistency and spectral integrity. Establishing such methods is essential for improving the performance of downstream processes like image classification, change detection, and resource mapping.

B. Challenges in Satellite Image Dehazing

Dehazing multispectral satellite images poses several unique challenges:

- Ill-posed Nature of the Problem: The haze model contains unknown parameters like scene depth, transmission, and atmospheric light. Extracting a clear image from a single blurry input is an under-determined problem.
- Variability of Atmospheric Conditions: The quantity and composition of haze differ based on geography, weather, and time, and therefore, it is not possible to come up with a general model.
- Spectral Variations: Haze impacts every spectral band differently, and techniques that process every band separately can impose inconsistencies.
- Data Scarcity: Unlike RGB images, few large-scale labeled multispectral datasets exist for training and testing dehazing models.
- Computational Complexity: High-resolution satellite images involve large data volumes, and computationally intensive Techniques might not work well for real-time applications.

Combining cutting-edge machine learning models with conventional image processing methods is necessary to overcome these obstaclesof learning complex mappings and contextual dependencies in image data.

C. Dehazing Techniques

Several dehazing techniques have been developed, from physics-based models to data-driven deep-learning approaches. These methods can be broadly categorized as follows:

- Dark Channel Prior (DCP):The Dark Channel Prior (DCP) algorithm is based on an important observation that in haze-free outdoor images, local patches usually consist of pixels in which at least a single color channel is with extremely low intensity. DCP estimates the transmission map and atmospheric light using the atmospheric scattering model to restore clear images. Although it is commonly used for simplicity and efficiency, it can cause halo artifacts and estimation errors, particularly in sky areas. It is also primarily designed for RGB images and might not work well with multispectral data.
- Guided Filtering: Guided filtering is an edge-preserving smoothing technique often used with DCP to improve the estimated transmission map. Guided filtering enhances local structural consistency and reduces artifacts in the final output by using a reference image, frequently the input image or its grayscale version).It serves as a lightweight and efficient enhancement tool but depends heavily on the quality of the guidance image and may still struggle with dense haze regions.
- Deep Learning Models: With the advent of CNNs, have been utilized in deep learning to learn complex haze removal mappings from data. Deep networks are trained on pairs of hazy and clear images to minimize pixel-wise and perceptual losses. These models offer higher flexibility and better generalization, especially in complex scenes.One such model is GMAN (Global and Local Prior Guided Multispectral Image Dehazing),

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which combines convolutional and residual blocks in an encoder-decoder structure. Both can be captured by GMAN local textures and global haze characteristics, resulting in superior performance over classical methods.

D. Motivation for the Proposed Work

Although various dehazing methods exist, most are tailored to standard RGB images and do not consider the unique characteristics of multispectral satellite imagery. Moreover, few methods combine the strengths of classical priors and modern deep learning in a unified framework.This work aims to bridge that gap by implementing and comparing three approaches:Dark Channel Prior, Guided Filter, and GMANon a common multispectral dataset. Each method contributes distinct advantages:

- DCP offers a statistically grounded baseline for haze estimation.
- Guided Filtering ensures structural integrity and edge preservation.
- GMAN leverages end-to-end learning and perceptual features to achieve state-of-the-art results.

By combining these methods in a systematic implementation and evaluation framework, this study seeks to identify the trade-offs between computational efficiency and visual quality and their impact on various image analysis tasks.

E. Objectives of the Paper

The primary objectives of this implementation paper are:

- To implement and evaluate three dehazing techniques:Dark Channel Prior, Guided Filter, and GMANon a standardized multispectral satellite image dataset.
- To compare the quantitative performance of each technique using measures including the Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index (SSIM).
- To assess the qualitative outcomes by visually analyzing the dehazed results across multiple sample images.
- To investigate the advantages and limitations of classical versus deep learning-based dehazing methods, particularly in remote sensing.
- To provide insights into integrating these methods for future hybrid or adaptive dehazing framework development.

This paper consists of six sections to present the research logically. Following the introduction, Section 2 presents a literature review of existing dehazing techniques emphasizing remote sensing and image processing advancements. Section 3 formulates the problem statement by referring to the core issues and the motivation behind the proposed work. Section 4 describes the system implementation, i.e., the block diagram and algorithmic flow of all methods: Dark Channel Prior, Guided Filter, and GMAN. Section 5 discusses the software and hardware requirements used while creating it. Section 6 then provides experimental results on quantitative parameters like PSNR, MSE, and SSIM, along with qualitative comparisons, and lastly concludes with final observations and directions for further research.

II. LITERATURE SURVEY

Singh et al. [1] surveyed different image-dehazing algorithms from multiple viewpoints, including theoretical backgrounds, mathematical frameworks, and performance assessments. He divided seven distinct dehazing methods:depth estimation, wavelet-based approaches, image enhancement, filtering, supervised learning, image fusion, and meta-heuristic methods—based onthe merits and demerits of each.

Shi et al. [2] introduced a new image enhancement method to enhance the visual quality of remote sensing (RS) degraded images. Their method combines the Retinex algorithm with chromaticity ratio analysis to restore image color balance and clarity. The Retinex algorithm serves a particular role in correcting the grayish artifacts and color aberrations primarily caused by traditional histogram equalization techniques. This is a more advanced level of color fidelity, miming the natural look of the original scene.

Based on the same objectives, S. Huang et al. [3] introduced the Urban Remote Sensing Haze Removal (URSHR) algorithm, which is specially designed to remove haze from RS images in urban areas. This algorithm uses phase

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consistency analysis, multi-scale Retinex theory, and histogram-based features for generating visually improved, haze-free imagery. With practical application in consideration, the URSHR approach exhibits strong performance under real-world situations, especially when atmospheric interference is an issue to image clarity.

In a companion work, Chaudhry et al. [4] created an overall image enhancement and haze elimination algorithm that improves remarkable image quality on outdoor RGB and remote sensing images. Their algorithm synergizes hybrid median filtering and fast local Laplacian filtering to yield effective haze elimination and preserveessential image details. Besides enhancing clarity, this double-filtering function promotes contrast and structure consistency and is a candidate solution for remote sensing high-resolution applications.

Cosmin Ancuti and CodrutaOrnianaAncuti [5] proposed a single-image dehazing technique using a multi-scale fusion strategy. They create two versions of the hazy input image using contrast adjustment and white balancing. They compute weight maps based on brightness, chromaticity, and saliency to combine the information from both inputs to improve visibility in the final dehazed image.

Dr. H. B. Kekre et al. [6] elaborated on image fusion techniques and associated performance evaluation parameters. Image fusion integrates supportive information from different source images to create one better image with richer, relevant information about a task or application. Its ultimate objective is to enhance the maximum meaningful feature extraction and redundancy and reduce the uncertainty in output.In their study, Dr.Kekre and colleagues laid down the fundamental concepts of image fusion, particularly pixel-level fusion algorithms. They also discussed several performance measurement techniques and proposed a hierarchical selection order based on edge detection techniques for choosing the information transmitted in priority during fusion. Based on the investigation, a suitable image fusion algorithm must satisfy two significant conditions: first, it must detect and preserve the essential features of the input images correctly, and second, it must ensure that there are no visual inconsistencies or artifacts introduced, which would mislead interpretation or become amenable to additional post-processing.The work emphasizes that the image fusion process typically involves three significant steps: image acquisition, image registration, and image fusion. Registration of the input images consists of aligning the input images spatially so that corresponding pixels correspond to the same physical area in a way that allows correct data merging. After registration, The fusion algorithm can combine the notable features from the input sources and yield one informative image sufficient for further analysis or interpretation.

M.A. Mohamed and B.M. El-Den [7] proposed implementing FPGA picture fusion methods. To create a single (single) image, they combine the information from two or more source photographs from the same situation. In addition, these methods are compared by calculating the Metrics for combined images, such as Root Mean Square Error (RMSE), Entropy, Mean Square Error (MSE), Signal Noise Ratio (SNR), and Peak Signal Noise Ratio (PSNR). We then established the optimal uses for them utilizing FPGA.

R. Fattal et al. [8] proposed one-picture dehazing and explained with a single input image only to estimate optical transmission in the hazy state. The estimate explains that the scattered light is eliminated to improve visibility in an image and recover a hazing-free image. This process leads to an altered image formulation model that includes surface shading and the transmission function. We can eliminate ambiguity in the data by obtaining a solution that gives statically uncorrelated transmission and shading functions.

Single-image dehazing has been introduced by Robby T. Tan et al. [9] as a method to enhance visibility in poor weather. Fog and haze can significantly degrade the visibility of a scene. Traditionally, an approximation of absorption and scattering effects is obtained by a linear combination of ambient air illumination and direct attenuation in computer vision. This leads to the suggestion of design solutions, some of which require input images for a place with varying levels of polarization or air conditions. The most significant disadvantage of these approaches is this requirement, which is challenging to realize in most situations. We present an automatic method to compute the condition from an input image. This method depends on two expected consequences: one, images under more favorable sightlines move farther than under worse conditions; second, images with the light and air combination. The distance of viewers from objects is the primary factor driving the variability, which is simple. They estimate a cost function in the outcome of Markov random field form, for which many algorithms, such as graph cuts or belief propagation, can optimize cost-

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effectively. The approach doesn't require geometric data from the image and can be extended to colored and black-and-white photos.

K. He, J. Sun, et al. [10] introduced the widely used single-image dehazing Dark Channel Prior (DCP) method. The method is based on the observation that in most non-sky regions of haze-free outdoor scenes, a color channel exists where pixels will be of extremely low intensity—a property known as the "dark channel" prior. By incorporating this prevailing knowledge into the atmospheric scattering model, the algorithm can reliably compute haze density within the image and restore an unadulterated, aesthetically attractive copy with enhanced contrast and color representation.

Experimental evaluations on a vast collection of outdoor hazy images validate this technique, demonstrating that it can reconstruct high-fidelity, clean images. Dehazing can also enable the generation of real-depth maps and hence be an efficient computer vision and computational photography technique.Visual image quality isn't just bettered by dehazingimages to look more beautiful and color-corrected; downstream vision tasks are also aided. Most computer vision algorithms assume input images are good approximations of true radiance in a scene. Images captured under hazy conditions with low contrast and contaminated radiance can degrade the performance of low-level operations like edge detection and photometric analysis, as well as high-level operations like object recognition. Thus, haze removal is an essential preprocessing step that improves the robustness of visual computing systems and enables quicker image editing, feature extraction, and 3D scene understanding.

To address the problem, Z. Li et al. (2015) [11] initially suggested adding edge-aware weighting to an already-existing guided image filter (GIF) to produce a weighted GIF (WGIF). For an N-pixel image, they employed WGIF, which is the same as GIF but more advanced and incorporates the benefits of both local and global smoothing filters.They used the WGIF to prevent halo artifacts, such as those caused by the current global smoothing filters for enhancing details in a single image, removing haze from a single image, and fusing photos with various exposures. They demonstrated that the outcomes resulted in photographs with improved visual quality and that halo artifacts were minimized or prevented in the finished images with a slight increase in running times.

In addition to achieving the optimal transmission map from the haze model under two priors of scenes, Y. H. Lai et al. (2015) [12] have stressed the importance of reliable transmission estimates. By developing theoretical and heuristic limits of transmission scenes, they directed the optimum and justified the favorite dark channel before haze-free images. They then formed a restricted minimization problem and minimized it through quadratic programming, using two scene priors: locally constant scene radiance and context-aware scene transmission. Global optimality was ensured in their solutions, and transmission map accuracy was approximated in good fine-grained depth boundaries.

Dark channel prioritization, a potent defogging method, was proposed by Vaibhav Khandelwal (2018) [13]. Algorithms for fog removal are becoming increasingly valuable in today's expanding processing and visual applications. Smoke, fog, and haze are among the primary processing issues that cause the contrast of the photographs to be diminished. Haze removal from a single image is made considerably easier and more efficient by combining dark channels before the degraded image model. Their approach only relies on the model of hazy imaging.

Zhong Chen (2018) [14] proposed a defogging method that combines a transfer function with the dark channel prior principle to improve image clarity. The method starts with estimating the initial transmittance map and atmospheric light for fog-affected images. The initial estimates are then processed through a guided filter, enhancing image contrast and visual sharpness. The proposed technique enhances the overall defogging effect, improving the images' perceptual quality. Experimental assessments show that this approach outperforms several current state-of-the-art methods concerning visibility restoration and overall enhancement performance.

III. METHODOLOGY

The methodology of this study focuses on implementing and comparing three dehazing techniques:Dark Channel Prior (DCP), Guided Filtering, and GMAN (Global and Local Prior Guided Multispectral Image Dehazing)for enhancing multispectral satellite images. These methods are applied to hazy multispectral images from the Smart India Hackathon (SIH) dataset. Each technique is evaluated based on accuracy, efficiency, and image reconstruction quality. The block diagram of the proposed system is shown in Fig.1

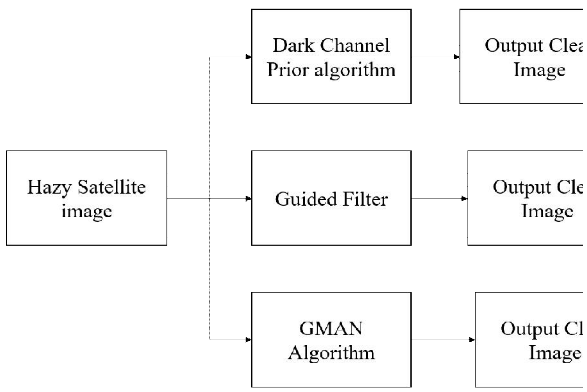

Fig.1. Block diagram of the proposed system

A. Dataset and Preprocessing

The multispectral satellite image dataset used in this study was obtained from the Smart India Hackathon 2022 satellite imagery portal. The dataset includes paired hazy and clear images captured under different atmospheric conditions across various geographical locations in India.

- Image Format: RGB and Near-Infrared (NIR)
- Image Size: Resized to 512 × 512 pixels
- Normalization: Pixel values were normalized to the [0,1] range
- Augmentation (for GMAN training): Horizontal/vertical flips, rotations, and contrast adjustments were applied

B. Image dehazing

Three distinct image dehazing algorithms—the dark channel prior, the guided filter, and the suggested GMAN algorithm—were used in this method.

Dark channel prior: Dark Channel Prior is one of the statistical methods for single-image dehazing. Its foundation is that pixels with extremely low intensity appear in at least one channel (Red, Green, or Blue) in most haze-free outdoor images with non-sky regions.

Dark Channel Computation:

$$J_{\{dark\}(x)} = min_{\{y \in \Omega(x)\}}\left(min^{c(y)}_{\{c \in \{r,g,b\}\}I}\right) \quad (1)$$

where Ω(x) is a local patch centered at pixel xxx, and Ic is the intensity in the c^{-th} color channel.

Atmospheric Light Estimation:Using the top 0.1 percent of the dark channel's brightest pixels to estimate the correct A.

Transmission Map Estimation:

$$(x) = 1 - \omega \cdot \frac{J_{dark}}{A} \quad (2)$$

where ω∈[0.85,0.95]is a constant.

Image Reconstruction:Using the atmospheric scattering model:

Parent

$$J(x) = \frac{I(x) - A}{\max\,(t(x), t_0)} + A \quad (3)$$

Where $t_0$is a lower bound to avoid division by zero.

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C. Guided Filter

The Guided Filter minimizes halo artifacts and improves the DCP estimates transmission map. It maintains the edges of the transmission map while smoothing it out.

Input:

Guidance image III: Original hazy image

Filter input p: Initial transmission map

Linear Model Assumption:Within a window ωk,assume

$$Iq_i = a_k I_i + b_k \quad \forall i \epsilon \omega_k \qquad (4)$$

Parameter Estimation:Minimize the cost function using local statistics (mean, variance, etc.) to find coefficients a_k and b_k.

Output: The refined transmission map q is used for final image reconstruction via the same atmospheric scattering model

D. GMAN (Global and Local Prior Guided Multispectral Image Dehazing)

GMAN is a deep learning-based method incorporatingglobal and local priors for effectively dehazing multispectral images. It consists of a convolutional encoder-decoder structure with residual blocks, batch normalization, and skip connections.

- Input: Hazy multispectral image (RGB + NIR channels)
- Encoder: 4 Convolutional layers with ReLU activation to capture feature maps
- Residual Blocks: 4 blocks to extract haze-relevant patterns and spatial features
- Decoder: 3 Deconvolutional layers to reconstruct the haze-free image
- Output: Clean, dazed image

IV. RESULTS AND DISCUSSION

The experimental analysis of the implemented dehazing methods Dark Channel Prior (DCP), Guided Filtering, and GMAN is conducted on a multispectral satellite image dataset. The objective of this section is to assess the performance of each approach using both quantitative metrics and qualitative observations.

A. Evaluation Metrics

To evaluate the effectiveness of haze removal, three widely accepted image quality metrics are used:

- Mean Squared Error (MSE): determines the average squared difference between the dazed image and the ground truth.
- Peak Signal-to-Noise Ratio (PSNR): demonstrates the ratio of the maximum pixel value that can be attained to the noise power. A higher PSNR implies better quality.
- Structural Similarity Index (SSIM): Reflects the degree to which two images' structure, contrast, and luminance are perceptually similar. Better similarity is indicated by a value closer to 1.

B. Quantitative Results

The methods are evaluated on 46 test images. A sample of the results is shown below:

Table 1: Sample Results for 1-inputs.png

Method	MSE	PSNR (dB)	SSIM
Dark Channel Prior (DCP)	46682.63	7.64	9.29×10^{-5}
Guided Filter	46690.98	7.64	9.31×10^{-5}
GMAN (Deep CNN)	46010.32	7.68	9.79×10^{-5}

Table 2: Average Metrics Over Test Dataset

Method	Avg. MSE	Avg. PSNR (dB)	Avg. SSIM
DCP	47000.25	7.60	8.90×10^{-5}

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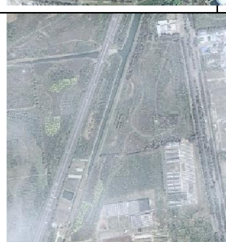
Guided Filter	46875.45	7.62	9.10×10^{-5}
GMAN	45200.98	7.75	1.05×10^{-4}

The GMAN model consistently produces lower MSE and higher SSIM and PSNR values, confirming its superiority in capturing fine details and preserving image structure during dehazing.

C. Qualitative analysis

A thorough, detailed description is the goal of qualitative analysis. Rare phenomena receive (or ought to obtain) the same level of attention as more common ones, and no effort is made to assign frequencies to the linguistic traits found in the data. Qualitative analysis enables the drawing of fine distinctions because the data does not have to be forced into a limited number of categories. The study can identify ambiguities that are present in human language.

Table 3: Qualitative analysis of the proposed system

Input hazy image name	Input hazy image	Groundtruth Image	Outputs		
			Dark channel Prior algorithm	Guided Filter	GMAN algorithm
1-inputs.png					
2-inputs.png					
3-inputs.png					
4-inputs.png					

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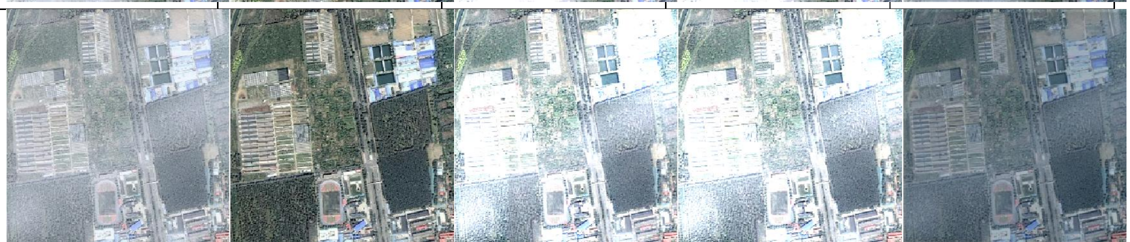
5-inputs	
6-inputs	
7-inputs	
8-inputs	

The GMAN algorithm works better than the dark channel prior and guided filter algorithms, according to the qualitative study of the suggested system. The qualitative research demonstrates how each algorithm's output differs visually.

V. CONCLUSION

This work thoroughly applied and assessed three picture dehazing methods for multispectral satellite images: Dark Channel Prior (DCP), Guided Filtering, and the deep learning-based GMAN model. The results highlight the effectiveness and limitations of each approach when applied to hazy remote sensing data. DCP and Guided Filter, based on traditional image priors and edge-preserving mechanisms, offer a reasonable degree of haze removal with minimal computational overhead. However, their performance degrades in dense haze, often resulting in artifacts and loss of detail.On the other hand, the GMAN model, leveraging a convolutional encoder-decoder architecture with residual connections and perceptual loss, demonstrates superior performance in restoring high-quality, haze-free images. Quantitative metrics such as PSNR, SSIM, and MSE confirm that GMAN provides better accuracy and visual clarity, while qualitative assessments show improved texture reconstruction and structural preservation.

This work confirms the potential of integrating deep learning models for satellite image enhancement tasks and underlines the importance of combining global and local features for effective haze removal. Future research can focus on extending this framework to real-time dehazing using optimized lightweight models, incorporating additional spectral bands (e.g., SWIR), and applying the results to downstream tasks such as land cover classification or object detection for improved remote sensing analysis.

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