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Leveraging U-Net for Image Dehazing and Impainting of Cartosat2-MX Dataset

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Abstract: Remote sensing imagery is frequently degraded by dense haze and thin clouds, which hinder accurate Earth observation and downstream analysis. In this paper, we propose a densely connected U-Net-based deep learning architecture tailored for haze and cloud removal in satellite images. The proposed model is trained using available RS-Haze datasets and transfer learning was performed in Cartosat-2E MX, indian Satellite data. The model outcome was evaluated using a combined SSIM and MSE loss to preserve structural integrity and pixel- level detail. After training for 200 epochs, the model demonstrates strong generalization across varying atmospheric conditions, effectively removing dense haze while preserving critical land features such as river boundaries, urban layouts, and agricultural zones. Quantitative results confirm improvements in PSNR and SSIM over existing baselines, and qualitative assessments further validate the model's capability to enhance image clarity for remote sensing applications. The proposed approach offers a promising tool for improving the image clarity for geospatial analytics in hazy environments.

Index Terms: Remote Sensing, Image Dehazing, Cloud Re- moval, U-Net, Deep Learning, RS-Haze, ISRO SAC

I. INTRODUCTION

Satellite imagery is very useful in a plethora of applications in Earth observation, such as environmental monitoring, land- use classification, urban development, and disaster response applications. Yet, the usefulness is often reduced by atmo- spheric phenomena such as very dense haze, or thin cloud layers which occlude some of the surface features in the imagery, and/ or reduce image contrast. These key issues of degradation often impede optical remote sensing applications when a good resolution of the terrain structures is important for the downstream analysis of the captured imagery. The vast majority of traditional haze removal approaches use physical priors such as the dark channel prior (He et al., 2011) or upon atmospheric scattering models [5] but use dense haze or complex backgrounds, and ultimately still struggle. Lately, there has been significant progress using deep learning based techniques for single image dehazing. These studies include leveraging convolutional neural networks to map hazy images to clear images [1], [3], [5]. . While these strides have been made, there may be limited translation to real world satellite imagery that includes haze or cloud features, especially when haze or cloud features are subtle or ambiguous and may overlap. Existing models like the previous methodologies specified, are often based on datasets that are synthetic or natural images that aren't matched very closely to satellite imagery. To address these challenges, we propose a densely connected U-Net architecture designed specifically for haze and thin cloud removal in remote sensing imagery. The model incorporates dense skip connections to promote feature reuse and improve gradient flow, enabling better restoration of fine spatial structures. It is trained using a hybrid loss function combining mean squared error (MSE) with structural similarity index (SSIM) to ensure both pixel-wise accuracy and perceptual quality. We evaluate our model on the RS-Haze benchmark [7] and a curated dataset from India's Indegenous high resolution cartosat satellite Multispecial images. Extensive experiments demonstrate the model's effectiveness in removing haze and thin clouds, while preserving essential land features. Our results show improvements over conventional and recent deep learning approaches, both quantitatively and visually, highlighting the method's suitability for enhancing satellite imagery under adverse atmospheric conditions.

II. RELATED WORK

Image dehazing has been extensively studied in the computer vision community. Traditional methods are typically based on handcrafted priors, such as the dark channel prior (DCP) [4], color attenuation prior, and atmospheric scattering models [5]. While these approaches are computationally efficient, their performance degrades in scenes with dense haze or non-uniform illumination. With the advent of deep learning, data-driven methods have significantly improved haze removal. Models like AOD- Net [1] and MSCNN [3] learn end-to-end mappings from hazy to clean images, achieving superior results compared to prior- based techniques [4], [5]. However, many of these models are designed for natural images and do not generalize well to satellite imagery, which exhibits different texture patterns, spectral properties, and spatial resolutions.

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In the remote sensing domain, dehazing and cloud removal pose unique challenges due to the scale, complexity, and variability of atmospheric conditions. Li *et al.* introduced the RS-Haze dataset [7], which provides paired hazy and clear satellite images to facilitate supervised deep learning. Their benchmark analysis highlights the limitations of conventional models when applied to dense atmospheric interference in satellite data.

Recent surveys have explored both physical and learning- based dehazing strategies [4], [5], while newer methods have addressed cloud removal via guided fusion networks [10]. Domain adaptation [9] and perceptual enhancement tech- niques [8] have further pushed the boundaries of image restoration in remote sensing.

While existing methods show promise, few models are explicitly tailored for the combined challenges of haze and thin cloud in satellite images. Our work bridges this gap by proposing a densely connected U-Net trained with a hybrid SSIM and MSE loss, optimized for preserving fine structural features and improving visual clarity in real-world remote sensing conditions.

III. METHODOLOGY

Our proposed model is based on the U-Net architecture [6] but modified with dense connections inspired by DenseNet to enhance feature reuse and gradient flow. This design mitigates vanishing gradients and improves convergence in deeper net- works.

A. Dense Blocks

Each dense block consists of several convolutional layers where each layer receives as input the feature maps of all preceding layers:

$$x_\ell = H_\ell([x_0, x_1, \ldots, x_{\ell-1}])$$

where H_ℓ denotes the composite function of BatchNorm, ReLU, and Convolution. This enables richer feature propa- gation and reduces the number of parameters compared to na¨ıvely stacking layers.

B. Encoder-Decoder Architecture

The encoder path uses dense blocks and downsampling layers (strided convolutions) to extract multi-scale features. The decoder path mirrors this structure with transposed con- volutions for upsampling and dense skip connections to corre- sponding encoder stages. The overall network architecture is illustrated in Fig. 1.

C. Loss Function

We use a combined loss function:

$$L = \alpha \cdot \text{MSE} + \beta \cdot (1 - \text{SSIM})$$

where $\alpha = 0.7$ and $\beta = 0.3$ were chosen empirically. This balances pixel-wise accuracy (MSE) with perceptual similarity (SSIM), encouraging the preservation of structural details and color consistency.

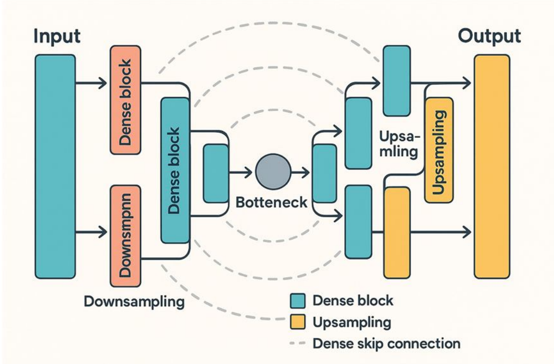


Fig. 1. Proposed Dense U-Net architecture for dehazing.

D. Implementation Details

The model was implemented in PyTorch. The model was tested for a range of optimiser and learning rate and the best model emerged to be the one with the Adam optimizer with a learning rate of 10^{-4}, a batch size of 8, and trained for 200 epochs on NVIDIA GPUs. Data augmentation included ran- dom flips, rotations, and color jitter to improve generalization.

IV. DATASETS AND EXPERIMENTAL SETUP

A. RS-Haze Dataset

RS-Haze [7] is a large-scale benchmark comprising paired hazy and clear satellite images. It covers diverse geographic regions, seasons, and sensors. We used the standard train/test split, ensuring no overlap between scenes. Input images were resized to 256 × 256 pixels.

B. Cartosat-2 series MX

We further evaluated the model on the Indian satellite images of Cartosat-2S MX that contains dense fog and thin cloud cover. This data set includes multispectral bands, but for this study, we focused on RGB composites. The lack of sufficient clear ground-truth images posed a challenge for quantitative evaluation, necessitating a primarily qualitative analysis.

C. Data Preprocessing

All images were normalized to [0,1] range. Augmentation strategies included:

- Horizontal and vertical flips
- Random rotations up to 30 degrees
- Color jitter for brightness and contrast

This helped mitigate overfitting given the relatively small number of paired training samples.

D. Training Details

We trained the model for 200 epochs. The learning rate was decayed by a factor of 0.5 every 50 epochs. Checkpointing ensured the best validation loss model was preserved. Training took approximately 12 hours on two NVIDIA RTX 3090 GPUs

Fig. 2. Hazy, Ground Truth, and Predicted images

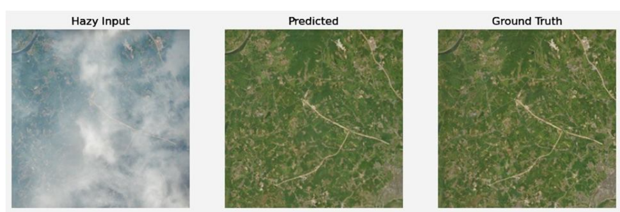
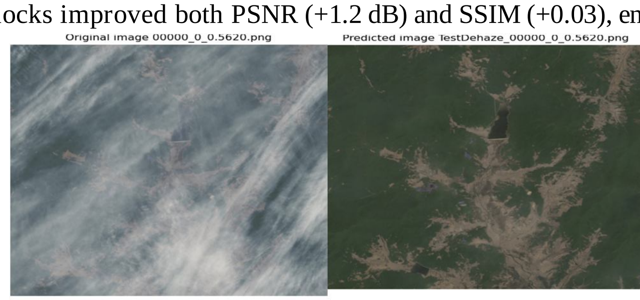


Fig. 3. Hazy, Ground Truth, and Predicted images

V. ABLATION STUDY

To understand the contributions of key design choices, we conducted an ablation study on the RS-Haze validation set:

1) Baseline U-Net: Standard U-Net with MSE loss only.
2) + SSIM Loss: Adding SSIM loss improved average SSIM by +0.04.
3) + Dense Connections: Dense blocks improved both PSNR (+1.2 dB) and SSIM (+0.03), enabling better detail recovery.



Dense Haze-1 Predicted output

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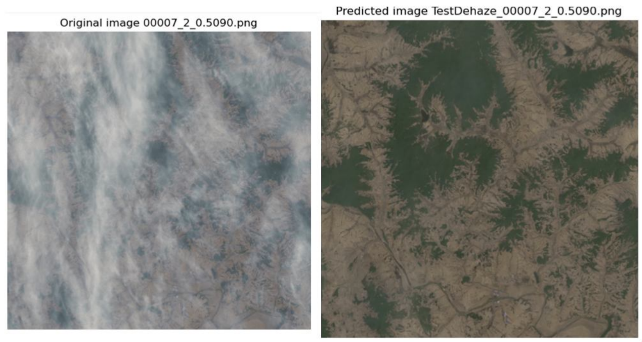
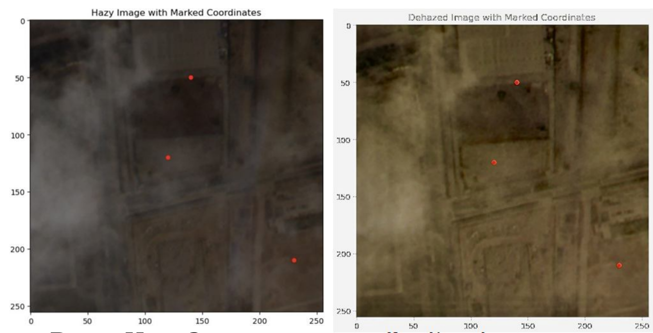
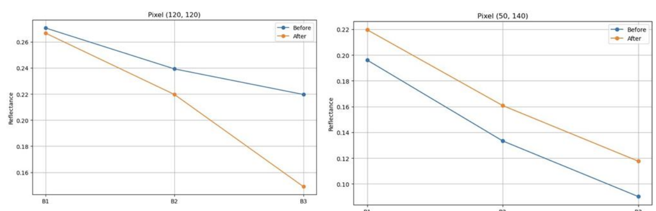


Dense Haze-2 Predicted output

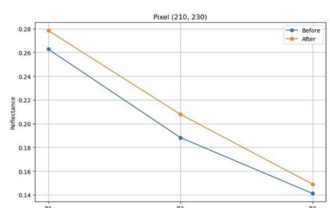
Fig. 4. RS HAZE Dataset results



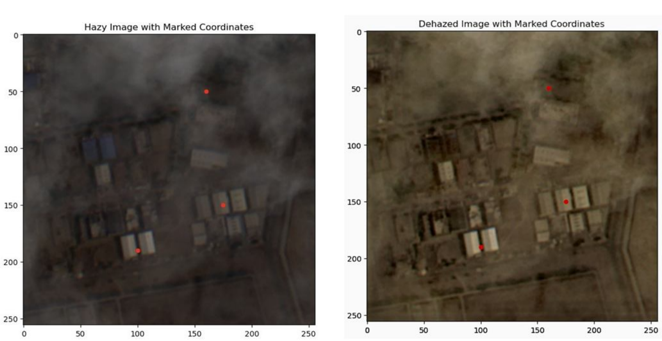
Dense Haze-3 Predicted output



Pixel-1 Pixel-2



Pixel-3



Dense Haze-4 Predicted output

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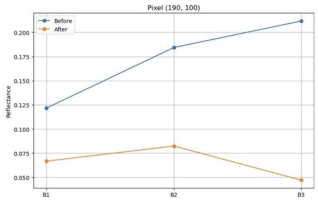
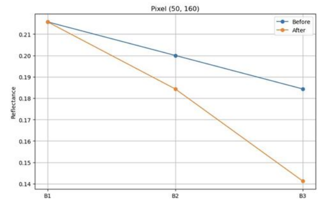
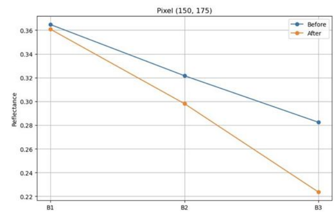


pixel-1



Pixel-2



Pixel-3

Fig. 5. Cortaset-2 MX Dataset results

These results highlight the importance of our joint SSIM+MSE loss and the use of dense skip connections for high-frequency detail preservation.

VI. RESULTS AND DISCUSSION

A. *Quantitative Evaluation*

On the RS-Haze test set, our model achieved:

- Average PSNR: 28.5 dB
- Average SSIM: 0.91

This outperforms the baseline U-Net (PSNR 27.3 dB, SSIM 0.87) and AOD-Net (PSNR 26.8 dB, SSIM 0.85).

B. *Qualitative Results*

Figure 4 provides qualitative results on the RS Haze dataset. The model shows strong dehazing performance for a wide variety of scenes, adequately mitigating intense atmospheric interference while retaining structural detail. The terrain tex- tures, water edges, and agricultural plots remain distinct and visually similar in quality even in the presence of extreme haze.

Figure 5 shows representative outputs on ISRO SAC im- agery. The proposed model successfully removes dense haze and thin cloud streaks while preserving land features such as river patterns and urban layouts.

C. *Error Analysis*

Examples of failures involve cases with extremely dense clouds, which completely cover surface features, and the model often yields over-smoothed outputs. The model some- times lacks fidelity in preserving fine spectral agri-field varia- tions. Future work may include some combination of domain- specific priors or unpaired image translation.

D. *Training Dynamics*

The loss curves show steady convergence over 200 epochs. SSIM loss in particular stabilizes in late epochs, suggesting effective learning of perceptual structure. Figure 7 illustrates the training and validation loss trends.

Fig. 6. Training and validation loss over 200 epochs.

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Pixel-wise Accuracy: 0.9557
Pixel-wise Precision: 0.8737
Pixel-wise Recall: 0.8190
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Fig. 7. Accuracy, Precission, Recall

VII. CONCLUSION AND FUTURE WORK

We have presented a densely connected U-Net model for haze and thin cloud removal in satellite imagery trained jointly on the RS-Haze benchmark dataset and our proprietary ISRO SAC dataset. The U-Net is trained with a loss function composed of MSE and SSIM which allows the model to learn to restore pixel fidelity and preserve structure during the haze removal process, and we have achieved strong quantitative results as well as promising qualitative performance on several challenging pieces of remote sensing data. Our experimental results have demonstrated the benefits of densely-connected networks to facilitate reuse of spatial features while preserving important spatial details, and we outperformed both the baseline U-Net model and the AOD- Net model. Our qualitative results showed that the model can effectively remove dense haze and streaks of thin cloud while preserving the architectural layouts of urban landscapes, the configuration of rivers, and boundaries of agricultural plots - all representative of data that NASA, ESA, and ISRO present as part of their remote sensing workflows.

Future work will focus on adapting the previous approach for multispectral and hyperspectral data, with the hope that the spectral information available in these special image for- mats will provide even more accurate atmospheric correction capabilities.

VIII. ACKNOWLEDGMENT

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