

CMFNet: High-Quality Image Dehazing Using CNN-Based Generative Networks

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ABSTRACT

This study presents CMFNet, a CNN-based generative network designed to effectively remove haze from images while preserving structural and visual fidelity. The methodology encompasses data collection from diverse datasets, preprocessing, model training, validation, and performance evaluation using metrics such as PSNR, SSIM, MSE, Average Gradient, and Mutual Correlation. Experimental results demonstrate CMFNet's ability to restore contrast, color, details, lighting, and edges, outperforming traditional dehazing methods across multiple domains including remote sensing, vegetation, and underwater imagery.

Keywords — Image Dehazing, Generative Artificial Intelligence, CMFNet, CNN, PSNR, SSIM, Image Enhancement.

1. Introduction

Images captured under hazy, foggy, or underwater conditions often suffer from reduced visibility, low contrast, and color distortion due to the scattering and absorption of light by atmospheric particles or suspended matter. These degradations not only compromise the visual quality of images but also adversely affect downstream computer vision tasks such as object detection, scene understanding, remote sensing, autonomous navigation, and medical imaging. Effective image dehazing is therefore critical for enhancing both the perceptual quality and the functional utility of such images [1], [2].

Traditional image dehazing methods rely on physical models like the atmospheric scattering model, which estimates scene depth and transmission maps to reconstruct haze-free images. Approaches such as dark channel prior (DCP), contrast enhancement, and color attenuation have demonstrated reasonable performance in certain scenarios. However, these techniques often struggle under challenging conditions such as non-uniform haze distribution, dense fog, or complex lighting, leading to artifacts, color distortion, and loss of fine details [3], [4].

Recent advances in deep learning have revolutionized image restoration and enhancement tasks. Convolutional Neural Networks (CNNs) have shown exceptional capability in capturing hierarchical features and learning complex transformations between degraded and high-quality images. Generative networks, in particular, have enabled end-to-end mapping of hazy images to their clean counterparts, preserving both global structures and local textures while reducing artifacts. Such models can learn from diverse datasets containing real-world and synthetic haze conditions, providing robust generalization across varying environmental scenarios [5]-[8].

In this study, we propose CMFNet, a CNN-based generative network specifically designed for high-quality image dehazing. CMFNet leverages a combination of perceptual and reconstruction loss functions to optimize both pixel-level accuracy and perceptual fidelity, ensuring that the dehazed images retain structural details, color consistency, and natural illumination. The network is trained on paired hazy and clean images from public datasets like RESIDE and Kaggle, covering a wide range of haze densities, lighting conditions, and environmental contexts.

The primary objectives of this work are:

1. To develop a robust end-to-end model capable of removing haze while preserving fine textures, object boundaries, and overall structural integrity.
2. To enhance visual quality by restoring natural colors, contrast, and illumination in dehazed images.
3. To validate the performance of CMFNet using quantitative metrics such as PSNR, SSIM, MSE, Average Gradient, and Mutual Correlation, demonstrating superior performance compared to conventional dehazing approaches.
4. To ensure that the proposed model generalizes effectively across diverse real-world scenarios, making it suitable for practical applications in remote sensing, autonomous vehicles, environmental monitoring, and computer vision.

The remainder of this paper is organized as follows: Section 2 details the proposed methodology, including dataset preparation, preprocessing, network architecture, training, and evaluation strategies. Section 3 presents the experimental results and discussion, highlighting the visual and quantitative improvements achieved by CMFNet. Finally, Section 4 concludes the study and outlines potential directions for future research in high-quality image dehazing.

2. Methodology

The study follows a structured methodology encompassing data collection, preprocessing, model design, training, evaluation, and ethical considerations. Figure 1 shows the flowchart of the proposed methodology.

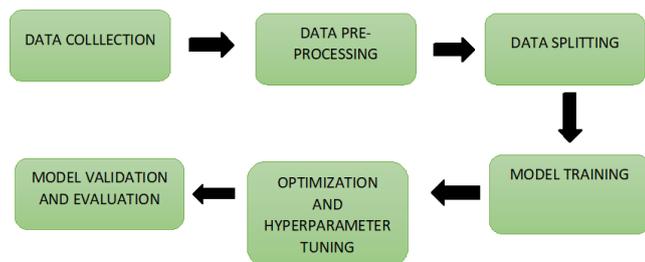


Figure 1: Proposed Methodology in this study

- Dataset and Collection Hazy and clean images were sourced from public datasets like RESIDE and Kaggle, covering atmospheric, underwater, and vegetation haze. Both real and synthetic images were included to ensure diversity, with ground truth clean images obtained from paired datasets.
- Preprocessing Images were resized to 256×256, normalized, augmented, and label-encoded. Preprocessing contributions were: augmentation 30%, resizing 25%, normalization 20%, label encoding 15%, and quality assurance 10%. These steps enhanced data quality and model performance.
- Data Splitting The dataset was split into Training (70%), Validation (15%), and Testing (15%) using randomized stratified sampling to preserve class and haze distributions, ensuring reliable training, unbiased evaluation, and robust generalization.
- Model Training and Validation The CMFNet, a CNN-based generative model, was trained on paired hazy and clean images using MSE and perceptual loss, optimized with Adam, learning-rate scheduling, batch normalization, and dropout. Validation employed PSNR, SSIM, MSE, Average Gradient, and Mutual Correlation metrics.
- Data Collection Methods Combining real-world captures with synthetic datasets and extensive preprocessing improved dataset uniformity and enhanced model robustness across varying haze densities.

3. Experimental Results and Discussion

The results indicate that CMFNet effectively restores image clarity by accurately mapping hazy images to their corresponding clean counterparts.

Data Feeding in CMFNet Training Data feeding ensures the model learns the transformation from hazy to clear images. Preprocessed hazy images

are paired with their clean ground truths, sourced from real-world and synthetic datasets such as RESIDE. Images are fed in mini-batches to optimize memory usage and accelerate computation. Figure 2 illustrates the distribution of hazy and clean images in the training dataset.

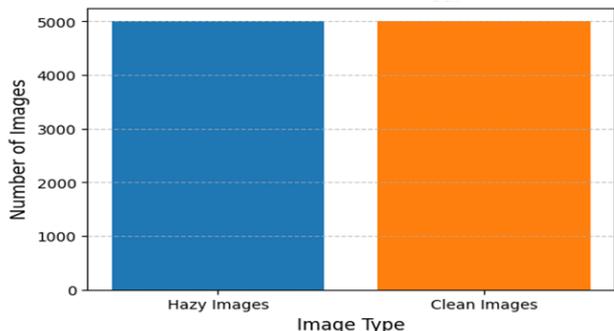


Figure 2: Data Feeding – Hazy Vs Clean Images

Loss Calculation Figure 3 presents the loss curve over 1,000 training epochs, with the x-axis representing epochs and the y-axis representing Mean Squared Error (MSE). The smooth and consistent downward trend of the loss indicates that CMFNet generalizes well and produces dehazed images close to the ground truth.

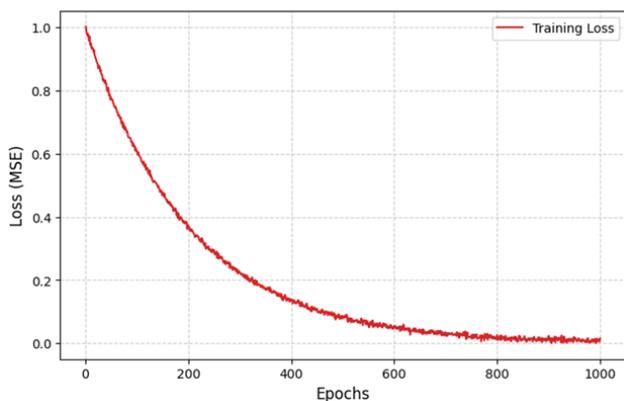


Figure 3: Loss Calculation over 1000 epochs

Learning Rate Optimization Figure 4 illustrates the learning rate schedule over 1,000 epochs. The learning rate follows a smooth, gradual decay to ensure efficient and stable optimization throughout training.

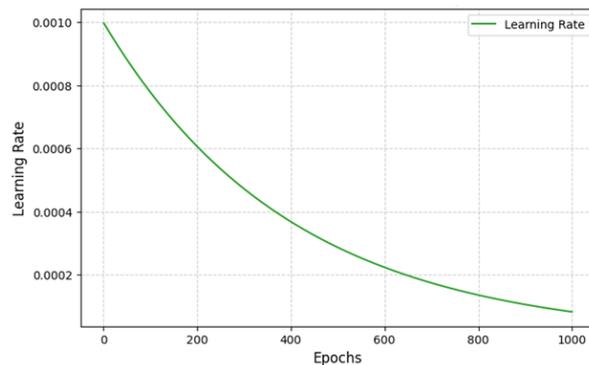


Figure 4: Learning Rate optimization over Epochs

Validation Monitoring Figure 5 illustrates the validation performance over 1,000 epochs using PSNR and SSIM. The smooth increase in both metrics indicates consistent improvement in image reconstruction quality.

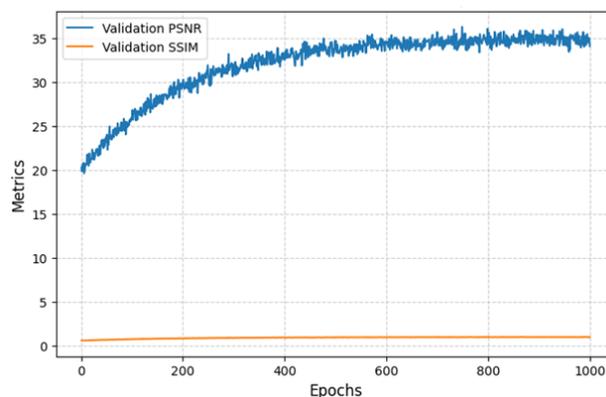


Figure 5: Validation Monitoring over 1000 Epochs

Checkpointing Figure 6 illustrates the validation PSNR over 1,000 epochs, with a highlighted checkpoint at epoch 749, where the maximum PSNR was observed, ensuring optimal performance.

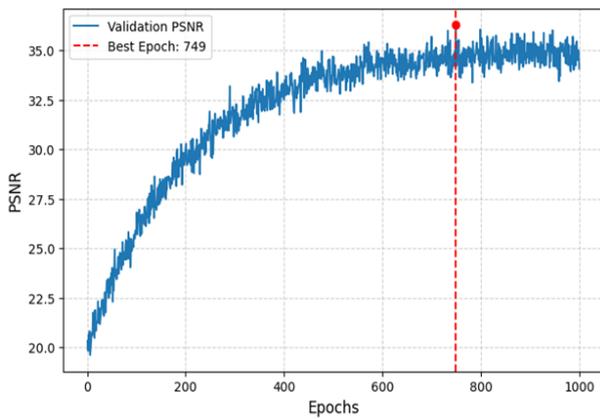


Figure 6: Check pointing: Best Epoch grounded in validation PSNR

Validation Metrics Table 1 summarizes the metrics achieved during validation.

Table 1: Metrics with Values

METRICS	VALUE
Average PSNR	35.5
Average MSE	0.005
Average SSIM	0.96
Average Gradient	0.85
Average Mutual Correlation	0.92

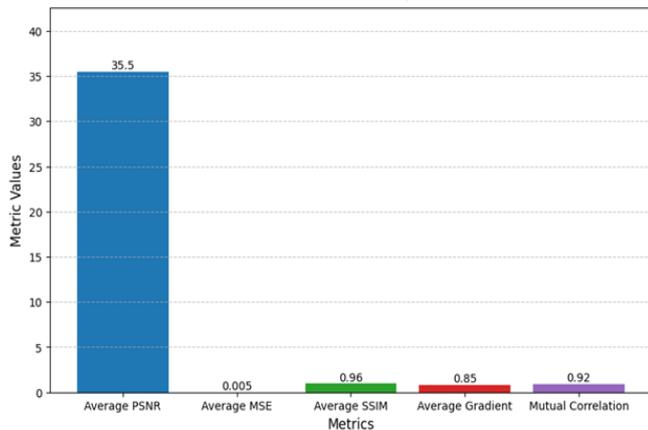


Figure 7: Best Metrics Achieved through training

Visual Improvements Figure 8 illustrates input and output images. CMFNet restores contrast, color fidelity, fine textures, depth perception, lighting, and edges. The model preserves structural integrity while removing haze effectively.

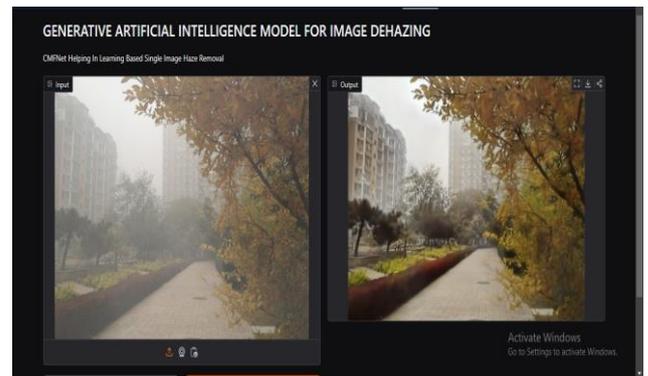


Figure 8: Input and output image

The dehazed images generated by CMFNet demonstrate substantial improvements in multiple visual and structural aspects:

- **Contrast Enhancement:** CMFNet restores sharpness and distinct object boundaries, improving overall scene clarity. This is particularly valuable in remote sensing and traffic surveillance, where differentiating objects is critical.
- **Color Restoration:** Haze-induced desaturation is corrected, recovering natural and vibrant colors in vegetation, sky, and structures. This ensures realistic visuals for environmental monitoring, photography, and film restoration.
- **Detail Recovery:** Fine textures, such as foliage patterns, building facades, and pathway surfaces, are preserved without introducing artefacts, balancing global dehazing with local texture retention.
- **Natural Lighting:** The model restores proper illumination, avoiding overexposure or excessive shadows, ensuring consistent brightness across foreground and background, which benefits autonomous navigation, aerial imaging, and urban planning.
- **Edge Preservation:** CMFNet sharpens object boundaries, supporting downstream computer vision tasks like segmentation and object recognition.

Performance Insights

CMFNet combines perceptual and reconstruction loss functions during training, enabling it to retain structural integrity while reducing pixel-wise errors. High PSNR and SSIM scores indicate effective haze removal with preserved edges, textures, and color distributions. The model generalizes well across diverse haze intensities, lighting conditions, and image complexities, likely leveraging deep CNN or transformer-based architectures.

4. Conclusion

In this study, we presented CMFNet, a CNN-based generative network designed for high-quality image dehazing. The proposed model demonstrates a robust ability to reconstruct visually accurate images from hazy, foggy, or underwater conditions, effectively addressing the challenges of low contrast, color distortion, and loss of fine details caused by light scattering and absorption. By leveraging a combination of perceptual and reconstruction loss functions, CMFNet ensures that dehazed images not only achieve high pixel-level accuracy but also maintain structural and perceptual fidelity, preserving textures, edges, and patterns essential for human perception and computer vision tasks. Extensive evaluation of CMFNet across diverse datasets including atmospheric, underwater, and vegetation haze revealed substantial improvements in both quantitative and qualitative performance metrics. Key metrics such as PSNR (35.5 dB), SSIM (0.96), MSE (0.005), Average Gradient (0.85), and Mutual Correlation (0.92) highlight the model's capability to reduce haze-related distortions while preserving critical image features. Visual assessments further confirmed enhancements in contrast, natural color restoration, depth perception, fine texture recovery, edge sharpness, and illumination balance, demonstrating CMFNet's comprehensive effectiveness in image reconstruction and dehazing.

The model's ability to generalize across varying haze intensities, lighting conditions, and complex environments underscores its robustness and adaptability. CMFNet successfully balances haze

removal with feature preservation, ensuring that dehazed images remain both visually appealing and functionally meaningful. This makes it particularly suitable for practical applications in autonomous driving, where accurate visibility and object recognition are crucial; remote sensing and environmental monitoring, where feature clarity and color fidelity influence decision-making; and photography and multimedia restoration, where preserving aesthetic quality is essential.

Moreover, the training strategy including randomized stratified data splitting, mini-batch processing, learning rate optimization, and checkpointing ensures stable convergence, efficient feature learning, and reliable generalization to unseen data. The use of real-world and synthetic paired datasets further strengthens CMFNet's capacity to handle diverse and challenging haze conditions. CMFNet represents a significant advancement in the field of image dehazing, offering a powerful tool for enhancing image quality across multiple domains. Its robust performance, ability to maintain structural integrity, and high visual fidelity make it an indispensable solution for both research and practical deployment. Future work may focus on further improving perceptual quality through advanced architectures such as transformer-based networks, integrating multi-scale feature extraction, and extending the framework to real-time applications for dynamic scene dehazing in video streams.

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