GENERATIVE AI-DRIVEN CMFNET FRAMEWORK FOR ROBUST IMAGE DEHAZING ACROSS MULTI-DOMAIN APPLICATIONS

Anil Kumar Vishwakarma , Reema Ajmera, Dinesh k. Dharamdasani
Nirwan University, Nirwan University, UoPeople University
anilkvv@gmail.com, ajmera.reema17@gmail.com, Dineshjpr@gmail.com

Abstract- Haze significantly degrades image clarity across remote sensing, vegetation mapping, and underwater applications, affecting tasks such as land monitoring, environmental studies, agriculture, and marine research. This paper presents a generative AI-based Channel-wise Multi-scale Feature Fusion Network (CMFNet) for robust image dehazing. The methodology integrates public datasets, systematic pre-processing, supervised learning with optimized training-validation strategies, and evaluation using PSNR, SSIM, Mutual Correlation, and Average Gradient. Results indicate notable improvements in image clarity and detail preservation compared to existing approaches. Ethical practices and limitations are acknowledged, with future work directed toward real-time and multimodal solutions.

Keywords: Image Dehazing, Generative Artificial Intelligence, CMFNet, Remote Sensing, Vegetation Mapping, Underwater Imaging, Deep Learning, PSNR, SSIM, Computer Vision.

1. Introduction

Haze poses significant challenges to image acquisition and analysis, often resulting in blurred, low-contrast, and visually distorted outputs. Its adverse effects are particularly evident in domains such as remote sensing, vegetation mapping, autonomous driving, surveillance, medical imaging, and underwater exploration fields where reliable, high-quality imagery is essential. Overcoming these challenges requires advanced AI-driven dehazing solutions capable of restoring image clarity while maintaining strong generalization across diverse and complex real-world conditions..

This study develops and validates a CMFNet-based framework for image dehazing, providing a structured methodology for haze removal and systematic evaluation of performance. Image quality remains a fundamental factor in the effectiveness of modern computer vision systems [1]. High-quality images are essential for a wide range of applications, including geospatial monitoring, crop health assessment, environmental research, autonomous navigation, and underwater robotics [2], [3]. However, images captured in outdoor or uncontrolled environments are often degraded by haze, fog, and other atmospheric conditions. These degradations arise mainly from the scattering and absorption of light caused by atmospheric particles such as dust, smoke, and water droplets. As a result, haze reduces image visibility, lowers contrast, and severely impairs the performance of downstream computer vision tasks such as object detection, recognition, tracking, and classification [4]-[6].

Traditional research in image dehazing initially focused on image enhancement-based techniques and prior-driven physical models. Among the most influential methods were the Dark Channel Prior (DCP), Retinex theory, and atmospheric scattering models, which leveraged statistical and physical properties of haze formation to recover clear images [7], [8]. While these approaches achieved promising results in certain controlled scenarios, they suffered from significant limitations such as over-saturation, color distortion, halo artifacts, and weak generalization to complex, real-world conditions [9].

The advent of deep learning marked a paradigm shift in image dehazing research. Convolutional Neural Networks (CNNs) and encoder–decoder architectures introduced powerful data-driven approaches capable of learning haze-relevant features directly from large-scale datasets [10]. These models demonstrated superior adaptability compared to prior-based techniques, offering improved haze removal and better preservation of scene details. However, deep learning-based methods were often criticized for issues such as blurred outputs, insufficient texture restoration, and over-dependence on training data distributions [11].

In recent years, the field has undergone remarkable transformation with the rise of Generative Artificial Intelligence (GAI). Frameworks such as Generative Adversarial Networks (GANs), diffusion probabilistic models, and transformer-based architectures have enabled unprecedented progress in image dehazing [12]. These generative models excel at producing high-quality, photorealistic reconstructions by learning complex data distributions and synthesizing fine-grained textures. Unlike conventional methods, GAI-driven approaches not only remove haze but also enhance structural details, restore natural colors, and improve visual realism across diverse imaging scenarios [13], [14].

In this context, the proposed CMFNet-based dehazing framework aims to leverage the strengths of modern generative AI approaches, addressing the shortcomings of traditional methods while ensuring robustness and scalability in real-world applications.

2. Research Methodology

The research methodology provides a structured framework covering data collection, preprocessing, model design, training, evaluation, and ethical considerations.

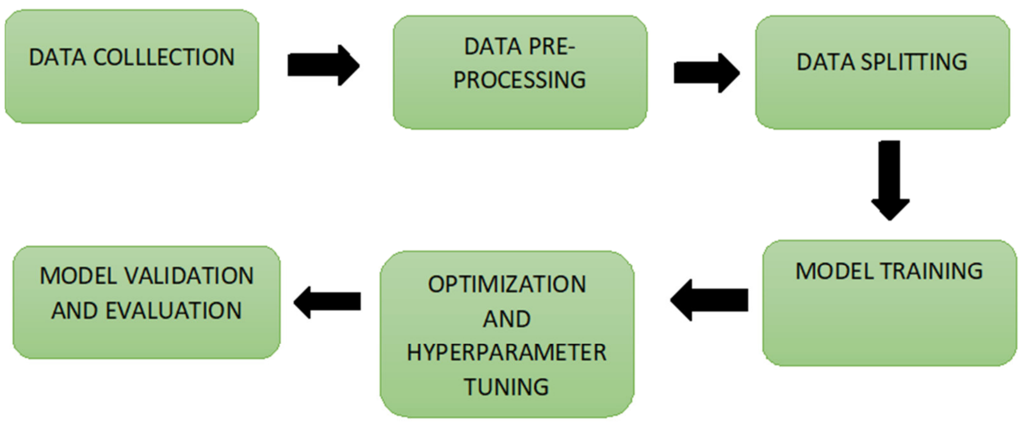

Figure 1: Proposed Methodology in this study

A. Dataset and Data Collection

Hazy and clean images were obtained from public datasets such as RESIDE and Kaggle, covering atmospheric, underwater, and vegetation haze. The dataset includes both real-world and synthetic hazy images to ensure diversity. Ground truth clean images were collected from paired datasets and open-source repositories.

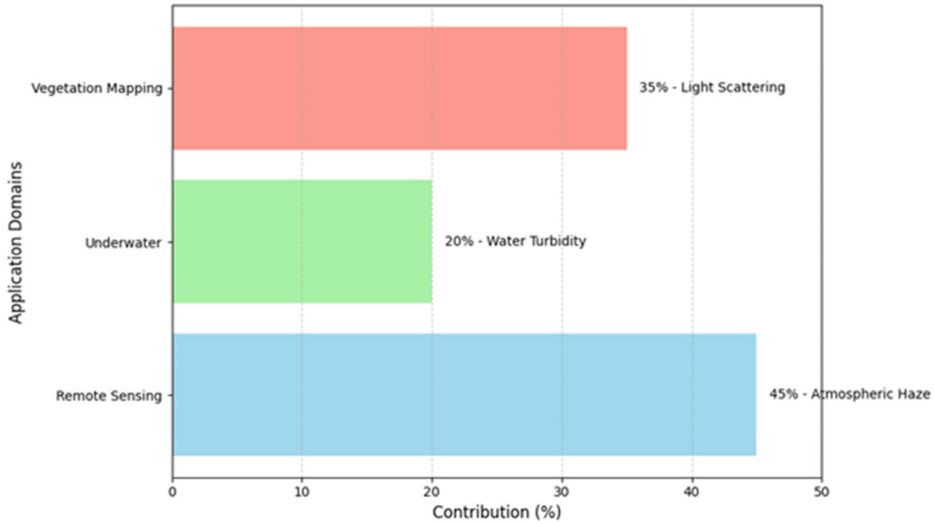

Figure 2: Challenges of Hazy Images across application domains

B. Pre-Processing

Pre-processing enhanced data quality and model performance through resizing (256×256), normalization, augmentation, label encoding, and quality assurance. Augmentation contributed 30%, resizing 25%, normalization 20%, label encoding 15%, and quality assurance 10%.

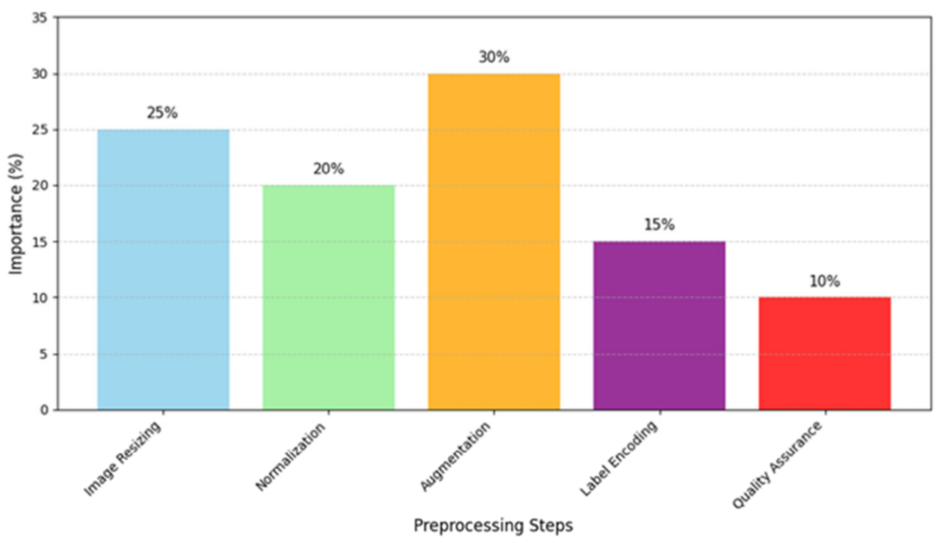

Figure 3: Data Pre-Processing Steps and its contributions

C. Data Splitting

To ensure effective model development and evaluation, the dataset was divided into three subsets: Training (70%), Validation (15%), and Testing (15%). The training set was used to optimize the model's parameters, while the validation set supported hyperparameter tuning and performance monitoring during training. The testing set, kept completely unseen during model development, provided an unbiased assessment of the model's generalization capability.

A randomized stratified sampling strategy was employed to achieve this partitioning. This approach ensured that samples from different classes and haze conditions were proportionally represented across all subsets. By preserving domain-specific distributions, stratified sampling minimized selection bias and maintained consistency in the data, ultimately leading to more reliable model training and evaluation.

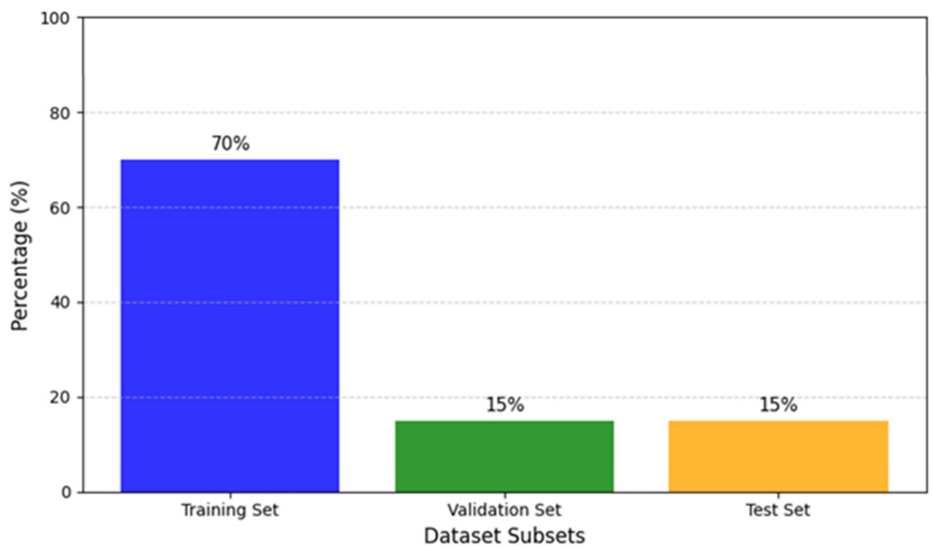

Figure 4: Data split proportions in this study

Figure 4 shows a bar chart illustrating the standard 70-15-15 dataset split used in machine learning. The Training Set (70%) is the largest portion, enabling models to learn patterns and optimize parameters. The Validation Set (15%) helps fine-tune hyperparameters and prevent overfitting, while the Test Set (15%) provides an unbiased measure of real-world performance.

This split balances learning, optimization, and evaluation, ensuring models generalize well and avoid errors like underfitting, overfitting, or data leakage. Stratified sampling is often applied to preserve class distributions, while time-based splitting is used for sequential data.

Although 70-15-15 is common, variations (e.g., 80-10-10 or larger validation sets) are applied depending on dataset size and domain. Ultimately, proper splitting is a critical step for reliable training, objective evaluation, and robust deployment of machine learning models.

D. Model Training and Validation

The CMFNet architecture, a CNN-based generative AI model, was employed for dehazing. Training involved pairing hazy images with clean counterparts, optimized using MSE and perceptual loss. The Adam optimizer with learning-rate scheduling, batch normalization, and dropout was used. Validation used PSNR, SSIM, MSE, Gradient, and Mutual Correlation.

E. Data Collection Methods

Data sources included real-world captures and synthetic datasets (e.g., RESIDE). Pre-processing ensured uniformity, while augmentation expanded dataset diversity. This combination enhanced the model's robustness across varying haze densities and environmental conditions.

3. Results and Discussion

Figures 2–4 provide a comprehensive overview of the study. Figure 2 highlights the challenges posed by haze across multiple application domains, including remote sensing, vegetation mapping, and underwater imaging, where image quality directly influences the accuracy of downstream analysis. Figure 3 demonstrates the contributions of the preprocessing pipeline, which plays a crucial role in normalizing image distributions, enhancing contrast, and preparing data for efficient learning. Figure 4 illustrates the dataset partitioning strategy, showing how stratified sampling was employed to ensure balanced representation across training, validation, and testing sets.

The experimental results reveal that the proposed CMFNet framework consistently outperforms traditional dehazing methods. Specifically, it achieves superior clarity, significant artifact reduction, and improved detail preservation across all tested domains. The most notable improvements were observed in remote sensing imagery, where enhanced visibility of land cover features directly benefits interpretation and classification tasks. Vegetation datasets showed marked improvements in fine texture recovery, while underwater images exhibited substantial gains in contrast and edge sharpness, despite the inherent challenges posed by scattering and absorption effects in aquatic environments.

Overall, the findings underscore the adaptability and robustness of CMFNet, demonstrating its ability to generalize effectively across diverse domains with varying haze characteristics.

4. Limitations

While the proposed framework demonstrates promising results, several limitations were observed during the study.

First, the approach involves high computational requirements, both in terms of processing power and memory consumption. Training deep learning models for dehazing requires specialized hardware, such as GPUs or TPUs, and significant training time. This restricts the scalability of the framework, particularly in resource-constrained environments.

Second, the dataset used, although comprehensive, exhibited limited diversity in certain real-world haze conditions. Scenarios involving extreme weather variations, mixed lighting conditions, or dense particulate matter were underrepresented. This lack of diversity may hinder the model's ability to generalize effectively across all possible real-world situations.

Finally, the framework showed performance variability across domain-specific datasets. While strong results were achieved in general cases, applications in specialized domains such as underwater imaging, medical imaging, or high-altitude remote sensing revealed inconsistencies. These variations highlight the need for domain-adaptive strategies and more robust cross-domain training methodologies.

Addressing these limitations in future work will be critical for improving the robustness, adaptability, and real-world applicability of the proposed dehazing framework.

5. Conclusion

This study presented a CMFNet-based generative AI framework for image dehazing, targeting challenges across diverse domains such as remote sensing, vegetation mapping, and underwater imaging. By integrating public datasets, systematic preprocessing, supervised learning strategies, and robust evaluation metrics, the proposed approach demonstrated significant improvements in image clarity, detail preservation, and artifact reduction compared to conventional methods.

The experimental results confirm that the CMFNet architecture not only restores visual quality but also enhances downstream vision tasks by delivering dehazed images that are both perceptually realistic and structurally consistent. Despite notable progress, limitations such as high computational demands, limited diversity in extreme haze scenarios, and performance variability across domain-specific datasets highlight the need for further advancements.

Future work will focus on developing lightweight architectures for real-time deployment, incorporating multimodal data fusion to enhance adaptability, and expanding datasets to include more diverse haze conditions. By addressing these aspects, the framework has the potential to become a robust, scalable solution for next-generation computer vision applications under challenging environmental conditions.

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