

A Multi-CNN-GAN Framework for Effective Image Dehazing

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Abstract

Image dehazing is an ill-posed low-level computer vision problem that substantially affects the reliability of outdoor vision systems, including autonomous driving, intelligent surveillance, remote sensing, and aerial imaging. Atmospheric degradations such as haze, fog, smoke, and rain scatter incoming light, resulting in poor visibility, contrast degradation, and color distortion. Although recent deep learning-based approaches, particularly, Generative Adversarial Networks (GANs), have shown promising performance in single image dehazing, most existing methods rely on a single convolutional generator and often suffer from generalization, artifacts, and color distortion. This paper presents a multi-CNN-GAN-based framework for effective image dehazing overcoming the existing limitations. The framework is designed to combinedly handle three salient issues, such low-level haze characteristics, mid-level transmission-aware representations, and high-level semantic consistency through three parallel CNN branches and feature fusion for realistic dehazing. In addition, a detailed experimental design for practical implementation along with future works has been provided. The proposed framework shows a way for next-generation image dehazing systems.

Keywords

Image Dehazing, Atmospheric Scattering, Convolutional Neural Networks, Generative Adversarial Networks, Multi-CNN Architecture

1. Introduction

Haze is a common atmospheric phenomenon caused by aerosols such as dust, smoke, fog, and rain suspended in the air. The scattering and absorption of light by these particles are causing significant degradation in image quality, including

reduced visibility, loss of contrast, and color distortion. Consequently, hazy images pose serious challenges to computer vision systems operating in outdoor environments, such as autonomous driving, traffic monitoring, aerial surveillance, remote sensing, and environmental analysis [1]-[4].

Early image dehazing methods are primarily based on physical atmospheric models and handcrafted priors. While these techniques are producing somehow enhanced visibility under constrained assumptions, they often fail in real-world scenarios characterized by non-uniform haze distribution, complex illumination, and large depth variations [5]. The introduction of deep learning techniques in the field of image dehazing shows promising results due to enabling data-driven learning of haze-related representations directly from image data.

Convolutional Neural Networks (CNNs) have been widely adopted for single image dehazing due to their strong hierarchical feature extraction capability. Representative CNN-based approaches such as DehazeNet [6], Multi-Scale CNN [7], and AOD-Net [8] demonstrated substantial improvements over traditional prior-based methods. However, CNN-only architectures frequently generate over-smoothed outputs and lack perceptual realism, particularly in dense haze conditions.

Generative Adversarial Networks (GANs), introduced by Goodfellow *et al.* [9], have emerged as a powerful tool for image-to-image translation tasks. GAN-based dehazing methods exploit adversarial learning to improve perceptual quality and visual fidelity. A detailed comparative analysis of GAN-based dehazing models by us demonstrated that adversarial learning consistently improves dehazing performance across diverse conditions [10]. In addition, our comprehensive review of GAN-based dehazing techniques systematically categorized existing approaches and highlighted the absence of multi-level feature integration as a serious research gap [11].

Motivated by these findings, this paper proposes a multi-CNN-based GAN conceptual framework for effective image dehazing that addresses the need for hierarchical and multi-scale feature learning.

The main contributions of this paper are as follows:

- To address the limitations of existing GAN-based dehazing methods a multi-CNN-GAN-based conceptual framework has been developed that prioritizes multi-level feature integration for improved image restoration is introduced.
- A comprehensive experimental roadmap is outlined, covering datasets, implementation, evaluation metrics, benchmarks, and limitations.

The remainder of this paper is organized as follows:

Section II presents the related work on dehazing, such as prior-based, CNN-based, and GAN-based image dehazing methods to extract the research gap. Section III describes the theoretical background of image dehazing based on the atmospheric scattering model and discusses key challenges in single image dehazing. Section IV explains the proposed CNN-GAN framework along with the overall architecture, adversarial learning formulation, and, generator loss. Section V

outlines the experimental design along with datasets, implementation details, and evaluation metrics. Section VI presents the comparative analysis with the existing GAN-based methods. Finally, Section VII concludes the paper by highlighting the main contributions along with limitations and future research directions.

2. Related Works

Image dehazing approaches can be broadly categorized into three categories, such as prior-based methods, CNN-based learning methods, and GAN-based adversarial methods.

2.1. Prior-Based Dehazing Methods

Prior-based techniques rely on assumptions derived from atmospheric optics. The Dark Channel Prior (DCP), proposed by He *et al.* [5], remains one of the most influential methods in this category. Other approaches, such as Retinex-based enhancement [12] and non-local priors [13], have also been widely used. However, despite their computational efficiency, these methods often fail in sky regions and under dense haze conditions.

2.2. CNN-Based Dehazing Methods

CNN-based methods learn haze-related features directly from training data. DehazeNet [6] estimates transmission maps using learned features, while Multi-Scale CNN [7] incorporates multi-scale learning to handle varying haze densities. AOD-Net [8] reformulates the atmospheric model to enable end-to-end training. Although effective, these models often suffer from color distortion and limited generalization to real-world haze.

2.3. GAN-Based Dehazing Methods

GAN-based methods utilizing adversarial loss to enhance perceptual realism. Conditional GANs (cGANs) [14] [15] have been widely used for paired image dehazing tasks. DHSGAN [16] demonstrated better robustness under haze and smoke conditions, while CycleGAN-based methods [17] [18] enabled unpaired training at the cost of structural consistency. Another GAN-based dehazing models that used attention-driven feature fusion to produce superior image [19]-[21]. Extensive experimental evidence indicates that GAN-based approaches outperform traditional CNN-based dehazing models in perceptual quality, although their training stability and architectural flexibility remain challenging [10] [11].

Despite significant progress in CNN- and GAN-based image dehazing, the review of existing literature reveals several unresolved challenges. Most CNN-based methods rely on single-stream architectures that inadequately capture the hierarchical nature of haze formation, while many GAN-based approaches prioritize perceptual realism without explicitly integrating multi-level haze-aware representations or physically motivated constraints. In addition, existing studies often evaluate models under limited experimental settings, with insufficient discussion

on architectural design rationale, benchmarking strategy, and practical limitations. To address these gaps, the present manuscript introduces a multi-CNN-based GAN framework that explicitly integrates hierarchical feature learning within an adversarial setting based on the atmospheric scattering model and informed by insights from prior comparative analyses. Furthermore, this work emphasizes a good experimental design, including dataset selection, implementation strategy, evaluation metrics, and benchmark comparisons, thereby providing a structured foundation for implementation and extension of the proposed framework.

3. Image Dehazing Background

3.1. Atmospheric Scattering Model

The majority of dehazing techniques are based on the atmospheric scattering model [1]-[4], expressed as

$$I(x) = J(x)t(x) + A(1 - t(x)) \quad (1)$$

therefore, the haze-free image is

$$J(x) = \frac{I(x) - A}{t(x)} + A \quad (2)$$

where $I(x)$ denotes the observed hazy image at pixel position x , $J(x)$ represents the haze-free scene radiance, $t(x)$ is the transmission map, and A denotes global atmospheric light. The transmission map is commonly modeled through an exponentially decaying function as

$$t(x) = e^{-\beta d(x)} \quad (3)$$

where β represents the atmospheric scattering coefficient and $d(x)$ represents scene depth. **Figure 1** shows the flow diagram of haze-free image from the observed hazy image.

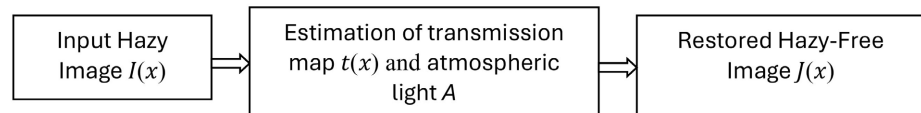


Figure 1. A simple image dehazing flow diagram based on scattering model.

3.2. Challenges in Single Image Dehazing

Single image dehazing is an inherently ill-posed problem due to unknown depth information, spatially varying haze density, and complex illumination conditions [5]-[7]. An effective dehazing model must balance visibility enhancement with color fidelity and structural preservation.

4. Proposed CNN-GAN Framework

4.1. Overall Architecture

The proposed framework comprises a multi-CNN generator and a discriminator

trained under an adversarial learning system. The generator integrates three parallel CNN branches followed by hierarchical feature fusion and reconstruction layers. The three parallel CNNs comprising 1) a low-level feature extraction network that captures edge information, color attenuation, and haze density cues; 2) a mid-level transmission-aware network that learns representations related to atmospheric scattering and depth-dependent haze; and 3) a high-level semantic refinement network that preserves global structure and semantic consistency. The feature maps from all three CNNs are fused through a hierarchical feature fusion module and passed to reconstruction layers to generate the final dehazed image. A PatchGAN discriminator with a patch size (70×70) is used to evaluate local realism by distinguishing generated dehazed images from ground-truth haze-free images, thereby guiding the generator through adversarial feedback.

The proposed framework is theoretically grounded in the atmospheric scattering model, the current GAN implementation is data-driven rather than explicitly estimating $t(x)$ and A as separate outputs for the final pass. The “mid-level transmission-aware network” is designed to implicitly learn these representations. In fact, the physics-based parameters provide the conceptual motivation for the multi-branch architecture rather than being explicitly supervised auxiliary outputs.

In the preprocessing, the images are normalized and resized to a consistent resolution (256×256). **Figure 2** shows our dehazing framework.

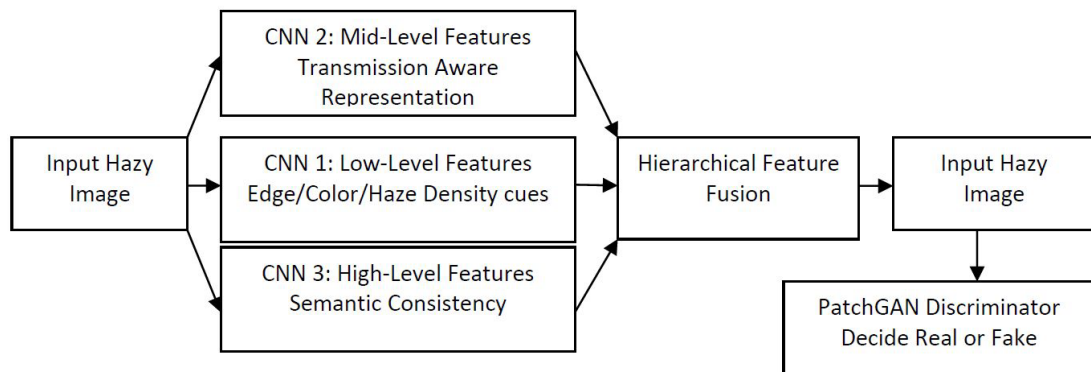


Figure 2. The framework for image dehazing using multi-CNN-based GAN.

The working algorithm of this proposed model is shown in Algorithm 1.

Algorithm 1: CNN-GAN-based dehazing

Input: Hazy image I .

Output: Clear dehazed image J through minimizing haze while preserving naturalness and fine details.

Step 1: Preprocessing

- Normalize and preprocess I .

Step 2: Multi-CNN Generator G

- Input Layer: Accept the preprocessed hazy image.
- Feature Extraction Layers: Use multiple parallel convolutional layers with var-

ying kernel sizes to capture multi-scale features.

- Attention Mechanism: Integrate a self-attention module to focus on regions with haze.
- Residual Blocks: Include residual blocks with skip connections to enhance feature learning and prevent vanishing gradients.
- Multi-scale Fusion: Fuse features extracted at multiple scales to generate dehazed image $J = G(I)$ with fine details.

Step 3: CNN Discriminator D

- Discriminator D evaluates J against ground truth.
- Compute reconstruction, perceptual, and adversarial losses.
- Update G to minimize total loss.
- Update D to maximize adversarial discrimination.
- Iterate until convergence, that means, the generator produces visually appealing dehazed images.
- Return clear dehazed image J .

Step 4: Optional post-processing

- Use a sharpening filter to enhance J through contrast enhancement and artifact removal.

4.2. Adversarial Learning

The proposed framework adopts an adversarial learning strategy based on the standard min-max formulation of Generative Adversarial Networks. Let G denotes the generator network and D denotes the discriminator network. The adversarial objective is defined by the standard min-max formulation [9]

$$\min_G \max_D E_{J \sim p_J} [\log D(J)] + E_{I \sim p_I} [\log (1 - D(G(I)))] \quad (4)$$

where I represents a hazy input image sampled from the probability distribution of hazy images p_h and J denotes the corresponding ground-truth haze-free image sampled from the probability distribution p_f . The generator G maps a hazy image I to a dehazed image $G(I)$, while the discriminator D outputs the probability that an input image is a real haze-free image.

During training, the discriminator aims to correctly distinguish real haze-free images J from generated images $G(I)$, whereas the generator attempts to produce dehazed images that are indistinguishable from real haze-free images. This adversarial process encourages the generator to learn realistic image distributions and improves the perceptual quality of the dehazed results.

$D(G(I))$ is the discriminator's estimated probability that the generated image $G(I)$ is a real haze-free image.

$E[\cdot]$ is the expectation operator, computed over the data distribution of real haze-free images J and hazy images I .

4.3. Generator Loss Function

To ensure both pixel-level accuracy and perceptual realism [22], the generator is

optimized using a combined loss function defined as

$$L_G = \lambda_1 L_{adv} + \lambda_2 L_{rec} + \lambda_3 L_{perc} \quad (5)$$

where L_G is the combined loss function, L_{adv} is the adversarial loss, L_{rec} is the reconstruction loss and L_{perc} is a perceptual loss computed using deep feature representations extracted from a pre-trained network, such as using a VGG-16 or VGG-19 backbone on ImageNet, specifically targeting the feature maps from the deeper layers to ensure semantic consistency [7] [19] and λ_1 , λ_2 , and λ_3 are positive weighting coefficients (For example, $\lambda_1 = 1$, $\lambda_2 = 100$ and $\lambda_3 = 1$ is a good choice. The reconstruction loss is weighted more heavily) that balance the contribution of each loss component for better image-to-image translation.

The adversarial loss for the generator is formulated as

$$L_{adv} = E_{I \sim p_I} \left[-\log(D(G(I))) \right] \quad (6)$$

This term encourages the generator to produce dehazed images that the discriminator classifies as real, thereby enhancing visual realism and reducing perceptual artifacts.

The reconstruction loss enforces pixel-wise similarity between the generated image and the ground-truth haze-free image. It is defined as

$$L_{rec} = E_{I,J} \left[\|G(I) - J\| \right] \quad (7)$$

where $\|\cdot\|$ denotes the L_1 or L_2 norm. This loss preserves structural details, color consistency, and low-level image fidelity, which are critical for effective haze removal. However, the use of the L_1 norm preserve the edge sharpness better.

The perceptual loss [22] measures the difference between high-level feature representations of the generated and ground-truth images, computed using a pre-trained deep network as mentioned earlier. It is expressed as

$$L_{perc} = E_{I,J} \left[\sum_l \left\| \phi_l(G(I)) - \phi_l(J) \right\|^2 \right] \quad (8)$$

where $\phi_l(\cdot)$ denotes the feature map extracted from the l -th layer of the pre-trained network. This loss promotes semantic consistency, texture preservation, and global perceptual coherence.

The combined loss formulation enables the generator to jointly optimize adversarial realism, pixel-level accuracy, and perceptual quality. Such a balanced objective is particularly important for single image dehazing, where excessive reliance on reconstruction loss may cause over-smoothing, while adversarial loss alone may introduce structural distortions. The proposed composite loss thus ensures robust and visually convincing dehazing performance.

5. Experimental Design

To facilitate practical implementation and validation, an experimental design is outlined below.

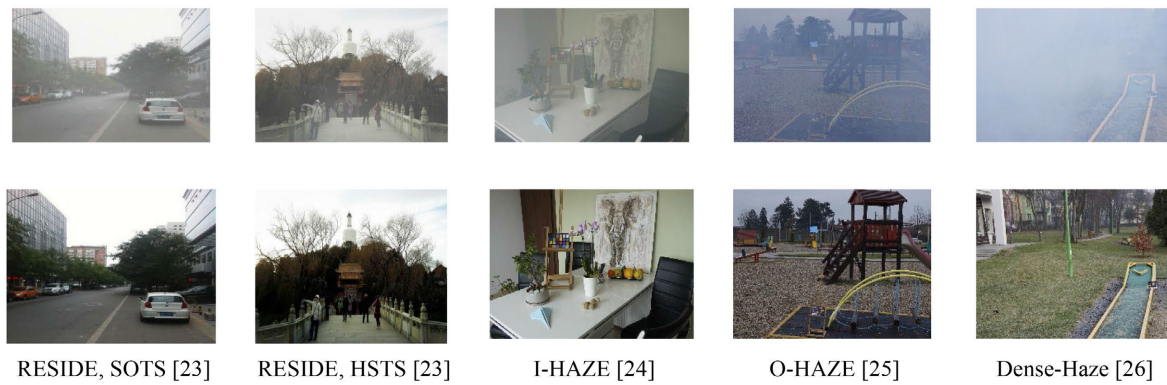


Figure 3. Sample image pairs from the widely used datasets [23]-[26]. In each column, hazy image (top) and the corresponding clear image (bottom).

5.1. Datasets

To evaluate the effectiveness and generalization capability of the proposed CNN-GAN framework, both synthetic and real-world image dehazing datasets should be employed. Diverse datasets are essential to capture variations in haze density, scene depth, illumination conditions, and real atmospheric effects. Synthetic datasets provide paired hazy and haze-free images, enabling supervised training and objective quantitative evaluation. Among these, the RESIDE benchmark [23] is the most widely adopted dataset for single image dehazing research and consists of multiple subsets, including the Outdoor Training Set (OTS), Synthetic Objective Testing Set (SOTS), and Hybrid Subjective Testing Set (HSTS). RESIDE has been extensively used to evaluate CNN- and GAN-based dehazing models due to its controlled haze synthesis and availability of ground-truth images.

In addition to RESIDE, other synthetic datasets commonly used in the literature include the I-HAZE [24] and O-HAZE [25] datasets, which provide real haze scenes with corresponding haze-free ground truth captured under controlled conditions. These datasets bridge the gap between fully synthetic data and real atmospheric environments. Furthermore, Dense-Haze [26] is another dataset characterized by dense and homogeneous hazy scenes, which were generated by professional haze machines. The hazy and haze-free corresponding scenes contain the same visual content captured under the same illumination parameters.

Real-world datasets, which lack ground-truth haze-free images, are critical for assessing model robustness and practical applicability. Unpaired real-world hazy images collected from outdoor environments and traffic scenes are frequently used for qualitative evaluation in recent studies [6]-[8] [10] [11] [15]-[17] [19]-[21]. Such real-world datasets expose models to non-uniform haze, complex lighting, and color distortions that are difficult to simulate synthetically.

By training and evaluating the proposed framework across a combination of synthetic and real-world datasets, a balanced assessment of reconstruction accuracy, perceptual quality, and generalization performance can be achieved.

The current framework is primarily designed for paired (supervised) learning.

- **Training Datasets:** For supervised training, the framework utilizes paired da-

tasets such as the RESIDE Outdoor Training Set (OTS), I-HAZE, and O-HAZE.

- Testing Datasets: Performance is evaluated using the RESIDE Synthetic Objective Testing Set (SOTS) and Hybrid Subjective Testing Set (HSTS), as well as Dense-Haze.

While training is conducted in a paired setting, however, to assess generalization, unpaired real-world images are used solely for qualitative (no-reference) testing.

5.2. Implementation Details

The proposed CNN-GAN framework is intended to be implemented using a deep learning platform such as PyTorch or TensorFlow, which supports flexible construction of adversarial architectures and efficient GPU-based training. The generator network adopts a multi-branch (3-branch) CNN design, where each branch is specialized for learning complementary representations at different semantic levels.

1) Generator Architecture

Each CNN branch in the generator is composed of a sequence of convolutional layers with small kernel sizes (e.g., 3×3) to preserve spatial resolution while capturing local haze-related features followed residual blocks. Residual learning is adopted through the residual blocks for stable gradient propagation and speedy convergence. Batch normalization, followed by non-linear activation functions such as ReLU or Leaky ReLU, is used in the generator branches to stabilize training and prevent vanishing gradients.

The three branches do not share weights; they are specialized to learn complementary representations at different semantic levels (low-level, mid-level, and high-level). The low-level feature extraction branch focuses on capturing edge information, color attenuation, and local contrast degradation. The mid-level transmission-aware branch is used to learn depth-dependent haze characteristics and atmospheric scattering effects. The high-level semantic refinement branch emphasizes global structure and semantic consistency to prevent distortion of scene content. The fusion of feature maps from all branches is performed via a hierarchical feature fusion module that employs concatenation followed by additional refinement convolutional layers. The fused representation is then passed to reconstruction layers to generate the final dehazed image.

2) Discriminator Architecture

The discriminator is implemented as a PatchGAN [15], which classifies local image patches rather than the entire image as real or fake. This process ensures local realism and sharpness in the generated dehazed images while reducing the number of model parameters. The discriminator consists of a series of convolutional layers with increasing feature depth and stride convolutions for spatial down sampling, followed by Leaky ReLU activations. Model training can be done through Adam optimizer with learning rate scheduling. Training continues until

the loss curves for both G and D reach a stable equilibrium.

5.3. Evaluation Metrics

To ensure a comprehensive and fair assessment of the proposed CNN-GAN framework, both full-reference and no-reference image quality metrics should be employed. Since image dehazing aims to improve not only pixel-level accuracy but also perceptual quality and visual realism, reliance on a single metric is not enough. Therefore, multiple complementary evaluation criteria are adopted, as commonly practiced in prior dehazing studies [10] [11] [27] [28].

1) Full-Reference Metrics

Full-reference metrics [11] require access to corresponding ground-truth haze-free images and are primarily used for evaluating performance on synthetic datasets. There are some full-reference metrics: Peak Signal-to-Noise Ratio (PSNR) is used to measure pixel-wise reconstruction fidelity between the generated dehazed image and the ground-truth image. Higher PSNR values indicate better reconstruction accuracy and lower distortion. Structural Similarity Index Measure (SSIM) evaluates perceptual similarity by considering luminance, contrast, and structural information. SSIM is more consistent with human visual perception than PSNR and is widely adopted in image dehazing research. For a model, PSNR and SSIM together express the insight of the detailed restoration and structural consistency preservation in haze-free regions.

2) No-Reference (Blind) Image Quality Metrics

No-reference metrics [27] are essential for evaluating real-world hazy images where ground-truth references are unavailable. There are some full-reference metrics: Natural Image Quality Evaluator (NIQE) measures deviations from natural scene statistics without requiring reference images. Lower NIQE scores correspond to better perceptual quality and have been widely used to assess real-world dehazing results. Blind Image Spatial Quality Evaluator (BRISQUE) assesses image quality based on locally normalized luminance coefficients and natural scene statistics. It complements NIQE by focusing on spatial distortions introduced during dehazing. These blind metrics are particularly important for assessing the generalization capability of dehazing models under uncontrolled atmospheric conditions.

3) Perceptual Quality Metrics

To better quantify perceptual similarity aligned with human judgment, Learned Perceptual Image Patch Similarity (LPIPS) [28] can be employed. LPIPS computes distances between deep feature representations extracted from pre-trained networks and has been shown to correlate well with human perceptual assessments. Lower LPIPS values indicate higher perceptual similarity.

4) Subjective Evaluation

In addition to objective metrics, subjective visual evaluation is recommended to assess color fidelity, residual haze, halo artifacts, and overall visual realism. User studies involving human observers have been commonly used in recent dehazing literature to complement quantitative results [11].

By jointly considering full-reference, no-reference, perceptual, and subjective metrics, a balanced and reliable evaluation of dehazing performance can be achieved across both synthetic and real-world datasets.

6. Comparative Analysis

To provide a meaningful comparison, the proposed CNN-GAN framework is evaluated against representative GAN-based image dehazing techniques that are widely reported in the literature [10] [11] [15]–[17] [21].

Specifically, conditional GAN (cGAN)-based model [15], DHSGAN [16], CycleGAN-based approach (Cycle-Dehaze) integrating cycle-consistency and perceptual losses for recovering textural and edge information [17], CycleGAN with attention-driven feature fusion method (A-CycleGAN) [21] are selected as benchmarks because they capture the dominant architectural trends and learning strategies in single image dehazing research. cGAN-based dehazing method [15] is the earliest and most extensively adopted adversarial approach for paired image dehazing tasks, serving as a baseline in numerous studies. DHSGAN [16] represents a more recent enhancement that introduces end-to-end convolutional network for directly generating realistic dehazed images through adversarial learning in a variety of haze conditions including fog, rain, underwater and smoke and has been validated across multiple datasets. Cycle-Dehaze [17] addresses the limitation of paired data availability by enabling unpaired training, making them particularly relevant for real-world dehazing scenarios due to integration of cycle-consistency and perceptual losses for ensuring somehow realistic visualization. A-CycleGAN [21] included the improved channel attention and domain attention mechanisms with CycleGAN to generate more realistic images by processing different features and different regions non-uniformly. **Table 1** qualitatively compares existing GAN-based dehazing methods with the proposed framework. **Figure 4** shows the qualitative dehazing results of the paper of Amina *et al.* [10] for a real hazy image taken from RESIDE SOTS dataset [23] by cGAN and DHSGAN methods. DHSGAN gives better performance than the cGAN. Similarly, **Figure 5** presents the qualitative dehazing results taken from the paper of Ma *et al.* [21] for two real hazy images by Cycle-Dehaze and A-CycleGAN methods. A-CycleGAN gives better performance than the Cycle-Dehaze. However, the methods are still behind the realistic dehazing.

Table 1. Subjective comparison of the proposed Multi-CNN-GAN with the existing GAN-Based Dehazing Methods.

Dehazing Method	Multi-CNN	Adversarial Learning	Semantic Preservation	Generalization
cGAN [15]	No	Yes	Moderate	Limited
DHSGAN [16]	No	Yes	Moderate	Good
Cycle-Dhaze [17]	No	Yes	Low	Moderate
A-CycleGAN [21]	No	Yes	Good	Good
Proposed Framework	Yes	Yes	High	High



Figure 4. Dehazing results taken from the paper of Amina *et al.* [10] for a real hazy image taken from RESIDE SOTS dataset [23] by cGAN [15] and DHSGAN [16] methods. DHSGAN gives better performance than the cGAN. The methods are still behind the realistic dehazing.

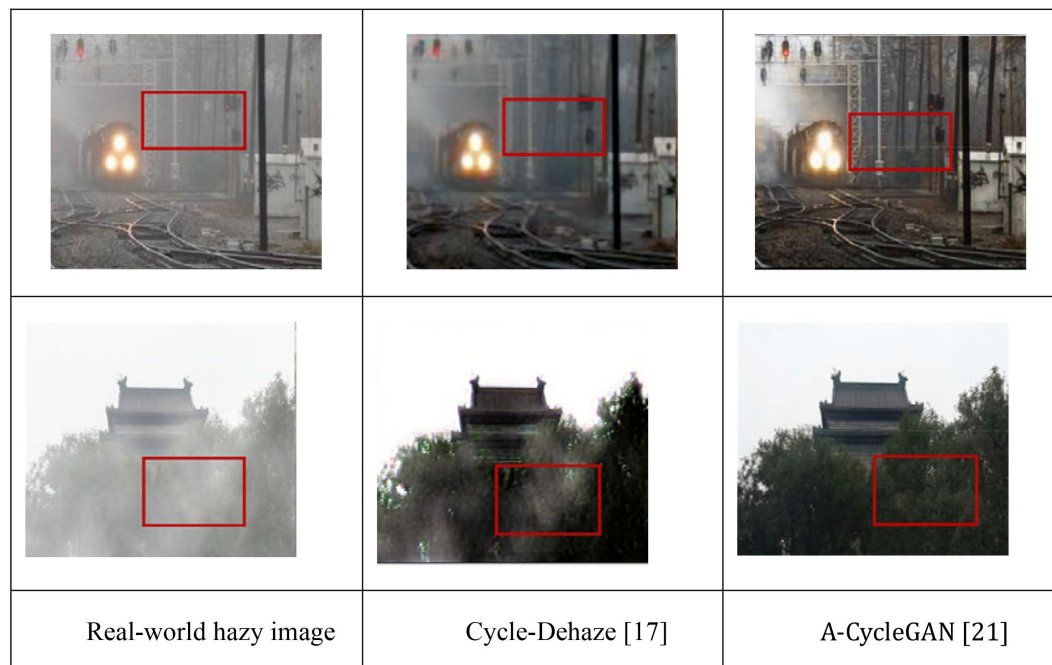


Figure 5. Dehazing results taken from the paper of Ma *et al.* [21] for two real hazy images by Cycle-Dehaze [17] and A-CycleGAN [21] methods. A-Cycle-GAN gives better performance than the Cycle-Dehaze. The detailed differences are shown in red rectangles between the real hazy image and the output dehazed image for each dehazing technique.

7. Conclusion

This paper presented a multi-CNN-GAN-based framework for effective image dehazing. By integrating multiple CNN branches within a unified adversarial learning architecture, the proposed framework addresses the limitations of existing single-generator GAN-based methods. Utilizing atmospheric scattering theory and informed by the prior comparative and review studies [10] [11] on GAN-based dehazing, the proposed framework provides an improved dehazing performance and generalization. Although the proposed framework offers strong con-

ceptual advantages, several limitations remain. First, as a conceptual design, the framework has not yet been empirically validated through large-scale experiments. Second, the multi-CNN architecture may introduce increased computational complexity, which could limit real-time deployment on resource-constrained devices. Third, training GAN-based models remains challenging due to potential instability and mode collapse. The future work will focus on full implementation and extensive experimental evaluation across diverse datasets. Model compression and lightweight network design will be investigated to enable real-time performance. Additionally, extending the framework to handle video dehazing, nighttime haze, and joint dehazing–denoising tasks represents promising research directions.

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AI-based tools were used only to improve the language and readability of the manuscript. All research content and conclusions are solely authors' work.

Conflicts of Interest

The authors declare that they have no conflict of interest.

References

- [1] Narasimhan, S.G. and Nayar, S.K. (2003) Contrast Restoration of Weather Degraded Images. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **25**, 713-724. <https://doi.org/10.1109/tpami.2003.1201821>
- [2] Narasimhan, S.G. and Nayar, S.K. (2002) Vision and the Atmosphere. *International Journal of Computer Vision*, **48**, 233-254. <https://doi.org/10.1023/a:1016328200723>
- [3] McCartney, E.J. (1976) Optics of the Atmosphere: Scattering by Molecules and Particles. Wiley.
- [4] Nayar, S.K. and Narasimhan, S.G. (1999) Vision in Bad Weather. *Proceedings of the Seventh IEEE International Conference on Computer Vision*, Kerkyra, 20-27 September 1999, 820-827. <https://doi.org/10.1109/iccv.1999.790306>
- [5] He, K., Sun, J. and Tang, X. (2011) Single Image Haze Removal Using Dark Channel Prior. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **33**, 2341-2353. <https://doi.org/10.1109/tpami.2010.168>
- [6] Cai, B., Xu, X., Jia, K., Qing, C. and Tao, D. (2016) Dehazenet: An End-to-End System for Single Image Haze Removal. *IEEE Transactions on Image Processing*, **25**, 5187-5198. <https://doi.org/10.1109/tip.2016.2598681>
- [7] Ren, W., Liu, S., Zhang, H., Pan, J., Cao, X. and Yang, M. (2016) Single Image Dehazing via Multi-Scale Convolutional Neural Networks. In: Leibe, B., Matas, J., Sebe, N. and Welling, M. Eds., *Lecture Notes in Computer Science*, Springer International Publishing, 154-169. https://doi.org/10.1007/978-3-319-46475-6_10
- [8] Li, B., Peng, X., Wang, Z., Xu, J. and Feng, D. (2017) AOD-Net: All-in-One Dehazing Network. 2017 *IEEE International Conference on Computer Vision (ICCV)*, Venice, 22-29 October 2017, 4780-4788. <https://doi.org/10.1109/iccv.2017.511>
- [9] Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A. and Bengio, Y. (2014) Generative Adversarial Nets. *Proceedings of the*

- International Conference on Neural Information Processing Systems*, Montreal, 8-13 December 2014, 2672-2680.
- [10] Khatun, A., Haque, M.R., Basri, R. and Uddin, M.S. (2020) Single Image Dehazing: An Analysis on Generative Adversarial Network. *Journal of Computer and Communications*, **8**, 127-137. <https://doi.org/10.4236/jcc.2020.84010>
 - [11] Khatun, A., Mostafiz, R., Shorif, S.B., Uddin, M.S. and Hadi, M.A. (2024) Dehazing Using Generative Adversarial Network—A Review. *SN Computer Science*, **6**, Article No. 57. <https://doi.org/10.1007/s42979-024-03571-0>
 - [12] Wu, J., Ding, B., Zhang, B. and Ding, J. (2024) A Retinex-Based Network for Image Enhancement in Low-Light Environments. *PLOS ONE*, **19**, e0303696. <https://doi.org/10.1371/journal.pone.0303696>
 - [13] Berman, D., Treibitz, T. and Avidan, S. (2016) Non-Local Image Dehazing. 2016 *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Las Vegas, 27-30 June 2016, 1674-1682. <https://doi.org/10.1109/cvpr.2016.185>
 - [14] Isola, P., Zhu, J., Zhou, T. and Efros, A.A. (2017) Image-to-Image Translation with Conditional Adversarial Networks. 2017 *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Honolulu, 21-26 July 2017, 1125-1134. <https://doi.org/10.1109/cvpr.2017.632>
 - [15] Li, R., Pan, J., Li, Z. and Tang, J. (2018) Single Image Dehazing via Conditional Generative Adversarial Network. 2018 *IEEE/CVF Conference on Computer Vision and Pattern Recognition*, Salt Lake City, 18-23 June 2018, 8202-8211. <https://doi.org/10.1109/cvpr.2018.00856>
 - [16] Malav, R., Kim, A., Sahoo, S.R. and Pandey, G. (2019) DHSGAN: An End to End Dehazing Network for Fog and Smoke. In: Jawahar, C., Li, H., Mori, G. and Schindler, K., Eds., *Lecture Notes in Computer Science*, Springer International Publishing, 593-608. https://doi.org/10.1007/978-3-030-20873-8_38
 - [17] Engin, D., Genc, A. and Ekenel, H.K. (2018) Cycle-Dehaze: Enhanced CycleGAN for Single Image Dehazing. 2018 *IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, Salt Lake City, 18-22 June 2018, 938-946. <https://doi.org/10.1109/cvprw.2018.00127>
 - [18] Zhu, J., Park, T., Isola, P. and Efros, A.A. (2017) Unpaired Image-to-Image Translation Using Cycle-Consistent Adversarial Networks. 2017 *IEEE International Conference on Computer Vision (ICCV)*, Venice, 22-29 October 2017, 2242-2251. <https://doi.org/10.1109/iccv.2017.244>
 - [19] Qin, X., Wang, Z., Bai, Y., Xie, X. and Jia, H. (2020) FFA-Net: Feature Fusion Attention Network for Single Image Dehazing. *Proceedings of the AAAI Conference on Artificial Intelligence*, **34**, 11908-11915. <https://doi.org/10.1609/aaai.v34i07.6865>
 - [20] Luo, Y., Chen, K., Liu, L., Liu, J., Mao, J., Ke, G., et al. (2020) Dehaze of Cataractous Retinal Images Using an Unpaired Generative Adversarial Network. *IEEE Journal of Biomedical and Health Informatics*, **24**, 3374-3383. <https://doi.org/10.1109/jbhi.2020.2999077>
 - [21] Ma, Y., Xu, J., Jia, F., Yan, W., Liu, Z. and Ni, M. (2022) Single Image Dehazing Using Generative Adversarial Networks Based on an Attention Mechanism. *IET Image Processing*, **16**, 1897-1907. <https://doi.org/10.1049/ipr2.12455>
 - [22] Johnson, J., Alahi, A. and Fei-Fei, L. (2016) Perceptual Losses for Real-Time Style Transfer and Super-Resolution. In: Leibe, B., Matas, J., Sebe, N. and Welling, M., Eds., *Lecture Notes in Computer Science*, Springer International Publishing, 694-711. https://doi.org/10.1007/978-3-319-46475-6_43

- [23] Li, B., Ren, W., Fu, D., Tao, D., Feng, D., Zeng, W., *et al.* (2019) Benchmarking Single-Image Dehazing and Beyond. *IEEE Transactions on Image Processing*, **28**, 492-505. <https://doi.org/10.1109/tip.2018.2867951>
- [24] Ancuti, C., Ancuti, C.O., Timofte, R. and De Vleeschouwer, C. (2018) I-HAZE: A Dehazing Benchmark with Real Hazy and Haze-Free Indoor Images. In: Blanc-Talon, J., Helbert, D., Philips, W., Popescu, D. and Scheunders, P., Eds., *Lecture Notes in Computer Science*, Springer International Publishing, 620-631. https://doi.org/10.1007/978-3-030-01449-0_52
- [25] Ancuti, C.O., Ancuti, C., Timofte, R. and De Vleeschouwer, C. (2018) O-HAZE: A Dehazing Benchmark with Real Hazy and Haze-Free Outdoor Images. 2018 *IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, Salt Lake City, 18-22 June 2018, 754-762. <https://doi.org/10.1109/cvprw.2018.00119>
- [26] Ancuti, C.O., Ancuti, C., Sbert, M. and Timofte, R. (2019) Dense-Haze: A Benchmark for Image Dehazing with Dense-Haze and Haze-Free Images. 2019 *IEEE International Conference on Image Processing (ICIP)*, Taipei, 22-25 September 2019, 1014-1018. <https://doi.org/10.1109/icip.2019.8803046>
- [27] Mittal, A., Moorthy, A.K. and Bovik, A.C. (2012) No-Reference Image Quality Assessment in the Spatial Domain. *IEEE Transactions on Image Processing*, **21**, 4695-4708. <https://doi.org/10.1109/tip.2012.2214050>
- [28] Zhang, R., Isola, P., Efros, A.A., Shechtman, E. and Wang, O. (2018) The Unreasonable Effectiveness of Deep Features as a Perceptual Metric. 2018 *IEEE/CVF Conference on Computer Vision and Pattern Recognition*, Salt Lake City, 18-23 June 2018, 586-595. <https://doi.org/10.1109/cvpr.2018.00068>