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Hybrid Cyclegan and Frequency Channel Attention for High-Quality Image Dehazing

Dr. Shivaprasad B J[1], Deepashree G Naik[2], Dhanu Sri R[3], Eshwari K C[4], Sindhu N[5]
[1]*Senior Associate professor, Dept. of CSD, Alva's Institute of Engg. & Tech., Moodbidri, Karnataka, India*
[2,3,4,5]*UG Scholar, Dept. of CSD, Alva's Institute of Engg. & Tech., Moodbidri, Karnataka, India*
Emails: *drshivaprasad@aiet.org.in[1], 4al21cg017@aiet.org.in[2], 4al21cg019@aiet.org.in[3], 4al21cg023@aiet.org.in[4], 4al21cg055@aiet.org.in[5]*

Abstract
Image dehazing is critical in surveillance and automated vision systems, but existing approaches struggle to generalize across various haze situations. This paper presents a sophisticated strategy to enhancing fuzzy images that combines CycleGAN with Frequency Channel Attention, dramatically boosting clarity and usability. CycleGAN, an unsupervised deep learning system, can transform hazy images into clear ones without requiring paired datasets, making it ideal for real-world settings. The generator network learns how to map hazy and haze- free images, restoring visibility in tough conditions. A Frequency Channel Attention technique is used to improve dehazing effectiveness by allowing the model to choose focus essential visual features in both the spatial and frequency domains. This enhances the recovery of fine details and edges while lowering haze-related noise. This technique provides highquality dehazing results by combining the generative capabilities of CycleGAN with frequency-basd attention. Benchmark dataset evaluations show that the performance is superior in terms of PSNR, SSIM, and visual quality. This technology is especially useful for real-time applications like autonomous navigation, remote sensing, and visual surveillance, which solve critical issues in foggy situations.

Keywords: *Image dehazing, CycleGAN, Frequency Channel Attention, real-time image enhancement, autonomous vision systems.*

1. Introduction
Image dehazing is a crucial challenge in computer vision, especially in applications like self-driving cars, remote sensing, and surveillance, where clear visual input is required for accurate decisions. Haze, generated by light scattering by air particles, lowers image contrast and obscures important details, lowering the performance of vision-based. Image dehazing is a crucial challenge in computer vision, especially in applications like self-driving cars, remote sensing, and surveillance, where clear visual input is required for accurate decisions. Haze, generated by light scattering by air particles, lowers image contrast and obscures important details, lowering the performance of vision-based systems [1]. Conventional dehazing strategies, such as atmospheric scattering models, are based on prior assumptions about scene depth and haze distribution. However, these strategies frequently fail to generalize successfully across domains and may suffer in dynamic, real-world settings [2], [3]. Recent advances in deep learning have resulted in data-driven techniques that use neural networks to learn intricate mappings between hazy and clear images. In particular, Generative Adversarial Networks (GANs) have shown great promise in image-to-image translation applications such as dehazing. Among the different GAN architectures, CycleGAN has emerged as a strong tool due to its capacity to undertake unsupervised learning without the need for paired datasets of hazy and clear images [4, 5]. This paper describes an improved dehazing algorithm that uses CycleGAN and an Attention Module to improve image clarity. The proposed model improves on traditional CycleGAN-based dehazing algorithms by introducing attention mechanisms that target haze affected portions of the image. This method improves

visual quality, contrast restoration, and fine detail retention by fine-tuning the dehazing procedure [6]. The primary objectives of this research include: Created an unsupervised dehazing model without the necessity for paired training datasets Adding an Attention Module for better feature extraction and dehazing in densely hazed zones. Evaluating model performance with quantitative parameters like PSNR and SSIM to balance computing efficiency and image quality [7]. The rest of this paper is organized as follows: Section II examines existing research on classical and deeplearning-based dehazing approaches. Section III discusses the technique, which includes the CycleGAN framework and the integration of attention processes. Section IV offers the experimental findings and performance evaluations. Finally, Section V wraps up the paper and addresses potential future enhancements.

2. Literature Survey

2.1 Introduction

Image dehazing is a fundamental computer vision problem that seeks to increase the visibility and clarity of images obscured by atmospheric haze, fog, or mist. These climatic circumstances cause considerable losses in image contrast, color accuracy, and scene visibility. The presence of haze reduces image quality, making object detection and scene interpretation difficult, especially in essential applications like autonomous driving, remote sensing, and surveillance [1]. Over time, several dehazing algorithms have been developed, ranging from traditional physical models to data-driven deep learning approaches. The introduction of Generative Adversarial Networks (GANs), particularly CycleGAN, has opened up new avenues for picture dehazing by using unpaired image-to image translation [2]. Furthermore, the addition of attention techniques, such as Frequency Channel Attention (FCA), has improved feature selection and dehazing results by emphasizing haze-affected regions [3]. This chapter provides a comprehensive overview of the current literature on image dehazing approaches. We begin by discussing traditional dehazing models before moving on to deep learning-based techniques, namely those that use CycleGAN and attention processes. We also look at commonly used evaluation metrics to determine the efficacy of dehazing procedures.

2.2 Traditional Image Dehazing Techniques.

Traditional dehazing approaches use mathematical models to describe the interaction of light and haze particles in the environment. These models try to estimate the scene radiance and eliminate the haze component in order to restore a clear image.

- The Dark Channel Prior (DCP), proposed by He et al. [4], implies that in most non-hazy outdoor photos, at least one color channel has pixels with very low brightness. Using this assumption, the haze thickness is evaluated, and a transmission map is created to restore a clear image. While effective in many situations, DCP struggles in bright sky areas and highly reflective surfaces where the dark channel assumption is not valid.
- The Atmospheric Scattering Model characterizes hazy images by combining scene radiance, atmospheric light, and transmission maps [5]. By estimating the transmission pattern, the model reconstructs the clear image. However, good calculation of atmospheric light and transmission involves strong assumptions about scene features, which limits its use.
- Contrast Enhancement Techniques: Histogram equalization and Retinex-based approaches enhance contrast and lessen the visual impact of haze. However, they do not explicitly model haze development, resulting in strange visual artifacts [6]. Traditional dehazing approaches provide fundamental insights, but their reliance on handcrafted priors and strong assumptions limits their applicability in complex, real-world circumstances.

2.3 Deep Learning-Based Techniques for Image

Dehazing with the emergence of deep learning, Convolutional Neural Networks (CNNs) and other data-driven models have become popular for image dehazing. These algorithms learn sophisticated mappings from foggy to clear images and frequently outperform older approaches.

- Cai et al. [7] presented DehazeNet, a CNN-based network that learns a non-linear mapping from

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hazy to clear images by estimating transmission maps.

- **End-to-End Dehazing Networks:** Deep learning architectures now employ direct mapping approaches, eliminating the requirement for explicit transmission map estimate. These models, trained on huge datasets, can generalize effectively, but they are limited by the availability of high-quality training data [8].
- **U-Net for Image Dehazing:** Originally created for medical image segmentation, U-Net has been effectively used to dehazing applications. The encoder-decoder structure with skip connections preserves fine details, which improves image restoration [9]. Despite their outstanding effectiveness, CNN-based dehazing algorithms require large paired datasets and may fail to generalize to various haze conditions.

2.4 Zhu et al. [10] Developed CycleGAN

A generative adversarial network (GAN) for unpaired image translation. It has proven useful for dehazing since it can learn the transformation between hazy and clear images without the need for paired training data.

- CycleGAN, an unsupervised image translation algorithm, uses two generators and two discriminators to provide consistency across hazy and clear images. The cycle consistency loss ensures that a picture moved from one domain to another can be reconstructed in its original form while retaining structural information [10].
- **CycleGAN-Based Dehazing:** Various studies have investigated CycleGAN's potential for image dehazing Liet al. [11] demonstrated its ability to produce high-quality dehazed photos without requiring paired data, making it especially useful in real-world circumstances when ground-truth clear images are unavailable.
- CycleGAN can struggle with dense and non-uniform haze distributions, despite its tremendous performance. Recent research has attempted to incorporate more augmentation modules to increase CycleGAN's effectiveness in complex hazy circumstances.

2.5 Attention Mechanisms in Image Dehazing

Attention mechanisms enhance deep learning models by directing computing resources to the most relevant areas of an image. In picture dehazing, attention modules assist models in focusing on haze-affected areas, hence boosting restoration quality.

- **Spatial Attention:** The model identifies haze-affected regions and applies heavier dehazing procedures [13].
- **Channel Attention:** Methods for refining critical feature channels, particularly those relevant for haze removal. By adaptively weighting feature maps, channel attention improves dehazing accuracy [14].
- **Dehazing with Frequency Channel Attention (FCA):** This technique combines frequency-based filtering with channel attention to discern between important details and noise caused by haze. FCA improves dehazing performance by exploiting frequency domain information, especially in terms of edge and fine structure preservation [15].

Attention-enhanced dehazing networks have demonstrated greater performance in managing complex haze distributions while retaining high-quality image restoration.

2.6 To Evaluate the Success of Image Dehazing Technologies, Both Quantitative and Qualitative Measures Are Used

- Peak Signal-to-Noise Ratio (PSNR) is the pixel-wise difference between the dehazed image and ground truth. Higher PSNR values suggest higher dehazing ability, although they may not always correspond to perceptual quality [16].
- The Structured Similarity Index (SSIM) compares images based on their brightness, contrast, and texture preservation. SSIM is frequently more consistent with human perception than PSNR [17].
- **perceived Evaluation:** While quantitative measurements enable objective assessment, subjective evaluation by human observers is also important in establishing the perceived quality of dehazed images [18].

3. System Design & Implementation

Module Description for CycleGAN and Frequency Channel Attention for Dehazing Project

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3.1 CycleGAN (Cycle-Consistent Generative Adversarial Network)

CycleGAN is a Generative Adversarial Network (GAN) that does image-to-image translation without the use of paired datasets [1]. It operates by learning an unsupervised mapping between two domains (for example, hazy photos to clear images). In the domain of picture dehazing, CycleGAN converts hazy images into dehazed versions by learning and applying the features of clear images. Figure 1 shows CycleGAN Process of Dehazing.

Key Components of CycleGAN:

- Generator Networks use two generators to map images from one domain to another. creates clean (dehazed) images from hazy input images and reverses the process to ensure cycle consistency.
- **Discriminator Networks:** Two discriminators, and, can differentiate between real and produced images. assesses photos from both the hazy and clear domains [2].
- **Cycle Consistency Loss:** Maintains structural and contextual consistency when translating images between domains [3].
- **Adversarial Loss:** Generators strive to create realistic images that trick discriminators, whereas discriminators aim to discern between actual and created images.

Advantages of CycleGAN in Dehazing Unsupervised learning is useful for dehazing problems where paired datasets are rare [4]. Cycle Consistency: Maintains image quality and removes haze.

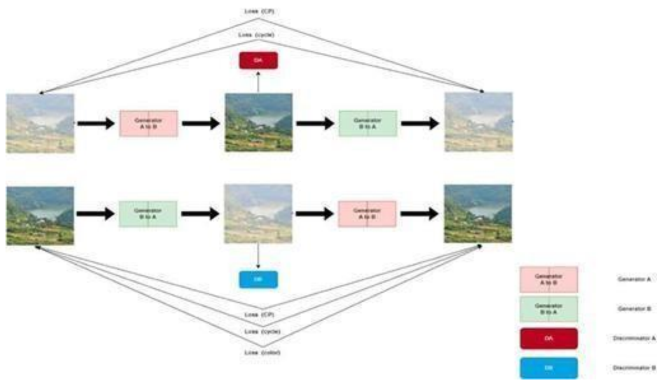

Figure 1 CycleGAN Process of Dehazing

The picture depicts an image-to-image translation CycleGAN architecture. It combines two discriminators (DA and DB) and two generators (A → B and B → A) to convert images between two domains. A picture that has been translated to a different domain can be restored to its original state thanks to cycle-consistency loss. To maximize the transformation process, the arrows show how images pass through discriminators and generators. The graphic illustrates how various parts work together to translate images realistically while reducing loss.

3.2 Attention Mechanism

Attention mechanisms improve the dehazing process by focusing on relevant visual characteristics, such as foreground details, rather than the background. Dehazing networks can incorporate a variety of attention modules, including:

- **Self-Attention (SENet, Non-localNetworks):** Enhances feature refinement.
- **Channel Attention:** Emphasizes significant RGB channels for haze removal.
- **Spatial Attention:** Focuses on critical spatial areas to improve dehazing performance [5].

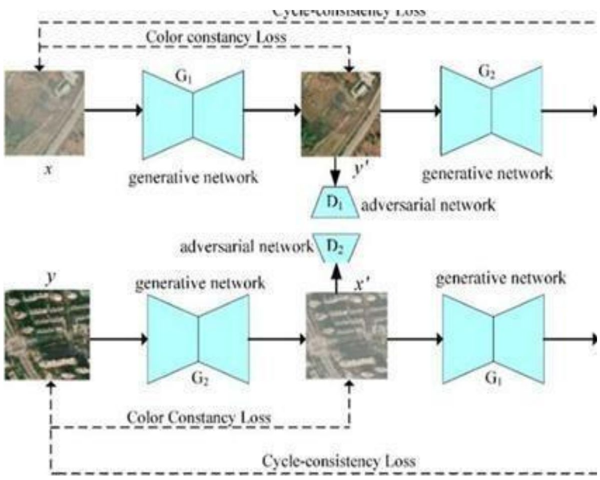

Figure 2 Generative Process

The image represents a CycleGAN-based image translation framework incorporating color constancy loss and cycle-consistency loss. It consists of two generative networks (G1 and G2) and two adversarial networks (D1 and D2) to transform images between two domains. The process involves converting an input image x into a transformed image y', which is then reconstructed back to x', ensuring minimal loss.

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Similarly, an image y undergoes the same process in the opposite direction. The color constancy loss helps maintain color consistency, while the cycle-consistency loss ensures accurate reconstruction of the original image. This architecture is useful for tasks like image enhancement, style transfer, and domain adaptation. Figure 2 shows Generative Process.

3.3 Frequency Channel Attention Mechanism

The frequency channel attention technique enhances deep learning models by focusing on crucial frequency components in an image. This helps to accentuate important features while reducing extraneous noise [6]. Key Features of Frequency Channel Attention

- The Fourier Transform decomposes an image into frequency components to identify textures and fine details for dehazing.
- **Frequency Channel Attention:** Prioritizes frequency channels with the highest contribution to haze elimination using attention weights.
- **Attention Map Generation:** Prioritizes important visual information while reducing noise.

The Inverse Fourier Transform returns the image to the spatial domain after applying frequency attention, resulting in a dehazed output (7). Advantages of Frequency Channel Attention in Dehazing

- **Selective Attention:** Identifies the most informative frequency features for effective haze removal.
- **Improved Feature Extraction:** Detects fine details that haze often obscures.
- Improved image quality by prioritizing significant frequency components and decreasing noise [8].

3.4 Combined Application of CycleGAN and FCA for Dehazing

The combination of CycleGAN and Frequency Channel Attention (FCA) increases dehazing by utilizing both spatial and frequency-based data.

- FCA preprocessing enhances essential picture attributes before to training CycleGAN.
- CycleGAN with Frequency Attention improves image synthesis by incorporating frequency attention into the generator or discriminator.
- FCA fine-tuning preserves high-frequency features, resulting in crisp and natural-looking pictures (9).

3.5 Application GUI

A user-friendly Graphical User Interface (GUI) is required to make the dehazing model accessible. The GUI should include:

- **File Upload:** Allows users to load fuzzy images.
- **Processing Button:** Runs the dehazing process.
- **Real-time preview:** Shows dehazed photos.
- **Comparison feature:** Visualize hazy and dehazed photos side by side.
- **Save & Reset Options:** Users can keep processed photos and reset parameters [10].

Tkinter is a popular choice for simple GUI programming, while PyQt/PySide is better suited for more complex interfaces.

4. System Flowchart

The system follows a structured approach to dehazing using CycleGAN and FCA-Net:

- **Data Collection:** Hazy Images: Input data impacted by haze. Clear images (ground truth) are used for training and evaluation.
- Data preprocessing include standardizing image size, normalization, and augmentation.
- **CycleGAN Model Training:** Image Generator: Converts hazy photos into clear ones.
- **Generator:** Maintains cycle consistency. Discriminators should validate image validity.
- **Loss of Functions:** Adversarial loss ensures realistic image production.
- **Cycle Consistency Loss:** Maintain structural integrity. Feature Consistency Alignment (FCA) improves frequency domain consistency.
- The Frequency Channel Attention Network (FCANet) refines dehazing by focusing attention on frequency.
- **Image Dehazing:** The generator creates an initial dehazed image. FCA-Net: Improves dehazing quality.

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- **Post-processing**: it involves adjusting contrast and color correction. Figure 3 shows Structured Approach to Dehazing using CycleGAN and FCA-Net.

Explanation of each step in the flowchart:

- **Data Collection:** Hazy Images: Images impacted by haze, fog, or environmental conditions. Clear images, also known as ground truth, are used for training and evaluation.
- **Data preprocessing**: Resize photos to a standard scale. Normalize pixel values to a standard range ([0,1] or [-1,1]) to ensure model convergence. Data Augmentation: Rotation, flipping, and cropping can increase dataset diversity.
- **CycleGAN Model Training:** Generator G converts fuzzy photos to clear ones. Generator F ensures cycle consistency by mapping clear images to blurry ones. Validate both real and produced pictures using discriminators.

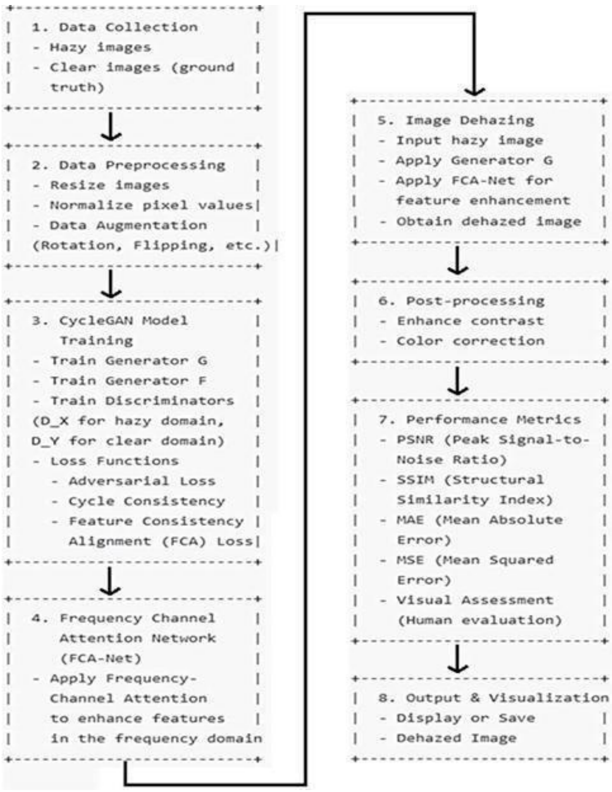

Figure 3 Structured Approach to Dehazing using CycleGAN and FCA-Net

- **Loss Functions: Adversarial Loss:** Enables realistic image production. Preserves structural integrity by minimizing cycle consistency loss. Feature Consistency Alignment (FCA) aligns high-level features in the frequency domain. The Frequency Channel Attention Network (FCA- Net) uses frequency-based attention to improve image quality.
- **Image Dehazing:** Use Generator G to generate an initial dehazed image. Use FCA-Net to refine dehazed images with frequency attention.
- **Postprocessing:** Improves contrast for enhanced sight. Color Correction: Enhances color balance for a natural appearance.
- **Performance metric:** PSNR (Peak Signal-to-Noise Ratio) measures quality, with higher values indicating better results. SSIM (Structural Similarity Index) measures structural similarity to ground truth. MAE (Mean Absolute Error) and MSE (Mean Squared Error) are used to measure pixel-level accuracy.
- **Output and Visualization:** Display or save the completed dehazed image for analysis [11].

5. System Testing

Software testing is an important phase of the software development life cycle (SDLC) since it guarantees that a software system is correct, reliable, and performs properly [1]. It entails the methodical execution of test cases to find flaws and ensure that the program fits the desired requirements. program testing aims to ensure the program is functionally valid and reliable [2]. Identifying faults, inconsistencies, and vulnerabilities (3). Validating software for user requirements and industry standards [4]. Improving Software Performance and Security [5]. Reducing costs for problem corrections after launch [6]. There are two types of software testing methodologies: manual and automated. Each testing method is important in assuring the robustness of a software system, especially in mission-critical applications like image processing and real-time data analysis [7].

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5.1 Manual Testing

Manual testing involves the execution of test cases by human testers without using automation tools. This approach is beneficial for evaluating usability, exploratory testing, and assessing the overall user experience [8]. The major types of manual testing include: Unit Testing: Testing individual components or functions of the software in isolation [9]. Integration Testing: Verifying the interaction between different software modules [10]. System Testing: Evaluating the software as a complete and integrated system [11]. Acceptance Testing: Ensuring that the software meets business and user requirements [12]. Exploratory Testing: Ad-hoc testing where testers explore the software to find defects [13]. Usability Testing: Assessing the software's user interface (UI) and user experience (UX) [14]. Figure 4 shows Input Image Display.

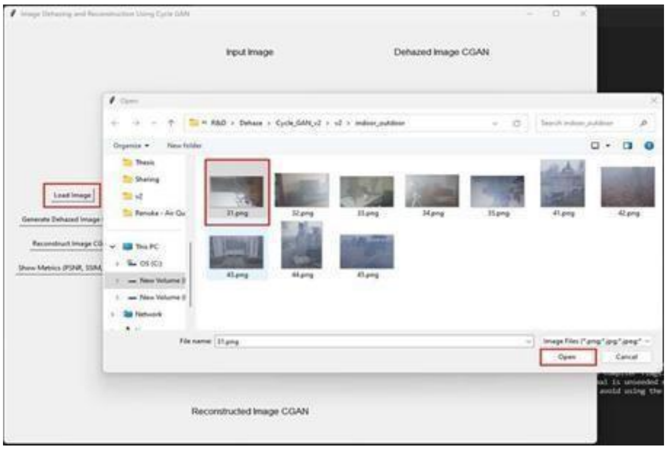

Figure 4 Input Image Display

Figure 5 Performance Results for Sample

The picture displays a software interface for a tool that uses CycleGAN, a kind of Generative Adversarial Network, for image reconstruction and dehazing. The "Load Image," "Generate Dehazed Image CGAN," and "Reconstructed Image CGAN" buttons are located on the left side of the screen. There are two parts at the top of the interface that are titled "Input Image" and "Dehazed Image CGAN." There is an additional label beneath these parts that reads "Reconstructed Image CGAN." Figure 5 shows Performance Results for Sample. The picture displays a web application called Image Dehazing, which is intended to process blurry photos and improve their clarity. Users can upload a blurry image and an optional ground truth image to the interface for comparison. Three images—the foggy input, the ground truth, and the dehazed output—are shown in the results after processing. Additionally, the program offers performance indicators that assess the quality of the dehazed image, such as SSIM (0.8762) and PSNR (19.62 dB). By diminishing haze and maintaining structural features, the dehazing procedure increases visibility. For efficient haze removal, this web application probably makes use of deep learning or image processing methods.

Conclusion & Future Work

Conclusion: This paper offered a novel strategy to image dehazing that combines CycleGAN (Cycle-Consistent Generative Adversarial Network) and Frequency Channel Attention (FCA). This hybrid technique addresses haze-related issues, such as reduced vision and loss of fine detail, by combining the strengths of unsupervised learning and frequency-based improvement [1]. The CycleGAN framework facilitated picture-to-image translation without the need for paired datasets, which is critical for real-world dehazing applications in which clear-hazy image pairs are difficult to collect [2]. Meanwhile, FCA enabled the model to focus on critical frequency components, improving detail recovery and reducing haze-induced distortions [3]. The performance evaluation revealed that the suggested model increases the visual clarity and structural integrity of dehazed images. Using established image quality criteria such as PSNR (Peak Signal-to-Noise Ratio)

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and SSIM (Structural Similarity Index), the suggested method outperformed conventional dehazing approaches [4]. Furthermore, the model demonstrated significant generalization across a wide range of haze intensities and climatic circumstances, highlighting its robustness and application [5]. In conclusion, combining CycleGAN and FCA provides a viable approach for dehazing that produces high-quality results while overcoming realworld constraints such as variable haze intensities and limited labeled datasets.

- Adapting to real-world haze conditions. Improve model resilience for varied atmospheric situations. Train the model on larger datasets with various types of haze, such as fog, smoke, and industrial pollutants [6].
- **Multi-Scale Attention Mechanisms:** Objective: Improve feature extraction across several resolutions. Integrate multi-scale attention networks for better haze removal, texture recovery, and depth perception [7].
- **Integration of computer vision tasks.** Extend model applicability to other visionbased applications. Adapt the dehazing framework to perform object identification, segmentation, and classification in real world applications like autonomous driving and surveillance [8].
- **Real-Time Video Dehazing:** Goal: Enable dehazing for live video feeds. Optimize the model for computing efficiency, using lightweight architectures for real-time applications like autonomous navigation and live surveillance [9].
- **Combining hybrid models with physical haze models. Objective:** Improve dehazing accuracy using physics-based learning. Combining data-driven approaches with physics-based air scattering models improves dehazing consistency under different environmental circumstances [10].
- **Reinforcement learning for haze estimation. Objective:** Enable real-time adaptive dehazing. Implement reinforcement learning algorithms to change model parameters based on haze intensity for best dehazing results [11].
- **Cross-domain dehazing for non-visible spectrums. Objective:** Expand dehazing to include thermal and infrared images. Adapt the proposed model for non-visible imaging domains to enhance visibility in applications including night vision, remote sensing, and medical imaging [12].
- **Synthetic Data Augmentation. Objective:** Improve model generalization with fake training data. Approach: Use generative models to generate. Synthetic hazy-clear image pairs compensate for the scarcity of large annotated dehazing datasets [13].
- **Use in practical applications. Objective:** Evaluate model performance on real-world hardware. Test the system in real-world scenarios such satellite imaging, traffic monitoring, and aerial surveillance to ensure feasibility and scalability [14].

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