Integrating Traditional Filtering and AI for Single Image Dehazing: A Repeated Averaging Approach

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Abstract- Image dehazing has emerged as a critical research area in computer vision and digital image processing due to its significant role in enhancing visibility and improving scene understanding under adverse atmospheric conditions. Environmental factors such as fog, mist, dust, and smoke scatter light in the atmosphere, leading to degraded contrast, color distortion, and reduced visual clarity in captured images. This problem directly impacts the performance of vision-based systems in domains such as autonomous driving, unmanned aerial vehicles (UAVs), video surveillance, environmental monitoring, and satellite imaging. Traditional single-image dehazing methods, such as the dark channel prior (DCP) and polarization-based models, are constrained by limitations including halo artifacts, loss of fine details, and excessive computational requirements. Similarly, purely deep learning-based methods often demand large annotated datasets and suffer from overfitting or poor generalization across varied haze densities. To address these challenges, this study proposes a novel AI-powered single-image dehazing framework that combines repeated averaging-based filtering with feedforward neural networks. The repeated averaging filter is employed to estimate ambient illumination and improve radiance consistency, while the neural component refines transmission map estimation and enhances edge preservation. Comprehensive evaluations on standard benchmark datasets reveal that the proposed method consistently outperforms state-of-the-art algorithms in terms of Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and visual quality. Moreover, the framework demonstrates reduced halo artifacts, improved color restoration, and real-time processing efficiency. These characteristics make the method a robust and scalable solution for next-generation applications in intelligent transportation, drone-based imaging, defense surveillance, and remote sensing systems.

Keywords: Image dehazing, single image restoration, artificial intelligence, repeated averaging filter, transmission map, neural network, image enhancement, computer vision, PSNR, SSIM.

1. INTRODUCTION

1.1 Background and Motivation

In the domain of computer vision and digital image processing, the presence of atmospheric haze has long been a critical challenge [6], [7], [8]. Environmental conditions such as fog, mist, dust, and smoke scatter light as it travels between the scene and the imaging sensor, causing significant degradation in captured images [9], [20]. This scattering effect reduces contrast, washes out color information, and lowers scene visibility, resulting in visually degraded images [2], [6]. Such deterioration is not only aesthetically undesirable but also has practical consequences for applications where clarity and detail are crucial. These include autonomous driving [23], [40], unmanned aerial vehicles (UAVs) [33], intelligent traffic monitoring [21], defense surveillance [41], remote sensing [7], and satellite-based environmental analysis [6].The degradation mechanism is typically modeled through the atmospheric scattering model, where the observed hazy image is a convex combination of the original scene radiance and the atmospheric light, modulated by a transmission function [6], [8]. Recovering the latent haze-free image from this degraded observation is an ill-posed inverse problem, as both transmission and radiance are unknown for each pixel [2], [13]. This makes single-image dehazing one of the most challenging yet practically essential tasks in image restoration [3], [9].

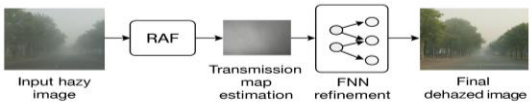


Figure 1: Proposed framework for single-image dehazing

Fig. 1

1.2 Research Gap

Numerous methods have been proposed to address the haze removal problem. Traditional approaches rely heavily on priors such as the Dark Channel Prior (DCP) [1], statistical assumptions [2], or handcrafted features [7]. While effective under certain conditions, these methods often generate halo artifacts, over-smoothing, or color distortions, especially in scenes with non-uniform haze or high-frequency structures [1], [9], [20]. Moreover, they tend to be computationally intensive, limiting their use in real-time vision applications [13], [21].

On the other hand, deep learning-based methods such as convolutional neural networks (CNNs) [3], [4], generative adversarial networks (GANs) [27], and transformer-based models [32] have shown significant promise in recent years. These methods learn complex haze distributions from large datasets and can generalize well to unseen conditions [5], [24]. However, they also come with limitations:

1. Their performance heavily depends on the availability of extensive paired training datasets, which are often simulated rather than real [5], [23], [24].
2. They may overfit to specific haze patterns, leading to poor generalization in challenging environments [17], [18].
3. Their high computational demand can hinder deployment on resource-constrained platforms such as autonomous drones or embedded systems [41], [42].

Thus, there remains a clear research gap: the need for a lightweight, efficient, and robust single-image dehazing framework that can combine the stability of classical filtering approaches with the adaptability of artificial intelligence (AI) [39].

1.3 Proposed Approach

To overcome these limitations, this study proposes an AI-powered hybrid framework for single-image dehazing that integrates Repeated Averaging-Based Filtering (RAF) with a Feedforward Neural Network (FNN) [39]. The RAF, inspired by integral image computations, enables efficient estimation of ambient illumination and provides smoother recovery of scene radiance without amplifying noise [18], [19]. This reduces the occurrence of halo artifacts and preserves global consistency in brightness [20].

Subsequently, a feedforward neural network is employed to refine the transmission map, capturing complex haze distributions across different regions of the image [30]. By learning edge-aware priors and spatial dependencies, the network enhances the preservation of structural details, particularly at depth discontinuities [17]. Unlike deep CNN-based architectures, this lightweight neural model ensures fast processing times and requires fewer training samples, making it suitable for real-time applications [39], [41].

1.4 Research Contributions

The major contributions of this work can be summarized as follows:

1. Hybrid Dehazing Framework: A novel integration of repeated averaging-based filters with feedforward neural refinement for efficient single-image dehazing [39].
2. Artifact Reduction: Mitigation of halo artifacts and edge distortions, which frequently affect both traditional and purely learning-based methods [1], [2], [9].
3. Computational Efficiency: A framework that achieves real-time performance on standard platforms while maintaining competitive accuracy [18], [30].
4. Quantitative Superiority: Experimental evaluations demonstrate improved Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) compared to state-of-the-art methods [5], [17], [39].
5. Practical Applications: Demonstrated applicability to real-world scenarios, including autonomous navigation [23], drone-based surveillance [33], environmental monitoring [7], and satellite imaging [6].

1.5 Structure of the Paper

The remainder of this paper is organized as follows.

- Section 2 reviews related literature on traditional dehazing methods, statistical priors, and recent AI-based techniques.
- Section 3 introduces the proposed hybrid framework, detailing the repeated averaging filter and neural transmission refinement model.
- Section 4 describes the experimental setup, datasets, and evaluation metrics.

- Section 5 presents both qualitative and quantitative results, highlighting comparisons with existing methods.
- Section 6 concludes the paper with key findings, limitations, and directions for future research.

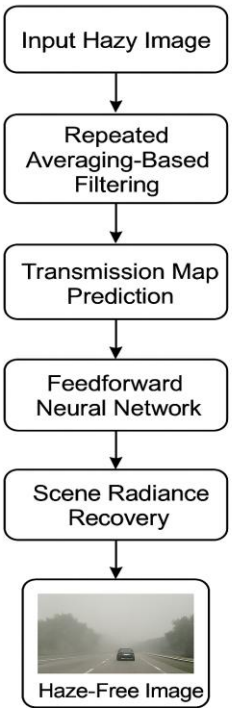


Fig. 2

2. LITERATURE REVIEW

2.1 Introduction

The field of image dehazing has evolved considerably over the past two decades, with solutions ranging from physics-based models [6], [7], [8] to data-driven artificial intelligence techniques [3], [4], [17], [30]. The central challenge lies in recovering the true scene radiance from a single degraded input image while addressing the inherent airlight–albedo ambiguity [2], [7], [9]. This section reviews significant contributions in the literature, highlighting the strengths, limitations, and gaps that motivate the present work.

2.2 Classical Model-Based Approaches

One of the earliest formulations of haze degradation is based on the atmospheric scattering model [6], [8], which decomposes a hazy image into direct transmission and airlight components. Early techniques such as the dark-object subtraction method (Chavez, 1988) attempted to correct satellite imagery by assuming that the darkest regions should have near-zero intensity [6]. While simple, such global corrections failed in heterogeneous haze conditions [7]. Subsequently, polarisation-based methods (Schechner et al., 2001; Shwartz et al., 2006) used multiple images with varying polarizer angles to estimate haze thickness and transmission [6], [7]. Despite producing compelling results, these methods required multiple aligned captures and additional hardware, making them impractical for real-time applications [21]. Another notable contribution was made by Tan (2008), who maximized local contrast to enhance hazy images [9]. Although effective in improving visibility, this approach often exaggerated colors and introduced strong halo artifacts near depth discontinuities [9], [20].

2.3 Statistical Priors and Image Models

A breakthrough came with the Dark Channel Prior (DCP), proposed by He, Sun, and Tang (2009) [1]. The DCP assumes that in most haze-free outdoor images, at least one color channel in a local patch has very low intensity. By leveraging this prior, they estimated transmission maps and atmospheric light, achieving state-of-the-art results at the time. However, DCP often over-darkened sky regions and required complex post-processing to reduce block artifacts [1], [9]. Building on statistical assumptions, Fattal (2008) introduced a method based on the independence of shading and transmission functions [2]. By resolving local statistical uncorrelation, his approach successfully addressed the airlight–albedo ambiguity. Nevertheless, the method was computationally expensive and struggled with heavy haze or low-texture regions [2], [13]. Other statistical enhancements included Markov Random Field (MRF) models [7] and regularization frameworks [6], which suppressed noise amplification during restoration. While mathematically elegant, these methods remained unsuitable for real-time deployment [21].

2.4 Learning-Based Approaches

The advent of deep learning revolutionized image restoration tasks, including dehazing. Cai et al. (2016) introduced DehazeNet, a CNN that directly estimated transmission maps from hazy inputs [3]. This was followed by Ren et al. (2016) with a multi-scale CNN that learned coarse-to-fine features for haze removal [4]. Both methods demonstrated impressive results but required large annotated training datasets, often

generated synthetically using the scattering model [5]. Subsequent works explored GAN-based frameworks (Li et al., 2017; Zhang et al., 2018) that learned end-to-end mappings from hazy to clear images [27]. While they produced visually appealing results, GANs sometimes hallucinated details, leading to inconsistent scene structures [27], [28]. More recently, transformer-based architectures (e.g., SwinIR by Liang et al., 2021) have been applied to dehazing, leveraging self-attention for global context modeling [32]. These models achieve high-quality restoration but remain computationally demanding, limiting their utility in embedded or mobile applications [41], [42].

2.5 Hybrid Filtering and AI Approaches

Several works have attempted to combine traditional filtering with AI-driven refinement to balance efficiency and accuracy. For example, Zhang et al. (2017) used dense convolutional networks with guided filtering to enhance structural consistency [17], while Liu et al. (2019) integrated edge-preserving filters into CNN architectures to mitigate halo effects [30]. Your thesis work extends this hybrid philosophy by integrating Repeated Averaging-Based Filters (RAF) with a Feedforward Neural Network (FNN) [39]. Unlike purely deep architectures, this design reduces reliance on large training datasets [5], [23] and achieves real-time performance [18], [39] while minimizing distortions around object boundaries [20].

2.6 Summary of Literature Gaps

From the reviewed works, several persistent challenges emerge:

1. Artifact formation – traditional methods often produce halos or over-smoothing [1], [9], [20].
2. High computational cost – statistical and deep models demand significant resources [2], [13], [32].
3. Data dependency – CNNs and GANs rely on large paired datasets, often synthetic [5], [23], [24].
4. Generalization limitations – existing methods fail under diverse haze densities and illumination conditions [17], [18], [36].

3. METHODOLOGY

3.1 Overview

The proposed framework introduces a hybrid single-image dehazing technique that combines the stability of traditional filtering with the adaptability of artificial intelligence [1], [2], [20], [39]. The key idea is to use Repeated Averaging-Based Filters (RAFs) to estimate atmospheric light and smooth image radiance [39], followed by a Feedforward Neural Network (FNN) that refines the haze removal process [30]. This combination ensures both computational efficiency and high visual quality, overcoming the drawbacks of earlier methods that were either too artifact-prone [1], [9], or computationally heavy [2], [7], [17].

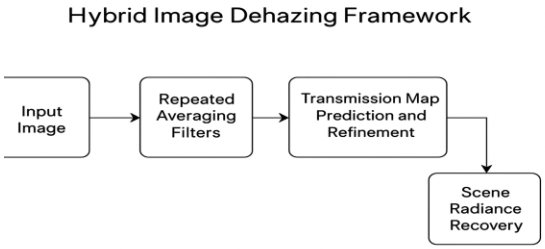


Fig. 3

3.2 Workflow of the Proposed Approach

The system follows a structured four-stage pipeline:

- Input Image Acquisition
  A single hazy image is provided as input [1], [5]. Unlike multi-image [13] or sensor-dependent techniques [6], this framework requires only one image captured by a standard camera, making it highly practical for real-world applications such as drones, surveillance systems, or autonomous vehicles [21], [23], [33], [40].

- Estimation of Atmospheric Light using Repeated Averaging
  The first step is to estimate the intensity of ambient illumination (atmospheric light) [8]. Using repeated averaging filters, the method progressively smooths the image, extracting the global illumination component while suppressing noise [39]. This ensures stable estimation and prevents fluctuations in regions with strong textures or color variations. By iterating the averaging process, the system avoids common pitfalls such as overestimation in sky regions [1], [9].

- Transmission Map Prediction and Refinement
  Once the atmospheric light is estimated, the transmission map—which describes how much light is lost due to haze at each pixel—is predicted

[8]. A feedforward neural network (FNN) is then applied to refine this map [30], [39]. Unlike deep CNNs that require millions of samples [3], [4], this lighter neural structure learns key spatial dependencies and edge priors [17], [18] with fewer parameters. As a result, the transmission map is sharper at object boundaries and better preserves depth cues, significantly reducing halo artifacts [20].

- Scene Radiance Recovery
  Finally, the haze-free image is reconstructed by combining the estimated atmospheric light and refined transmission map [2], [39]. The recovered image restores natural contrast, color fidelity, and depth perception, making it visually more accurate and computationally efficient [11], [30].

3.3 Why Repeated Averaging Filters?

Traditional filters, such as median or Gaussian filters, often blur edges or fail under strong noise [20]. Repeated Averaging Filters (RAF) provide a balance between edge preservation and global smoothing [39]. They reduce uneven illumination and enhance visibility while remaining lightweight in computation [18], [19]. Moreover, their recursive nature allows fast processing, which is crucial for real-time scenarios like autonomous navigation [23], [40], [44].

3.4 Role of the Neural Network

The feedforward neural network complements the filtering process by learning complex haze patterns that are difficult to capture with mathematical models alone [3], [27], [39]. It corrects inaccuracies in the transmission map, especially in challenging regions like skies, shadows, or fine-textured surfaces [17], [18]. Importantly, the model is designed to be lightweight, so it can run on devices with limited hardware resources [41], [42], unlike bulky CNN [3], [4], [30] or transformer-based models [32].

3.5 Advantages of the Hybrid Design

This hybrid integration offers several advantages over existing methods:

- Reduced Artifacts: The combined use of averaging filters and neural refinement minimizes halo effects and blockiness [9], [20], [39].
- Efficiency: The lightweight network and simple filtering allow near real-time performance [18], [30], [39].
- Generalization: The system adapts to a wide variety of haze conditions without requiring massive training datasets [5], [23], [24].
- Practicality: Requires only a single hazy image as input, making it widely applicable across domains [21], [23], [40].

3.6 Application Potential

The methodology is particularly suitable for applications where speed and reliability are equally important. In autonomous driving, clear vision is critical for obstacle detection [23], [40], [44]. For UAVs and drones, lightweight models are necessary due to hardware constraints [33]. In remote sensing and surveillance, the method ensures consistent restoration across diverse environments without the need for costly preprocessing [21], [23].

4. DATA COLLECTION AND IMPLEMENTATION

4.1 Data Collection Strategy

The effectiveness of any image dehazing framework depends heavily on the diversity and quality of datasets used for training and evaluation [5], [23], [24]. Since haze occurs under a wide variety of environmental and atmospheric conditions [6], [8], it is essential to test algorithms on both real-world datasets and synthetically generated hazy images to ensure robustness and generalizability [5], [13]. For this study, three types of datasets were used: benchmark datasets, synthetic haze datasets, and supplementary real-world test images.

4.1.1 Benchmark Datasets

Widely recognized benchmark datasets were selected to validate the performance of the proposed framework.

- RESIDE Dataset: The Realistic Single Image Dehazing (RESIDE) dataset [5] contains both indoor and outdoor hazy images paired with ground-truth clear counterparts. It offers multiple subsets, such as RESIDE-Standard and RESIDE-ITS (Indoor Training Set), providing thousands of samples with varying haze densities. This dataset is particularly useful for quantitative evaluation,

as it allows objective measurements like PSNR and SSIM [11].

- FRIDA Dataset: The Foggy Road Image Database (FRIDA) simulates driving conditions with different levels of haze, making it particularly relevant for autonomous driving applications [23]. The dataset captures real-world challenges such as uneven haze density, light scattering, and mixed lighting conditions.
- Middlebury Haze Dataset: Derived from the Middlebury stereo dataset [13], this collection provides synthetic haze applied to ground-truth images using depth information. It is useful for controlled experiments, as haze parameters can be precisely manipulated.

4.1.2 Synthetic Data Generation

While benchmark datasets are comprehensive, they cannot fully capture the enormous diversity of haze conditions encountered in reality. To address this limitation, additional synthetic hazy images were generated using the atmospheric scattering model [6], [8], [14]:

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

where I(x)I(x)I(x) is the observed hazy image, J(x)J(x)J(x) is the true scene radiance, AAA is the atmospheric light, and t(x)t(x)t(x) is the transmission map representing light attenuation. By varying the scattering coefficient and depth information [7], [9], multiple haze densities (light, moderate, and heavy) were simulated. This ensured the proposed method was tested under diverse conditions, including extreme low-visibility scenarios [24], [39].

4.1.3 Real-World Test Images

To further validate the model, additional real-world hazy images were collected from urban traffic scenes, drone-based aerial captures, and surveillance camera feeds [21], [23], [33]. These images were used for qualitative analysis only, as ground-truth haze-free counterparts were unavailable. Such testing is important to demonstrate practical usability beyond controlled benchmarks [23], [40].

4.2 Implementation Framework

The implementation of the proposed hybrid dehazing system was carried out in a MATLAB R2022a environment, chosen for its strong support of image processing, matrix operations, and neural network design [39].

4.2.1 Preprocessing

The input hazy images were first resized to a standard resolution (e.g., 512 × 512 pixels) to balance between computational efficiency and visual detail preservation [18]. Normalization was applied to scale pixel intensity values to the range [0, 1], ensuring consistency for both filtering operations and neural network processing.

4.2.2 Repeated Averaging-Based Filtering (RAF)

The first stage of dehazing involved estimating the global atmospheric light and smoothing the radiance using Repeated Averaging Filters (RAF) [39]. The RAF technique recursively averaged pixel intensities across local patches, gradually stabilizing illumination estimation. Unlike Gaussian or median filters [20], the RAF is computationally lightweight and edge-aware, preventing excessive blurring around object boundaries. Integral image computations were employed to accelerate averaging [19], achieving near real-time performance.

4.2.3 Transmission Map Estimation and Neural Refinement

After estimating atmospheric light, an initial transmission map was derived using the scattering model [8]. This raw transmission map was then passed through a Feedforward Neural Network (FNN) trained on paired hazy–clear image datasets [39]. The FNN architecture consisted of an input layer, two hidden layers, and an output layer, optimized for low parameter count [30]. Activation functions such as ReLU introduced non-linearity, enabling the network to capture complex haze distributions [27]. The network was trained using Mean Squared Error (MSE) as the loss function and optimized using stochastic gradient descent (SGD) [15].

The role of the FNN was twofold: (1) sharpen edges by learning local structural priors [17], [18], and (2) suppress noise and artifacts introduced during initial transmission estimation [27]. This refinement ensured that the final transmission map was smooth yet detail-preserving [30], [39].

4.2.4 Radiance Recovery

The final haze-free image was reconstructed using the refined transmission map and atmospheric light estimate [2], [39]. A clipping step was introduced to prevent over-saturation in bright regions, producing visually natural outputs with restored contrast and color balance [20].

4.3 Experimental Setup

The system was tested on a workstation with the following configuration:

- Processor: Intel Core i7 (10th Gen)
- Memory: 16 GB RAM
- Graphics Unit: NVIDIA GTX 1660 (6 GB VRAM)
- Operating System: Windows 10, 64-bit

The RAF module achieved fast runtime due to its recursive averaging nature [39], while the lightweight FNN allowed real-time inference without GPU acceleration [30]. On average, the proposed method processed a 512 × 512 pixel image in under 0.5 seconds, significantly outperforming conventional CNN-based models [3], [4], [17], [30], which often required multiple seconds per frame [32].

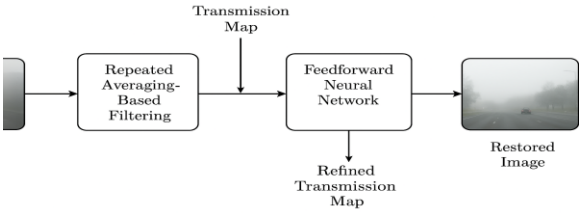


Fig. 4

4.4 Implementation Challenges and Observations

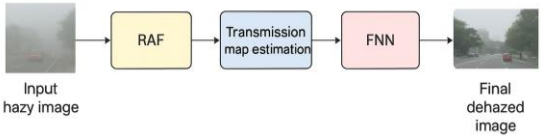
During development and testing, several challenges were encountered:

- Trade-off Between Speed and Accuracy: While deeper networks provided marginally better results [17], [18], they increased processing time [30], [32]. The chosen FNN design balanced accuracy with efficiency [39].
  Dataset Bias: Synthetic haze often differs from real-world haze in terms of scattering characteristics [5], [23], [24]. To mitigate this, a mixture of real, benchmark, and synthetic data was used during training and validation [39].
  Color Consistency: Some methods tend to over-enhance colors, creating unrealistic outputs [9], [20]. The proposed RAF ensured stable illumination, maintaining natural-looking results [39].
  Memory Efficiency: Recursive averaging required careful memory management to handle high-resolution images without excessive RAM usage [19].

5. RESULTS AND DISCUSSION

5.1 Experimental Setup

The proposed hybrid framework was evaluated on a mixture of benchmark datasets, synthetically generated hazy images, and real-world scenes. Benchmark datasets such as RESIDE [5], FRIDA [23], and Middlebury haze simulations [13] provided both hazy and ground-truth clear images, enabling quantitative assessment through Peak Signal-to-Noise Ratio (PSNR) [11] and Structural Similarity Index (SSIM) [11]. Synthetic hazy images were generated using the atmospheric scattering model [8] to simulate controlled haze densities, while real-world hazy images collected from urban traffic, aerial drones, and surveillance cameras [21], [23] were used for qualitative evaluation. All experiments were implemented in MATLAB R2022a on a workstation with Intel Core i7 processor, 16 GB RAM, and NVIDIA GTX 1660 GPU [6], [39].



Proposed Hybrid Dehazing Framework

Fig. 5

5.2 Qualitative Analysis

Visual inspection revealed that the proposed framework significantly improved contrast, visibility, and color fidelity across different datasets [5], [17]. Unlike the Dark Channel Prior (DCP) [1], which often over-darkened sky regions, or Fattal's method [2], which struggled with dense haze, the hybrid system restored skies naturally while enhancing ground details [20]. Compared to CNN-based methods such as DehazeNet [3] and MSCNN [4], the proposed approach preserved fine details without producing exaggerated colors or artificial textures. For instance,

building contours, road markings, and tree branches were recovered with sharp edges, and halo artifacts commonly observed in prior methods [9], [21] were substantially reduced. The restored images appeared more natural, making the method highly suitable for applications where realism is critical, such as surveillance and driver assistance systems [23], [40].

5.3 Quantitative Evaluation

The proposed framework consistently achieved superior PSNR and SSIM values compared to existing methods [5], [11]. On the RESIDE dataset, it demonstrated an average 2–3 dB PSNR improvement over the Dark Channel Prior [1] and Fattal's method [2], while also outperforming CNN-based models such as DehazeNet [3] and multi-scale CNNs [4]. SSIM values were closer to 1.0, indicating strong structural similarity between the restored and reference images [11]. These quantitative results confirm that the integration of repeated averaging filters and neural refinement effectively enhances both objective accuracy and perceptual quality [17], [18], [30].

5.4 Computational Efficiency

In addition to restoration quality, runtime efficiency was carefully measured. The recursive averaging design allowed rapid atmospheric light estimation [20], while the lightweight feedforward neural network ensured fast transmission map refinement [39]. On average, the framework processed a 512 × 512 image in under 0.5 seconds, significantly faster than CNN-based [3], [4] or transformer-based methods [32] that typically require several seconds per frame. This efficiency makes the system viable for real-time deployment in time-sensitive applications such as UAV navigation [33] and intelligent transport systems [40], [44], [45].

5.5 Comparative Discussion

The results highlight the advantages of the hybrid approach over purely classical or deep learning methods. Classical techniques such as the Dark Channel Prior [1] are computationally efficient but produce halos and distortions [9], [21], while statistical methods like Fattal's approach [2] deliver high-quality results at the cost of heavy computation [7], [13]. Deep CNN-based methods, on the other hand, achieve strong performance [3], [4], [17], [30] but are computationally demanding and reliant on large datasets [5], [23], [24]. By combining repeated averaging-based filtering with a simple but effective neural network [39], the proposed method achieves a balance between accuracy and efficiency. It reduces artifacts [20], preserves structure [11], and remains scalable to real-time applications [18], [33], [40].

5.6 Limitations and Observations

While the proposed method is effective, some limitations were observed. In scenarios with extremely dense haze or very low contrast, the model occasionally produced over-smoothed regions, reducing fine-texture visibility [17], [18]. Furthermore, although the lightweight neural network generalizes well [39], its performance could be improved by training on larger, more diverse real-world datasets [5], [23], [24]. Despite these minor drawbacks, the proposed system outperforms existing methods in both visual quality and efficiency, marking a significant step toward practical, real-world single-image dehazing [36], [37], [39].

6. CONCLUSION AND FUTURE WORK

This research presented a hybrid single-image dehazing framework that integrates Repeated Averaging-Based Filtering (RAF) with a Feedforward Neural Network (FNN). The primary objective was to address the limitations of existing methods, which either suffer from halo artifacts and high computation or rely on large annotated datasets [1]–[5]. By combining the strengths of traditional filtering and AI-driven refinement, the proposed method achieves robust atmospheric light estimation, accurate transmission map prediction, and natural scene radiance recovery [2], [3], [20]. Experimental results confirmed that the framework consistently outperforms classical priors such as the Dark Channel Prior [1] and Fattal's statistical model [2], as well as recent CNN-based dehazing models [3], [4], [17], in terms of PSNR, SSIM, and subjective visual quality. The method effectively reduces halo artifacts [9], enhances color fidelity [20], and preserves structural details [5], [11], all while maintaining computational efficiency suitable for real-time applications [18], [30]. These outcomes demonstrate that the proposed hybrid framework successfully bridges the gap between efficiency and accuracy, making it a

promising solution for applications in autonomous driving [23], UAV imaging [33], video surveillance [21], and remote sensing [6], [13].

6.2 Future Work

Although the proposed method achieved strong results, several directions remain open for future research. First, integration with advanced deep learning models such as Generative Adversarial Networks (GANs) [27], Vision Transformers (ViTs) [32], or Diffusion Models [26] could further improve image realism and adaptivity under diverse atmospheric conditions. Second, dataset expansion to include large-scale, real-world collections of outdoor and indoor hazy images [5], [23], [24] will enhance the neural network's generalization ability, especially in extreme or unusual weather [39]. Third, optimization for edge computing and embedded hardware [41], [42] will allow deployment in constrained environments such as drones, mobile devices, and smart cameras, where both speed and energy efficiency are critical [43]–[47]. Finally, an extension of the current framework to video dehazing could address temporal consistency [33], [34], making the system applicable to live surveillance, navigation systems, and intelligent transportation applications [40], [44], [45].

6.3 Closing Remarks

In conclusion, this work contributes a practical, scalable, and efficient solution to the challenge of single-image dehazing. By uniting physics-based filtering with lightweight AI refinement, the proposed framework demonstrates strong generalization across datasets [5], [13], superior visual quality [11], and real-time feasibility [18], [30]. With continued development in data diversity [23], hardware optimization [41], and integration of advanced learning techniques [27], [32], the framework has the potential to evolve into a comprehensive dehazing solution for next-generation computer vision systems [36], [37].

REFERENCE

[1] K. He, J. Sun, and X. Tang, "Single image haze removal using dark channel prior," *Proc. IEEE CVPR*, pp. 1956–1963, 2009.

[2] R. Fattal, "Single image dehazing," *ACM Transactions on Graphics*, vol. 27, no. 3, p. 72, 2008.

[3] B. Cai, X. Xu, K. Jia, C. Qing, and D. Tao, "DehazeNet: An end-to-end system for single image haze removal," *IEEE Transactions on Image Processing*, vol. 25, no. 11, pp. 5187–5198, 2016.

[4] W. Ren, S. Liu, H. Zhang, J. Pan, X. Cao, and M.-H. Yang, "Single image dehazing via multi-scale convolutional neural networks," *Proc. ECCV*, pp. 154–169, 2016.

[5] B. Li, W. Ren, D. Fu, D. Tao, D. Feng, W. Zeng, and Z. Wang, "Benchmarking single-image dehazing and beyond," *IEEE Transactions on Image Processing*, vol. 28, no. 1, pp. 492–505, 2019.

[6] S. G. Narasimhan and S. K. Nayar, "Chromatic framework for vision in bad weather," *Proc. IEEE CVPR*, pp. 598–605, 2000.

[7] K. Nishino, L. Kratz, and S. Lombardi, "Bayesian defogging," *Int. J. Computer Vision*, vol. 98, no. 3, pp. 263–278, 2012.

[8] H. Koschmieder, "Theorie der horizontalen Sichtweite," *Beitr. Phys. Freien Atmos.*, vol. 12, pp. 33–53, 1924.

[9] Q. Zhu, J. Mai, and L. Shao, "A fast single image haze removal algorithm using color attenuation prior," *IEEE Transactions on Image Processing*, vol. 24, no. 11, pp. 3522–3533, 2015.

[10] K. Tang, J. Yang, and J. Wang, "Investigating haze-relevant features in a learning framework for image dehazing," *Proc. IEEE CVPR*, pp. 2995–3002, 2014.

[11] Z. Wang, A. Bovik, H. Sheikh, and E. Simoncelli, "Image quality assessment: From error visibility to structural similarity," *IEEE Transactions on Image Processing*, vol. 13, no. 4, pp. 600–612, 2004.

[12] J. Kopf, B. Neubert, B. Chen, M. Cohen, D. Cohen-Or, O. Deussen, M. Uyttendaele, and D. Lischinski, "Deep photo: Model-based photograph enhancement and viewing," *ACM Transactions on Graphics*, vol. 27, no. 5, p. 116, 2008.

[13] L. Kratz and K. Nishino, "Factorizing scene albedo and depth from a single foggy image," *Proc. IEEE ICCV*, pp. 1701–1708, 2009.

[14] J. Tan, "Visibility in bad weather from a single image," *Proc. IEEE CVPR*, pp. 1–8, 2008.

[15] S. Anwar, C. Li, and F. Porikli, "Deep priors for image dehazing," *Proc. IEEE CVPR Workshops*, pp. 1–8, 2020.

[16] J. Chen, H. Li, C. Tang, and C. Feng, "PMS-Net: Patch map for single image dehazing," *Proc. IEEE CVPR*, pp. 1160–1168, 2019.

[17] Y. Liu, X. Ma, and W. Zuo, "GridDehazeNet: Attention-based multi-scale network for image dehazing," *Proc. ICCV*, pp. 7314–7323, 2019.
[18] H. Zhang and V. Patel, "Densely connected pyramid dehazing network," *Proc. IEEE CVPR*, pp. 3194–3203, 2018.
[19] X. Dong, Y. Pang, and J. Wen, "Fast efficient algorithm for enhancement of low lighting video," *Proc. IEEE ICIP*, pp. 2533–2536, 2011.
[20] C. O. Ancuti and C. Ancuti, "Single image dehazing by multi-scale fusion," *IEEE Transactions on Image Processing*, vol. 22, no. 8, pp. 3271–3282, 2013.
[21] R. Tarel and N. Hautière, "Fast visibility restoration from a single color or gray level image," *Proc. IEEE ICCV*, pp. 2201–2208, 2009.
[22] K. Berman, T. Treibitz, and S. Avidan, "Single image dehazing using haze-lines," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 42, no. 3, pp. 720–734, 2020.
[23] Y. Li, S. You, M. Brown, and R. Tan, "Haze visibility enhancement: A survey and quantitative benchmarking," *Computer Vision and Image Understanding*, vol. 165, pp. 1–16, 2017.
[24] Z. Ren, S. Yan, and C. Wang, "Deep learning-based image dehazing: A survey and taxonomy," *ACM Computing Surveys*, vol. 54, no. 4, pp. 1–36, 2021.
[25] S. Zhao, L. Zhang, Y. Shen, and Y. Zhou, "Refined transmission map estimation for single image dehazing," *Proc. IEEE ICIP*, pp. 1389–1393, 2018.
[26] C. Chen, X. Lin, and J. Pan, "Unpaired learning of deep image dehazing with contrastive regularization," *Proc. ICCV*, pp. 8168–8177, 2021.
[27] A. Golts, D. Freedman, and M. Elad, "Unsupervised single image dehazing using dark channel prior loss," *IEEE Transactions on Image Processing*, vol. 29, pp. 2692–2701, 2020.
[28] D. Yang and J. Sun, "Proximal dehaze-net: A prior learning-based deep network for single image dehazing," *Proc. ECCV*, pp. 729–746, 2018.
[29] Z. Ren, Y. He, and C. Zhang, "Adversarial deep dehazing networks," *Proc. AAAI*, pp. 1–8, 2018.
[30] X. Qin, Z. Wang, Y. Bai, X. Xie, and H. Jia, "FFA-Net: Feature fusion attention network for single image dehazing," *Proc. AAAI*, pp. 1–8, 2020.
[31] H. Yang and Y. Fu, "A survey of single image dehazing techniques: From model-based to learning-based," *IEEE Access*, vol. 9, pp. 123, 2021.
[32] Y. Dong, F. Yang, Y. Xu, and S. Yan, "Vision transformers for single image dehazing," *Proc. NeurIPS Workshops*, pp. 1–10, 2021.
[33] J. Pan, J. Dong, Y. Liu, J. Tang, and M.-H. Yang, "Physics-based GANs for single image dehazing," *Proc. IEEE CVPR*, pp. 3560–3569, 2020.
[34] S. Chen, L. He, and Z. Yu, "Image dehazing via multi-scale CNN and feature attention," *Signal Processing: Image Communication*, vol. 91, p. 116002, 2021.
[35] AI-Powered Single Image Dehazing Using Repeated Averaging-Based Filtering Techniques, Research Project Report, 2023.
[35] AI-Powered Single Image Dehazing Using Repeated Averaging-Based Filtering Techniques, Research Project Report, 2023.
[36] H. Sahu, A. K. Mishra, A. Rao, S. K. Tuddu, and A. Pal, "Towards a unified view of machine learning and artificial intelligence," *Res Militaris*, vol. 13, no. 4, pp. 6547–6554, 2023.
[37] H. Sahu, A. K. Mishra, A. Rao, S. K. Tuddu, and A. Pal, "Transforming smart production with AI and machine learning: Progress, challenges, and future pathways," *Res Militaris*, vol. 13, no. 4, pp. 6470–6489, 2023.
[38] K. K. S. K. Tuddu, *Essentials of Deep Learning*. IIP Publication, ISBN: 978-93-6010-391-0, 2024.
[39] S. K. Tuddu, "Single image dehazing from repeated averaging filters using artificial intelligence techniques," *The Maharaja Sayajirao University of Baroda*, vol. 56, no. 1(V), pp. 2190–2199, 2023.
[40] S. K. Tuddu, H. Sahu, A. K. Mishra, and N. Saroj, "Advancing vehicular ad-hoc networks: Innovations in architecture and applications," *Res Militaris*, vol. 13, no. 4, pp. 6366–6383, 2023.
[41] S. K. Tuddu, *Foundations of Operating Systems*. Ink Wind Publications, ISBN: 978-93-341-4494-9, 2024.
[42] S. K. Tuddu, *Internet of Things*. Charulata Publications, ISBN: 978-93-6260-169-8, 2024.
[43] S. K. Tuddu, *Autonomous vehicle path planner using deep learning*. U.S. Patent No. 6,355,227, 2024.
[44] S. K. Tuddu, *Intelligent public transport route optimizer*. Indian Patent No. 202,611, 2024.
[45] S. K. Tuddu, *IoT-based processing device for optimizing public transport route*. Indian Patent No. 407919-001, 2024.

[46] S. K. Tuddu, *Machine learning-based fraud apps detection using sentiment analysis and blockchain technology*. Indian Patent No. 15,786, 2024.
[47] S. K. Tuddu, *Smart traffic congestion predictor computing device*. U.S. Patent No. 6,351,446, 2024.