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Review on Haze Removal Techniques using Image Processing and Deep Learning

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Abstract: *Haze removal, or dehazing, is a crucial process in image processing aimed at restoring clarity to images obscured by atmospheric conditions. This review explores recent advancements in haze removal techniques, emphasizing image processing and deep learning methodologies. Traditional dehazing methods, such as dark channel prior and color attenuation prior, effectively enhance image quality but often fall short in scenarios with complex lighting or dense haze. With the rise of deep learning, techniques using convolutional neural networks (CNNs), generative adversarial networks (GANs), and attention mechanisms have emerged, offering robust dehazing solutions across diverse atmospheric conditions. For instance, models like DehazeNet and AOD-Net streamline the haze removal process, while multi-scale and pyramid-based networks capture haze effects across varying depths. Attention-guided GANs and feature fusion networks further improve haze detection and detail retention. Despite these advancements, challenges persist, particularly in handling non-uniform haze, optimizing real-time performance, and achieving consistency across variable haze intensities. The integration of domain adaptation and transfer learning presents potential solutions, enhancing generalizability in cross-domain applications. This review identifies significant research gaps, including the need for lightweight architectures, adaptive techniques for different lighting environments, and efficient methods suitable for real-time application. By examining 25 recent studies, this review highlights the latest methodologies, their strengths and limitations, and outlines future directions to advance haze removal technologies. The insights gathered aim to guide further development in image restoration for applications in environmental monitoring, autonomous vehicles, and remote sensing..*

Keywords: Haze removal, dehazing, image processing, deep learning, dark channel prior, convolutional neural networks (CNNs), generative adversarial networks (GANs), attention mechanisms, multi-scale networks, pyramid-based networks, feature fusion, real-time performance, non-uniform haze, domain adaptation, transfer learning, environmental monitoring, autonomous vehicles, remote sensing, image restoration

I. INTRODUCTION

Haze removal, or dehazing, is a vital aspect of image processing, aiming to restore visual clarity to images affected by atmospheric conditions such as fog, mist, and smoke. These conditions lead to reduced visibility, color distortion, and loss of detail, impacting various applications in environmental monitoring, remote sensing, autonomous navigation, surveillance, and even consumer photography. Traditionally, dehazing relied on image enhancement techniques that were largely heuristic-based, utilizing priors such as the dark channel prior, color attenuation prior, and various depth estimation methods. The dark channel prior, proposed by He et al., has been one of the most influential in traditional dehazing techniques, assuming that haze-free outdoor images often contain pixels in one color channel with low intensity values.

However, while this method works effectively in many cases, it encounters limitations when applied to scenes with complex lighting conditions, bright or white objects, and low-light environments. Similarly, other heuristic-based approaches, like the color attenuation prior and atmospheric scattering models, aim to estimate haze thickness and transmission maps by leveraging color information and depth cues, which, despite notable successes, often fail to generalize across varying scenes and haze intensities. With the advancement of deep learning, dehazing has witnessed a significant transformation, allowing for data-driven approaches that learn complex features from large datasets rather than relying solely on assumptions or priors. Convolutional neural networks (CNNs), generative adversarial networks (GANs), and attention mechanisms have emerged as powerful tools in this domain, enabling robust haze removal in diverse atmospheric conditions. CNN-based architectures, such as DehazeNet and AOD-Net, introduced end-to-end dehazing models that learn to predict haze-free images directly, bypassing the need for explicit transmission maps and atmospheric light estimation. These models marked a breakthrough in single image dehazing by streamlining the haze removal process and offering improved performance across a variety of scenes. Multi-scale convolutional neural networks further advanced the field by capturing haze effects at different depths, enhancing detail retention, and handling the complex distribution of haze across an image. However, these models often face challenges in real-time applications due to their computational demands. To address these limitations, research has turned toward more efficient architectures, such as pyramid-based multi-layer networks and dense fusion frameworks, which aim to preserve image quality while reducing processing time. GANs have also gained traction in dehazing, particularly for their ability to generate high-quality images by learning the underlying distribution of haze-free and hazy images. By utilizing a generator-discriminator framework, GANs can refine image details and produce realistic outputs, making them effective in diverse environmental conditions.

Nevertheless, training GANs for dehazing requires extensive data, and they may suffer from stability issues, particularly when haze density varies significantly. Incorporating attention mechanisms within GANs and CNNs has further improved haze removal, as these mechanisms allow models to focus on haze-affected regions selectively, enhancing image clarity and detail recovery. Attention-guided models, such as FFA-Net, demonstrate high-quality dehazing with minimal artifacts, but they also demand substantial computational resources and large datasets, highlighting the need for optimization to achieve scalability and efficiency. Additionally, approaches such as domain adaptation and transfer learning have been explored to improve the generalization of dehazing models, allowing them to adapt to different atmospheric conditions and lighting scenarios with minimal retraining. For instance, conditional GANs and semi-supervised learning frameworks aim to address the limited availability of labeled haze-free and hazy image pairs by leveraging synthetic data for model training. This synthetic-to-real adaptation has shown promise but remains limited in consistency when applied to real-world haze patterns. Despite these advancements, challenges persist in developing lightweight and efficient dehazing models suitable for real-time applications and varying haze intensities. Existing models often struggle with non-uniform haze, where haze density varies significantly across the image, or in scenes with complex illumination, where shadows and reflections add to the complexity of haze estimation and removal.

As a result, there remains a research gap in designing dehazing models that are both robust and computationally efficient, balancing the trade-offs between quality and speed. Moreover, while many current approaches focus on single image dehazing, expanding these techniques to video dehazing presents further opportunities and challenges, as temporal consistency must be maintained to prevent flickering and artifacts between frames. Given the growing demand for haze-free image and video data across various sectors, continued research into adaptive, efficient, and high-quality dehazing techniques is crucial. Future work may explore hybrid architectures that combine the strengths of traditional priors and deep learning, integrate more advanced attention mechanisms, and incorporate reinforcement learning for adaptive haze removal based on real-time scene analysis. This review aims to present a comprehensive analysis of recent developments in haze removal, examining the strengths and limitations of traditional and deep learning-based techniques, highlighting the primary challenges faced by existing models, and outlining promising directions for future research in this evolving field.

To address the limitations of current approaches, research has explored domain adaptation and transfer learning to improve model generalization and adaptivity. These methods allow models to utilize knowledge from synthetic datasets or domains with labeled haze-free images, which is beneficial given the scarcity of real-world paired hazy and clear images. Conditional GANs and semi-supervised learning frameworks have also been introduced, leveraging synthetic-to-real adaptation to improve performance in real-world conditions. While these approaches demonstrate promising results, their consistency is often limited when applied to natural haze variations, underscoring the need for models that

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can seamlessly adapt to diverse environmental conditions without extensive retraining. Additional approaches, such as the integration of depth information, have been proposed to refine dehazing in scenes with complex spatial structures, enabling better performance in three-dimensional environments.

Another area of interest in haze removal research is lightweight and efficient dehazing models that can operate in real-time, particularly for applications like autonomous driving, where immediate image processing is critical. Many state-of-the-art models are computationally intensive, hindering their deployment in scenarios with limited processing power or memory. To address this, techniques like pruning, quantization, and knowledge distillation have been applied to simplify network architectures and reduce inference time, without sacrificing too much in terms of visual quality. Furthermore, hybrid models that combine the strengths of traditional physical models and deep learning are being developed, offering a balanced approach that leverages physical priors to guide neural networks, particularly in low-data scenarios or applications where interpretability is essential.

As haze removal techniques continue to advance, there is an increasing need for comprehensive evaluation metrics that accurately reflect the perceptual quality of dehazed images. Standard metrics like PSNR and SSIM provide objective measures but often fail to capture the nuanced quality differences that are perceptually significant in dehazed images. Thus, perceptual quality assessment methods, including user studies and the development of specialized metrics, are crucial for evaluating the effectiveness of haze removal models in real-world applications.

II. LITERATURE SURVEY

Zhang, et al. [1]propose a fast haze removal algorithm that leverages the dark channel prior to improve visibility in hazy images by estimating transmission maps and refining them with guided filtering. The approach is efficient, enhancing both processing speed and artifact reduction, making it particularly suitable for real-time applications. However, challenges arise in handling complex scenes, especially in low-light conditions and when reflective or bright surfaces are present. While the method effectively restores color and contrast in hazy environments, it struggles to achieve the same quality in diverse lighting scenarios, highlighting a gap that could be bridged by integrating adaptive approaches. Future research could focus on hybrid methods that enhance robustness and adaptability across varying haze and lighting conditions.

He, et al. [2] introduce the dark channel prior (DCP) for single-image haze removal, marking a significant advancement in dehazing techniques. DCP is based on the observation that haze-free outdoor images typically have pixels in at least one color channel with low intensity, allowing for effective estimation of the transmission map. Although DCP works well in dense haze, it shows limitations in handling scenes with bright, white, or reflective objects, often introducing distortions or color shifts in such scenarios. The approach has demonstrated high-quality results but lacks adaptability to varying atmospheric conditions, particularly in low-light or complex lighting environments. To overcome these challenges, future work may focus on enhancing DCP's robustness across diverse scenes and lighting conditions.

Cai, et al. [3] In "DehazeNet: An End-to-End System for Single Image Haze Removal," Cai et al. present a convolutional neural network (CNN) specifically designed for haze removal. DehazeNet directly learns haze-relevant features from training data, removing the need for explicit transmission map estimation. The model utilizes multiple convolutional layers to capture haze characteristics, resulting in notable improvements in haze removal accuracy and image quality. However, DehazeNet requires extensive training data and computational resources, limiting its applicability in real-time or resource-constrained settings. While the results underscore the effectiveness of CNNs in haze removal, there is a need for optimizing the network architecture to reduce computational demands without sacrificing accuracy, potentially by exploring lighter or more efficient model variants.

Ren, et al. [4] introduce a multi-scale convolutional neural network (MSCNN) for single-image dehazing, focusing on enhancing depth perception and detail retention across different haze intensities. The multi-scale structure captures haze effects at varying depths, improving clarity and contrast while preserving fine details. Although MSCNN performs well in dense haze scenarios, it can produce artifacts in areas with low texture, where feature extraction is more challenging. Results indicate that multi-scale approaches significantly improve dehazing quality, though achieving a balance between detailed feature retention and artifact minimization remains challenging. Future research could refine multi-scale dehazing techniques to enhance their robustness across texture variations and depth levels, potentially improving performance in complex scenes.

Qin, et al. [5]propose the Feature Fusion Attention Network (FFA-Net), an attention-based architecture that selectively emphasizes haze-affected regions to improve dehazing accuracy. FFA-Net incorporates an attention mechanism to focus on specific regions, thereby enhancing the model's ability to recover image clarity and detail, particularly in highly hazy areas. This network achieves impressive results across a wide range of haze intensities but requires significant training data to maintain high performance. While FFA-Net demonstrates the potential of attention mechanisms for enhancing dehazing, it remains computationally demanding. Future work may involve developing adaptive attention mechanisms that require less training data, thereby increasing the model's efficiency and making it more practical for real-time applications and broader environments.

Berman, et al. [6] introduce a non-local image dehazing technique that uses a haze-line prior to differentiate between hazy and clear regions. This approach leverages the observation that pixels within the same object often follow a similar haze line, enabling the model to isolate haze-affected areas more effectively. While the model performs well in outdoor scenarios, it struggles in indoor or complex lighting environments where haze lines are less distinct. The results demonstrate substantial improvements in outdoor image clarity, but the approach's effectiveness decreases in low-light or multi-source lighting scenes. This gap suggests the need for adaptable priors or combined approaches that can better handle diverse lighting and scene compositions, enhancing performance across varied environments.

Li, et al. [7]: propose AOD-Net, an "All-in-One Dehazing Network" that simplifies traditional multi-step dehazing processes into a single, streamlined CNN model. AOD-Net is designed for efficiency, significantly reducing computational demands while achieving comparable results to more complex models. However, AOD-Net's performance is limited in scenarios with high-density haze, where finer adjustments to transmission estimation are required. The study underscores the potential of lightweight, single-stage dehazing models, although the model's adaptability to thick haze remains a concern. Future research may focus on adding depth-aware or context-sensitive components to AOD-Net, improving its robustness to varying haze intensities while maintaining its efficiency advantage for real-time applications.

Zhu, et al. [8] propose a color attenuation prior-based method for haze removal, leveraging the relationship between color saturation and depth in hazy images. The model uses a linear model to estimate haze thickness, yielding satisfactory results for outdoor images with distinct color gradients. However, its reliance on color cues limits its applicability in grayscale or low-saturation scenes where color information is insufficient. The study highlights the effectiveness of color attenuation for depth estimation, but the approach lacks versatility for diverse scenes. Enhancing this method to accommodate scenes with low or monochromatic saturation could broaden its applicability, making it more robust in complex or color-limited environments.

Yang, et al. [9]present Proximal Dehaze-Net, a haze removal framework that employs proximal operators for fast and efficient dehazing. This approach achieves real-time dehazing by minimizing computational overhead, making it suitable for applications that require quick processing. While the model performs effectively in lightly hazed conditions, it struggles with denser, layered haze, where more sophisticated depth management is required. Results indicate that the approach is promising for speed-sensitive applications but lacks the depth-awareness necessary for highly hazy scenes. Future work could explore depth-adaptive components to enhance Proximal Dehaze-Net's performance in complex haze conditions, potentially increasing its adaptability across varied haze densities.

Dong, et al. [10] introduce a multi-scale boosted dehazing network with dense feature fusion, a framework designed to capture haze effects across multiple scales. This approach enables the network to retain fine details while effectively removing haze, especially in scenes with depth variations. Although the model significantly improves dehazing quality, its complex architecture results in high computational resource demands, making it challenging to deploy in low-power settings. The study suggests that multi-scale fusion is beneficial for detail preservation, but further optimization is necessary to reduce the model's complexity. Future research may focus on developing lightweight fusion models to make this approach feasible for real-time or mobile applications.

Li, et al. [11] propose a semi-supervised image dehazing framework that uses adaptive perceptual loss to address the limitations of traditional supervised methods. By combining supervised and unsupervised learning, the model performs well without extensive labeled data, making it more adaptable to new scenes. However, it requires further refinement to handle variable haze patterns effectively. Results indicate that semi-supervised learning can effectively address data scarcity issues in dehazing, although its generalizability in different atmospheric conditions remains a challenge. Future

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work could focus on improving the model's adaptability to varying haze densities and lighting conditions, thereby enhancing its performance across broader scenarios.

Zheng, et al. [12] apply a generative adversarial network (GAN) for haze removal, focusing on generating realistic haze-free images. The model employs an adversarial training framework, with a generator that produces dehazed images and a discriminator that refines them by distinguishing between real and synthetic results. While the model demonstrates strong visual outcomes, stability issues arise when haze density varies significantly, affecting consistency across scenes. The study highlights the potential of GANs for high-quality dehazing, though future research may focus on stabilizing GAN architectures to enhance their robustness in scenes with fluctuating haze intensities, ultimately improving reliability for diverse real-world applications.

Chen, et al. [13]introduce a pyramid-based multi-layer network to capture haze effects across varying depths, using a hierarchical structure that enhances image clarity in dense haze conditions. The pyramid approach allows the model to manage haze across depth layers, improving detail preservation and visual clarity. However, the layered architecture demands high computational power, limiting its feasibility for real-time applications. While results indicate significant improvements in dense haze scenarios, optimizing the pyramid structure to reduce resource requirements is essential. Future work may focus on refining the model's efficiency, potentially making it viable for faster, real-time applications while retaining its high-quality dehazing capabilities.

Lai, et al. [14] explore bidirectional GANs for haze removal, focusing on low-light conditions where traditional methods struggle. The model's bidirectional framework allows for better adaptation in dimly lit environments, producing high-quality results. However, the model performs inconsistently in dense haze scenarios, where the GAN's bidirectional nature lacks the granularity to manage depth-wise haze variations effectively. While this approach is promising for low-light applications, further optimization is needed to extend its effectiveness in varying haze intensities. Future research may focus on integrating depth-sensitive components into bidirectional GANs to enhance performance in scenes with substantial depth and haze variation.

Liu, et al. [15]present an improved dark channel prior approach, integrating edge-aware refinement to address issues commonly encountered with traditional DCP-based methods. The edge-aware technique enhances transmission map accuracy, resulting in better preservation of edges and fine details. Although this approach shows substantial improvements over standard DCP, it remains computationally intensive, limiting its application in real-time scenarios. Additionally, it struggles in low-light conditions, where edge estimation becomes challenging. Results highlight the effectiveness of edge-aware refinement for clearer dehazing, though future work could focus on reducing the computational complexity and enhancing robustness in diverse lighting conditions, ultimately broadening its applicability for real-time dehazing.

Kim, et al. [16]propose an end-to-end dehazing network based on an encoder-decoder architecture, focusing on a streamlined process that enhances speed and efficiency. The encoder extracts haze-related features, while the decoder reconstructs haze-free images, achieving high clarity and contrast. Although the model demonstrates strong results, its complexity limits its use in real-time applications. The study underscores the benefits of encoder-decoder structures for dehazing but highlights the need for lighter architectures. Future research may focus on optimizing encoder-decoder networks for faster processing, making them more practical for deployment in scenarios that require immediate dehazing results, such as autonomous driving or real-time surveillance.

Park, et al. [17] introduce an adaptive transmission estimation method tailored for robust haze removal across different depths and scene complexities. By dynamically adjusting the transmission map according to scene depth, this approach effectively handles varying haze intensities, producing high-quality results in outdoor environments with complex backgrounds. However, it faces challenges in scenes with non-uniform haze distribution, where haze thickness varies unpredictably. Although results show improvements in image clarity and adaptability, the model's performance in diverse atmospheric conditions remains limited. Future work could focus on enhancing adaptability to non-uniform haze distributions and expanding the model's generalizability, potentially incorporating machine learning techniques for more precise, real-time estimation across varied environments.

Wang, et al. [18]explore the use of conditional GANs for image dehazing, utilizing synthetic-to-real adaptation to bridge the gap between controlled datasets and real-world applications. The model is trained on synthetic images with haze and adapts to real haze conditions, demonstrating improved consistency and visual quality in real-world scenes.

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While the model shows promise in handling natural haze patterns, its generalization across different haze intensities remains limited, often requiring additional fine-tuning. This approach highlights the potential of synthetic-to-real transfer for dehazing, although future work could focus on increasing model robustness across a wider range of atmospheric conditions, reducing the dependency on retraining for different haze scenarios.

Gao, et al. [19]introduce a dual discriminator GAN for multi-channel dehazing, aiming to improve haze distinction across color channels. The model uses two discriminators, each focusing on specific channel features, which allows for enhanced haze removal accuracy and sharpness. Despite achieving strong visual results, the model's complexity requires significant computational resources, limiting its feasibility in real-time applications. Results indicate that multi-channel GANs offer enhanced haze differentiation, though future research may focus on optimizing the model for resource-limited environments, making it viable for real-time use while retaining its high level of detail recovery.

Feng, et al. [20]propose a hybrid CNN for real-time haze removal that incorporates depth-enhanced features for improved dehazing accuracy. The model utilizes depth estimation to better manage haze density and retain image detail, achieving fast processing speeds suitable for real-time applications. While effective in outdoor scenes, the model lacks robustness in complex lighting conditions, particularly when shadows or high-contrast areas are present. Results suggest that depth-aware dehazing can enhance performance, but further improvements are needed to ensure adaptability across diverse lighting environments. Future research could explore integrating more sophisticated lighting correction mechanisms to enhance model robustness in varying illumination conditions.

Xu, et al. [21] investigate domain-specific dehazing using transfer learning to enhance generalizability across different environments. By leveraging pre-trained models on synthetic haze datasets and transferring this knowledge to real-world scenes, the model adapts effectively to new haze distributions. Although transfer learning improves generalization, the approach still requires a significant amount of domain-specific data to achieve optimal performance. Results show that domain adaptation enhances the model's ability to handle diverse haze patterns, but further research could focus on reducing data dependency, potentially developing models that generalize well with minimal retraining on new datasets.

Shi, et al. [22]present a depth-aware dehazing approach using a spatial attention mechanism, emphasizing depth-specific haze removal for clearer image recovery. The spatial attention helps the model focus on haze-affected regions according to depth, leading to improved clarity in images with variable depth features. Although effective in environments with depth variance, the model struggles in flat scenes with uniform depth, where spatial attention has less impact. The study underscores the effectiveness of spatial attention for depth-sensitive dehazing, but further refinement is needed to enhance adaptability in diverse scene compositions, ensuring the model's applicability across a broader range of visual scenarios.

Zhou, et al. [23]propose a dense dehazing network that utilizes residual learning to enhance image clarity and sharpness. The model's dense connections enable effective feature reuse, reducing the vanishing gradient problem and improving dehazing results. Despite its high-quality output, the model's dense structure increases computational demands, limiting its practicality in real-time settings. Results indicate that dense networks can improve dehazing performance, though optimizing the network's efficiency remains essential for broader applicability. Future research could explore lightweight variants of dense architectures, balancing detail recovery with processing speed to make real-time dehazing feasible in low-power environments.

Yan, et al. [24]develop a CNN-based atmospheric light estimation technique aimed at refining haze removal in complex lighting conditions. By optimizing atmospheric light estimation, the model achieves enhanced color accuracy and improved dehazing performance, particularly in outdoor scenes with high-contrast lighting. However, the model's effectiveness diminishes in low-contrast environments, where light estimation becomes challenging. Results show that accurate light estimation is crucial for high-quality dehazing, though the method's limitations in low-contrast settings suggest the need for more adaptable light estimation techniques. Future work could focus on combining light estimation with adaptive dehazing algorithms to improve consistency across varied lighting scenarios.

Jiang, et al. [25] introduce an attention-guided GAN for haze removal, utilizing attention mechanisms to focus on haze-affected regions and improve detail recovery. The attention component helps the GAN model selectively process areas with varying haze densities, leading to visually appealing dehazing results. However, the model's performance declines in scenes with extremely dense haze, where the attention mechanism struggles to isolate critical features. This study

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demonstrates the potential of attention mechanisms in GAN-based dehazing but suggests further enhancement for handling extreme haze intensities. Future research could focus on refining attention-guided GANs to improve adaptability in heavy haze conditions, ultimately achieving more reliable dehazing for diverse environmental applications.

III. SUMMARY OF THE LITERATURE SURVEY

This section synthesizes the core findings from existing studies on haze removal, underscoring the critical advancements and challenges within this field. As haze remains a persistent issue impacting visual clarity and image quality across various applications, a range of methodologies—from traditional techniques like dark channel prior and color attenuation to advanced deep learning models—have been developed to improve haze removal accuracy and efficiency. This section systematically reviews these methods, focusing on the effectiveness, adaptability, and limitations of both conventional and AI-based approaches.

Table: Summary of the Literature survey

Sr. No.	YOP	Title and Name of Author	Main Findings	Methodology	Limitations	Application
1	2017	Zhang, et al.	Efficient haze removal using dark channel prior and guided filtering.	Dark channel prior with guided filtering to estimate transmission maps.	Struggles with low-light and reflective surfaces.	Real-time dehazing
2	2009	He, et al.	Introduced dark channel prior (DCP) for haze removal.	Utilizes low-intensity pixels in color channels to estimate transmission.	Ineffective for bright/white objects or complex lighting.	Outdoor image clarity
3	2016	Cai, et al.	Developed DehazeNet, a CNN-based end-to-end haze removal model.	CNN layers capture haze features directly from training data.	Requires extensive data and computational resources.	Image restoration
4	2016	Ren, et al.	Multi-scale CNN enhances depth perception for haze removal.	Multi-scale CNN captures haze across varying depths.	Produces artifacts in low-texture regions.	Dense haze removal
5	2020	Qin, et al.	Attention mechanism improves dehazing accuracy.	Feature Fusion Attention Network (FFA-Net) focuses on hazy regions.	Requires extensive training data and is computationally intensive.	Complex haze scenarios
6	2016	Berman, et al.	Haze-line prior differentiates between hazy and clear regions.	Uses non-local haze line prior for clear vs. hazy pixel distinction.	Limited in indoor or complex lighting conditions.	Outdoor dehazing
7	2017	Li, et al.	AOD-Net simplifies dehazing stages into a single model.	All-in-One CNN streamlines multiple dehazing processes.	Limited performance in high-density haze.	Real-time applications
8	2015	Zhu, et al.	Color attenuation prior estimates haze thickness.	Linear model based on color attenuation and depth estimation.	Ineffective in grayscale or low-saturation scenes.	Depth-aware dehazing
9	2017	Yang, et al.	Proximal Dehaze-Net provides	Proximal operators reduce computational	Struggles with dense, layered haze.	Speed-sensitive tasks

			efficient real-time dehazing.	overhead for fast processing.		
10	2019	Dong, et al.	Multi-scale fusion improves depth management and detail.	Dense feature fusion captures haze across scales.	High computational requirements.	High-quality dehazing
11	2019	Li, et al.	Semi-supervised learning enhances dehazing with minimal labeled data.	Combines supervised and unsupervised approaches with adaptive loss.	Inconsistent performance across different haze patterns.	Data-scarce dehazing
12	2018	Zheng, et al.	GAN-based dehazing yields realistic haze-free images.	Generative adversarial framework with adversarial training.	Stability issues with varying haze thickness.	Visual improvement
13	2019	Chen, et al.	Pyramid-based approach captures haze effects across depths.	Multi-layer pyramid network enhances image clarity in dense haze.	High computational demand limits real-time use.	Dense haze scenarios
14	2018	Lai, et al.	Bidirectional GAN adapts well in low-light conditions.	Bidirectional GAN handles dimly lit environments.	Inconsistent results in dense haze conditions.	Low-light dehazing
15	2018	Liu, et al.	Edge-aware refinement enhances dark channel dehazing.	Edge-aware technique refines transmission map for better edges.	High computation and challenges in low-light.	Edge-preserving dehazing
16	2019	Kim, et al.	Encoder-decoder structure streamlines haze removal.	Encoder extracts haze features; decoder reconstructs clear image.	Model complexity limits real-time application.	Autonomous driving
17	2020	Park, et al.	Adaptive transmission estimation improves depth variation handling.	Adjusts transmission map based on scene depth.	Limited in non-uniform haze scenarios.	Outdoor image clarity
18	2021	Wang, et al.	Conditional GAN enables synthetic-to-real dehazing adaptation.	GAN trained on synthetic data adapted to real-world haze.	Requires fine-tuning for varying haze intensities.	Synthetic-to-real dehazing
19	2018	Gao, et al.	Dual discriminator GAN refines multi-channel haze removal.	Dual discriminators focus on distinct color channels.	Computationally intensive model.	Detailed dehazing
20	2019	Feng, et al.	Depth-enhanced hybrid CNN allows real-time haze removal.	Combines depth estimation with haze feature extraction.	Struggles with complex lighting conditions.	Real-time dehazing
21	2020	Xu, et al.	Transfer learning improves adaptability to new	Uses domain adaptation with pre-trained synthetic haze	High dependency on domain-specific data.	Cross-domain dehazing

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			haze patterns.	models.		
22	2021	Shi, et al.	Spatial attention aids depth-sensitive haze removal.	Spatial attention mechanism emphasizes haze-affected depth regions.	Limited in scenes with uniform depth.	Depth-variant scenes
23	2021	Zhou, et al.	Dense network with residual learning improves dehazing sharpness.	Dense connections with residual learning reduce vanishing gradients.	High computational demand limits real-time use.	High-quality dehazing
24	2022	Yan, et al.	CNN-based light estimation enhances color accuracy in dehazing.	Optimizes atmospheric light estimation for better haze removal.	Limited effectiveness in low-contrast scenes.	Outdoor imaging
25	2023	Jiang, et al.	Attention-guided GAN improves dehazing focus on hazy regions.	Uses attention within GAN to selectively process hazy areas.	Struggles with extreme haze conditions.	Hazy scene dehazing

IV. DISCUSSION

The field of haze removal has witnessed significant advancements in recent years, with a shift from traditional image processing techniques to sophisticated deep learning models that can more effectively address the challenges posed by atmospheric conditions. Traditional methods, such as the dark channel prior (DCP) and color attenuation prior, laid the foundation by using well-defined priors based on the statistical characteristics of outdoor images to estimate haze levels and improve visual clarity. These methods demonstrated good performance in specific scenarios but faced challenges in scenes with complex lighting, bright or reflective surfaces, and low saturation. As a result, these early approaches were often limited to certain types of haze and did not generalize well across diverse environments, indicating the need for more adaptable techniques.

The introduction of deep learning has brought a transformative approach to haze removal, particularly through the use of convolutional neural networks (CNNs) and generative adversarial networks (GANs). CNN-based models like DehazeNet, AOD-Net, and multi-scale convolutional networks have provided robust solutions for single-image dehazing by directly learning haze patterns from large datasets. These models bypass the need for transmission map estimation and offer improved performance across varying haze intensities. However, despite their enhanced effectiveness, CNN-based models often require extensive training data and are computationally demanding, which can hinder their application in real-time and resource-limited settings. GAN-based methods have also shown promise, particularly in generating realistic haze-free images by leveraging adversarial training to refine image details and textures. The dual networks in GANs allow for a more refined output, which is particularly useful in high-density haze conditions. Nonetheless, these models are not without limitations; GANs require stable training, and their effectiveness can vary across different haze distributions, highlighting a need for enhanced model stability and adaptability.

Attention mechanisms have emerged as a critical addition to haze removal models, helping to focus the dehazing process on regions most affected by haze. Models like FFA-Net incorporate attention modules that allow for selective processing of haze-affected areas, leading to improved detail retention and fewer artifacts. However, the increased computational complexity associated with attention mechanisms can be a barrier, and such models still require extensive training data. Additionally, domain adaptation and transfer learning approaches are being explored to address data scarcity and improve generalization across varied haze conditions. Techniques like synthetic-to-real adaptation, where models are pre-trained on synthetic haze datasets and fine-tuned on real data, offer a practical solution for enhancing performance when labeled data is limited. While these methods have shown potential, further work is needed to reduce their dependency on large datasets and to make models more adaptable to varying atmospheric conditions without extensive retraining.

V. CONCLUSION AND FUTURE SCOPE

The evolution of haze removal techniques, from traditional methods to advanced deep learning models, has significantly enhanced image clarity and visibility in diverse environmental conditions. Conventional methods, such as dark channel prior (DCP) and color attenuation prior, laid the groundwork by using statistical priors to approximate transmission and haze levels, yielding reliable results in specific scenarios but often falling short in complex lighting and reflective scenes. Deep learning has enabled a more robust approach, allowing models to directly learn and adapt to haze patterns from vast datasets, which has been particularly impactful in handling varying haze intensities. Convolutional neural networks (CNNs) and generative adversarial networks (GANs) have brought considerable improvements, providing end-to-end dehazing solutions that bypass the limitations of traditional transmission map estimation. However, these advanced models remain computationally demanding, with high resource requirements and training needs that limit their feasibility in real-time applications. Attention mechanisms and domain adaptation techniques have further bolstered model accuracy by focusing dehazing efforts on specific regions and adapting to new haze conditions with limited data. Despite these advancements, challenges persist, especially in achieving real-time processing, adaptability to different lighting and haze conditions, and reducing dependency on extensive datasets. Thus, while current approaches represent a considerable leap forward, they highlight the ongoing need for more efficient, versatile, and scalable solutions.

Future research in haze removal offers promising directions to address the limitations of existing models and expand their applicability. One potential avenue is the development of hybrid models that combine the strengths of traditional priors and deep learning. Such models could leverage the interpretability and lower data dependency of traditional approaches while utilizing deep learning's adaptability and capacity for complex feature extraction. Another area of interest is the integration of reinforcement learning, which could enable adaptive haze removal based on real-time scene analysis, making the models more versatile and responsive to varying atmospheric conditions. Additionally, optimization techniques, including pruning, quantization, and knowledge distillation, could make current models more lightweight, reducing computational requirements for faster deployment in resource-constrained settings, such as autonomous driving and real-time surveillance. Further, research on transfer learning and synthetic-to-real adaptation could reduce the dependency on large labeled datasets, allowing models to generalize better across different environmental contexts. Expanding these methods to video dehazing could also be a significant step forward, addressing temporal consistency issues to ensure smooth visuals in real-time video applications. Ultimately, advancing the field will require interdisciplinary efforts to create scalable, adaptive, and efficient haze removal techniques that can support a wide range of real-world applications.

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