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A COMPREHENSIVE REVIEW OF SINGLE IMAGE DEHAZING METHODS: FROM CLASSIC PRIORS TO DEEP LEARNING

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Abstract:

Fog and haze not only reduce visibility, but also remove the contrast of the image, mute its colour, and erase the fine texture. Restoring such an image, a task called single image dehazing, has become a standard preprocessing step in many visual channels. In the past decade, handmade prior knowledge and deep learning models have been developed rapidly, but neither of them has solved the problem of reliable dehazing in the real environment. Most investigations remain in a family of methods a priori, transformer, or diffusion models. This review has a broader perspective. It regards a priori based, deep learning and hybrid methods as part of a story, and always focuses on the actual obstacles to deployment. We start with the atmospheric scattering model, which is the physical basis of most recovery frameworks. On this basis, we focus on the development of this field: Handmade prior knowledge, such as dark channel prior knowledge, convolutional network, generative confrontation model, attention-based transformers and diffusion model. In this process, our concerns are often pushed aside by cross domain generalization, the computational cost of edge devices, and the gap between the composite benchmark score and the perceived quality of the real world. Finally, we determined the direction that we should do more work: physical knowledge learning, unsupervised adaptation and lightweight system design. These directions are related to the deployment of infrastructure monitoring, autonomous navigation and public safety, in which reliable dehazing is not optional.

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Atmospheric Scattering, Domain Generalization, Deep Neural Networks, Image Dehazing.



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Introduction

Outdoor imaging rarely occurs in clean air. Fog and haze will interfere with the light before it reaches the sensor, while the returned image has weak contrast, dark colour and soft texture (Narasimhan & Nayar, 2003). These effects are not surface effects. In autonomous navigation and traffic monitoring, degraded inputs can be directly translated into unreliable decisions (Li et al., 2017). Therefore, dehazing a single image has become a conventional preprocessing step to keep the visual system working when the weather gets worse (Zhu et al., 2026).

The core difficulty of dehazing is that the problem is ill-posed. In the atmospheric scattering model, the blurred pixels are not a single measurement, but a mixture: part of the scene radiation is weakened by the medium, and part of the ambient light is scattered into the line of sight, which is usually called airlight (McCartney & Hall Jr, 1977; Nayar & Narasimhan, 1999). In order to restore a clear scene from an image, we must estimate three quantities: clear radiation, transmission map and atmospheric light. There is only one observation, and the system is under constrained, which requires some form of auxiliary knowledge: statistical prior knowledge, learning mapping or physical constraints.

Early dehazing work relies on handmade prior statistics or physical assumptions, that is, the behaviour of haze-free scenes. The previous dark channel (he et al., 2010) was the most influential and soon became the standard baseline. Subsequently, other prior knowledge emerged, including colour attenuation prior knowledge (Zhu et al., 2015) and nonlocal prior knowledge (Berman & Avidan, 2016). These methods are transparent and low-cost, but their assumptions are fragile. Dense or spatially varying haze usually violates these rules, resulting in a corresponding decline in performance (Anvari & Athitsos, 2020).

Deep learning has turned this field in another direction. Instead of explicitly estimating physical parameters, the neural network learns the direct mapping from blurred to clear images. Early convolution model (CAI et al., 2016; Ren et al., 2016) show that this is possible; Later work added confrontational training, attention mechanism and transformer backbone (Qin et al., 2020; Zhang et al., 2024). The diffusion model further promotes perceived quality (Zhu et al., 2026). But these achievements have brought new problems. Synthetic training data rarely match the real fuzzy scene, and the calculation cost is high. The benchmark score does not always reflect the quality of the real world (Kankanala, 2026).

Existing surveys often remain in a sub field. GUI et al. (2023) focused on deep learning taxonomy, Zhang et al. (2024) on transformers, and Zhu et al. (2026) on diffusion models. What is missing is a single discussion that transcends previous, deep learning and hybrid

approaches, taking into account deployment barriers. This review fills this gap from three aspects. First, it follows a continuous narrative, from handmade prior to diffusion-based generation, which makes it possible to directly compare assumptions, advantages and failure modes. Secondly, it continues to focus on the topics of robustness gap, real-time constraints and data dependency, which are usually regarded as secondary topics in the algorithm centred review. Third, it critically examines the evaluation practice and believes that the heavy reliance on comprehensive benchmarks masks the seriousness of the generalization problem.

Atmospheric Scattering Model And Problem Formulation

Haze will change the image before any algorithm touches the image. The atmospheric scattering model was first proposed by Koschmieder and then extended by McCartney (1977). It is the theoretical pillar of most classic or learning based dehazing work (an et al., 2024). In this model, light leaves the scene point and propagates to the camera through particles, water droplets, dust and smoke in the air. These particles scatter and absorb light. Images with weak contrast, soft colour and soft edges reach the sensor (Nayar & Narasimhan, 1999).

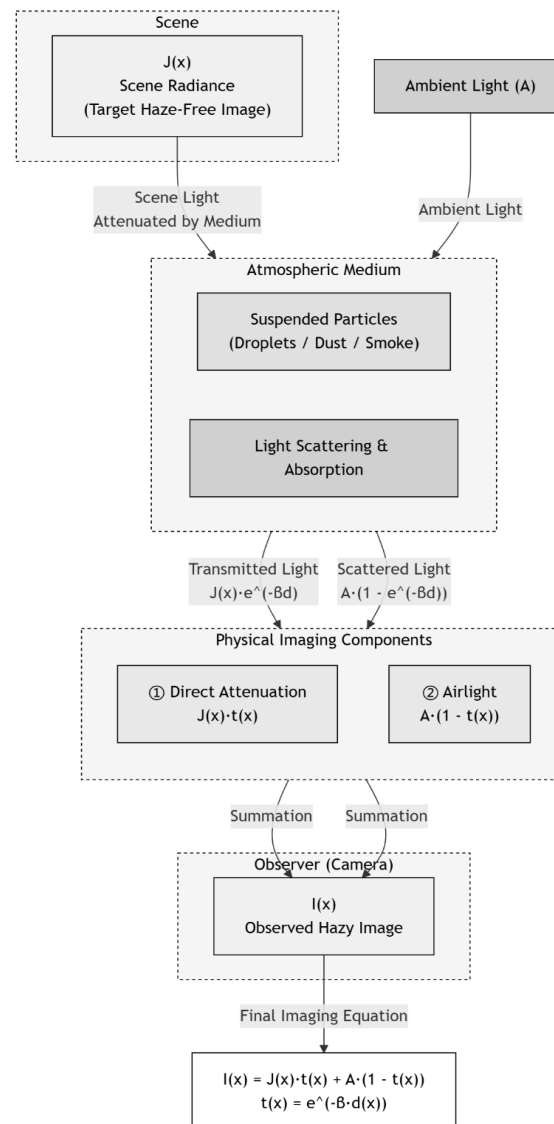


Figure 1: Schematic Illustration of the Atmospheric Scattering Model

Figure 1 shows that the two parts together form a blurred image. The first is direct attenuation: a part of the scene radiation that survives along the line of sight. It decays exponentially with distance. The second is airlight: ambient light scattered by particles in the direction of observation. Unlike direct attenuation, airlight increases with depth. It is the airlight that makes the hazy image have the appearance of fading and low contrast (Narasimhan & Nayar, 2003).

This relationship is usually expressed as:

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

In this equation, $I(x)$ is the hazy intensity observed at pixel x . $J(x)$ is the clear scene radiance we want to recover. A is the atmospheric light. $t(x)$ is the transmission map—the fraction of scene light that reaches the camera without being scattered.

The transmission map $t(x)$ is governed by scene depth $d(x)$ and the atmospheric scattering coefficient β , following the Beer–Lambert law:

$$t(x) = e^{-\beta d(x)} \quad (2)$$

Transmission therefore drops exponentially as depth increases. Objects far from the camera are attenuated more strongly and appear blurrier and less saturated; foreground objects keep more contrast and colour (He et al., 2010). The coefficient β reflects the optical density of the medium. Larger values mean denser haze or fog and faster signal loss with distance (Cai et al., 2016).

Rearranging Eq. (1) gives the clear-scene radiance:

$$J(x) = \frac{I(x) - A(1 - t(x))}{t(x)} = A + \frac{I(x) - A}{t(x)} \quad (3)$$

Since the problem is ill-posed, inversion is difficult. From a hazy image $I(x)$, we need to estimate the three unknowns—the clean image $J(x)$, the transmission map $t(x)$, and the atmospheric light A without any additional observation. Therefore, the system is constrained. Multi-image or multi-spectral settings can provide additional information, but for a single image, it must rely on auxiliary knowledge: statistical prior knowledge, learning mapping or physical constraints.

Around this ill-posed problem, three broad strategies have been formed. The prior based method uses manual assumptions about natural scenes, such as dark channel prior, colour attenuation prior and nonlocal prior to estimate transmission and atmospheric light. They are efficient and easy to explain, but in practice, their assumptions often fail. Deep learning methods use different paths: they use large, paired datasets to learn the direct mapping from blurred images to clear images. They perform well in benchmark tests but have poor generalization of unknown fields and limited interpretability (Ren et al., 2016; Qin et al., 2020; Zhang et al., 2024). The hybrid method combines the physical prior with the neural network to maintain the robustness and physical consistency of the model-based method while benefiting from the representativeness of deep learning (Ayoub et al., 2025; Zhu et al., 2026).

With this model, the rest of this article will follow how each paradigm evolves. We study the prior-based, deep learning and hybrid methods, and compare their principles, advantages, disadvantages and behaviours on synthetic benchmark and real data.

Classic Prior-based Dehazing Methods

Before the beginning of deep learning, dehazing is mainly hand-made. These are statistical or physical assumptions about the behaviour of haze-free natural scenes. They are located in the atmospheric scattering framework, and their work is to estimate the transmission map $t(x)$ and atmospheric light A without any training data. Their appeal is straightforward: they are transparent and low-cost, which makes them very useful for hardware with fast processing or limited resources. But their success is conditional. When it is assumed that dense haze is not included, the spatially varying haze performance may collapse.

Dark Channel Prior (DCP)

The Dark Channel Prior (DCP), introduced by He et al. (2010), is probably the best-known handcrafted prior in dehazing. It has become a standard baseline. Its starting point is a simple observation about haze-free outdoor images: in most local patches that do not contain sky or bright objects, at least one colour channel has pixels with intensities near zero. The reason is that natural scenes are full of shadows, colourful objects, and dark surfaces.

The dark channel of an image J is defined as:

$$J^{dark}(x) = \min_{y \in \Omega(x)} \left(\min_{c \in \{R, G, B\}} J^c(y) \right) \quad (4)$$

where $\Omega(x)$ is a local patch centred at x . DCP assumes that $J^{dark}(x) \rightarrow 0$ for most non-sky patches in haze-free images.

Combining this prior with Eq. (1), He et al. derived a direct estimate of the transmission map. If atmospheric light A is assumed constant, transmission can be approximated as:

$$t(x) = 1 - \omega \min_{y \in \Omega(x)} \left(\min_c \frac{I^c(y)}{A^c} \right) \quad (5)$$

where $\omega \in [0, 1]$ keeps a small amount of haze in the result to preserve depth perception and is usually set to 0.95. The atmospheric light A is taken from the top 0.1% brightest pixels in the dark channel.

DCP performs well on many outdoor images and has inspired a series of extensions. But it has three obvious limitations. Firstly, it decomposes in the sky and highlight areas, where colour shifts and gradient artifacts appear. Secondly, patch-based processing can generate halo effects near depth discontinuities. Thirdly, scenes dominated by large bright surfaces—snow, white exterior walls, water—violate the assumption of low intensity. These drawbacks have driven the search for alternative priors.

Colour Attenuation Prior (CAP)

Zhu et al. (2015) explored this issue from different perspectives. They noticed that the brightness and saturation in haze images are statistically related to haze density: as haze increases, brightness tends to rise and saturation tends to decline. This link can be modelled as a linear function of scene depth.

CAP constructed a linear model that relates the difference between brightness and saturation to scene depth:

$$d(x) \propto v(x) - s(x) \quad (6)$$

Where $v(x)$ is brightness (value channel in HSV space), $s(x)$ saturation, and $d(x)$ is depth. This model is trained on hazy images with known depths and can effectively predict depth for new inputs.

Once the depth is known, the transmittance is obtained from Eq. (2), and atmospheric light is estimated through quadtree subdivision. CAP is fast and tends to maintain natural colour. But it has two weaknesses. Linear models are trained on synthetic data and may not be transferable to real-world scenarios with complex depth or spatially varying haze. Under challenging lighting conditions, atmospheric light estimation remains difficult, and errors can significantly reduce output.

Non-Local Prior (NLP) and Haze-Lines

Berman and Avidan (2016) proposed a prior based on different observations. They noticed that the colours of fog free images can usually be approximated by a small number of different clusters in the RGB space. Pixels in the same cluster may not necessarily be close to each other in the image; They may be located in different areas and at different distances from the camera.

When there is haze, pixels that originally shared the same colour will attenuate by different amounts due to their location at different distances. Therefore, each colour cluster becomes a line in the RGB space - a fog line. This algorithm uses these fog lines to jointly restore atmospheric light, depth, and fog free images, all of which do not require training data.

The fog line method has several advantages: it is deterministic, runs in linear time, and works well on many image types, especially those with rich colour variations. When colour clusters are not prominent, their weaknesses become apparent, such as in scenes with limited colour diversity or in dense, uneven haze. Like other predecessors, it also struggles in the sky and high light areas where the assumed colour distribution does not hold true.

Other Priors and Their Limitations

Other handmade priors have also been proposed. Fattal (2008) hypothesized that shading and propagation are locally uncorrelated, providing a physically motivated pathway for propagation estimation. Tarel and Hautier (2009) proposed a fast visibility restoration method that uses a median filter to estimate atmospheric light, assuming that the haze changes smoothly and is limited by the minimum intensity of the colour channel; This avoids iterative optimization and maintains computational efficiency. Recent research has focused on the

specific weaknesses of DCP: the Dark Direct Attenuation Prior (DDAP) extends DCP to the sky region (Li et al., 2021), and the Region Line Prior (RLP) uses region segmentation to establish a quasi-linear relationship between hazy and non-hazy images (Ju et al., 2021).

Despite this diversity, there are several common limitations based on previous methods. Their effectiveness depends on scenarios and atmospheric conditions that may not always hold true. Atmospheric light estimation is still difficult and context dependent, with errors strongly affecting the final output. These methods are also non adaptive: they apply the same assumptions to each image regardless of the content or degradation mode. Finally, real haze images often contain degradation beyond simple haze that cannot be captured by simplified scattering models – noise, uneven lighting, and mixed weather.

Table 1: Comparison of Representative Prior-Based Dehazing Methods

Method	Prior/ Assumption	Main Advantage	Main Limitation
Dark Channel Prior (He et al., 2010)	Most local patches contain low-intensity pixels in at least one channel	Highly effective for most outdoor scenes; mathematically well-founded	Fails in sky and bright-object regions; halo artifacts
Colour Attenuation Prior (Zhu et al., 2015)	Brightness-saturation difference correlates with depth	Fast; preserves natural colours	Limited generalization to real-world scenes; relies on synthetic training
Non-Local Prior (Berman & Avidan, 2016)	Clear image colours form tight clusters; haze creates lines in RGB space	Deterministic; linear complexity; no training required	Degrades with limited colour diversity; fails in sky regions

Deep Learning-based Dehazing Methods

When the haze is complex or uneven, handmade priors may encounter difficulties. This weakness is driving the field towards data-driven alternatives. In the past decade, deep learning has become the primary method for de hashing, mainly because it can directly learn hierarchical features from large datasets. Classical methods explicitly estimate physical parameters; Neural networks are not available. They implicitly learned the mapping from blur to clarity. The return is higher than the accuracy of standard benchmark tests. The cost is relatively low in interpretability and heavily relies on training data. This section introduces the evolution of deep learning-based hashing, from early convolutional models to generative adversarial networks, attention mechanisms, transformers, and diffusion models.

Early CNN-Based Models

The first deep learning method used for deblurring considers transmission estimation as an intermediate step. Cai et al. (2016) proposed DehazeNet, a lightweight network that uses specialized feature extraction layers, multi-scale filters, and BReLU activation to directly transmit predictions from fuzzy patches. Then insert the predicted transmittance into the atmospheric scattering model to restore a clear image. This is a significant improvement compared to previous methods based on standard benchmarks, but two-stage pipelines may accumulate errors. Ren et al. (2016) later proposed a multi-scale CNN (MSCNN) strategy from coarse to fine: coarse networks estimate the transmission of global context at lower resolutions, while fine networks refine local details at full resolution. This design achieves a better balance between receptive field size and spatial accuracy.

Later work shifted towards encoder decoder architecture, which became the main focus of CNN based hashing. Li et al. (2019) proposed SEMI-CNN, a skip connected encoder decoder with two branches: the supervised branch trains on paired synthetic data, while the unsupervised branch is constrained by dark channels and gradient priors to improve real-world generalization ability. Tran et al. (2022) proposed EDN-GTM, which enhances U-Net for multi-scale feature extraction by guiding transmission maps and spatial pyramid pooling. Early CNN models still had common weaknesses. They rely on propagation estimation as an intermediate step, mainly based on synthetic data for training (generating domain gaps), and due to their local receptive fields, their ability to capture long-range dependencies is limited.

Generative Adversarial Network-Based Models

Generative Adversarial Networks (GANs) have brought different training paradigms. Early convolutional neural networks optimized with mean square error typically produced smooth outputs without fine textures. Based on GAN framework, a generator is used to generate denoised images, and a discriminator is used to distinguish them from real clear images. This adversarial setting pushes the generator towards pixel accurate and visually convincing output.

Several GAN based models have emerged. FFA Net (Qin et al., 2020) combines GAN targets with feature fusion attention mechanism, which adaptively weights feature in both spatial and channel dimensions, achieving strong benchmark performance at the time. GridDehazeNet (Liu et al., 2019) integrates attention based multi-scale processing within the GAN framework. A noteworthy trend is the dual generator architecture - TMS-GAN (Wang et al., 2021), DDN (Yang & Zhang, 2022), and DSD Net (Li et al., 2022) - which use one generator for structure and another generator for texture, balancing fidelity and perceptual quality.

The hashing based on GAN has its own problems. Training is usually unstable and may lead to pattern collapse, resulting in sensitivity to hyperparameters. More importantly, the lack of clear physical constraints can result in visually appealing but physically incredible outputs that deviate from the actual scene radiation. This has inspired a hybrid approach that combines physical priors with GAN based learning.

Attention Mechanisms and Transformer-Based Models

The attention mechanism has brought further improvements. By selectively emphasizing information features and reducing the weight of irrelevant features, they partially repaired the

limited receptive field of standard CNNs. Tang et al. (2023) showed that multi-scale convolution combined with attention can extract haze related features without explicit physical modelling. The feature fusion attention module in FFA Net (Qin et al., 2020) adaptively reweights features using channel and pixel weighting, thereby improving the performance of non-uniform haze. SCANet (Guo et al., 2023) introduced a self-paced semi course attention strategy to better handle severely occluded areas in non-uniform scenes.

Transformer based deblurring methods can be divided into three groups based on how they utilize physical or domain knowledge. Architecture centred designs, such as DehazeFormer (Song et al., 2022) and TID (Gao et al., 2022), view de concavity as a universal image to image task and rely on scale and capability to learn mappings; They achieve powerful benchmark numbers, but have almost no interpretability or physical consistency. Previous injection designs by DeHamer (Guo et al., 2022) and DHFormer (Wasi & Shiney, 2023) incorporated transmission perception embedding or haze density cues into attention mechanisms, sacrificing design complexity to improve generalization ability under non-uniform haze conditions. Data centric designs, such as Liu et al.'s (2023) dual branch ViT, prioritize robustness with limited training data and trade peak benchmark performance for cross domain stability. These three groups share a common weakness: the quadratic complexity of self-attention limits the deployment of low-resolution inputs, and none of them directly addresses the domain gap between synthetic and realistic hazy scenes.

Zhou et al. (2026) reported that compared to early CNN based methods, the transformer and diffusion-based model improved SSIM by 12% -18% and reduced perception error by 20% - 35%. These benefits are not free: the quadratic complexity of self-attention makes Transformers difficult to apply to high-resolution images, and their massive parameter counts pose challenges for real-time or edge deployment.

Diffusion Models for Image Dehazing

The diffusion model is the latest development in dehazing, setting new standards for perceived quality. As reviewed by Zhu et al. (2026), they learned to reverse a progressive noise process: during the training process, the image is gradually corrupted by Gaussian noise until it becomes pure noise; During the inference process, the model gradually denoises the fuzzy conditional input. Three main formulas have been used – Denoising Diffusion Probability Model (DDPM), Noise Conditional Fractional Network (NCSN), and Stochastic Differential Equation (SDE) – all of which can be adapted to deblurring by adjusting the reverse process on fuzzy observations. This allows for the restoration of fine textures and details that are often lost in deterministic pipelines.

Several diffusion-based dehazing methods have been proposed for different scenarios. Qiao et al. (2024) proposed an uncertainty aware diffusion model that considers the uncertainty of transmission estimation and improves robustness to real blurry images. Zhang et al. (2024) introduced a density aware variant that adapts denoising plans to local haze density, improving the efficiency of non-uniform scenes. Wang et al. (2024) developed a frequency compensation model for recovering high-frequency components, while Yin et al. (2025) solved the gap problem of synthesizing to reality through haze density sensing design.

The diffusion-based dehazing still faces practical obstacles. The computational cost of iterative sampling is high, which limits real-time performance or edge usage. These models also require a large amount of training datasets and provide limited physical interpretability. As pointed out by Zhu et al. (2026), combining diffusion models with physical priors through hybrid architecture or physics guided design is a promising direction, with early results showing a 27% reduction in colour deviation.

Table 2: Comparison of Deep Learning-Based Dehazing Paradigms

Paradigm	Representative Methods	Main Advantage	Main Limitation
Early CNNs	DehazeNet, MSCNN, SEMI-CNN	Computationally lightweight; establishes strong baselines	Constrained by local receptive fields; limited cross-domain transfer
Encoder-Decoder CNNs	EDN-GTM, MSBDN, U-Net variants	Effective multi-scale representation; preserves structural coherence	Captures limited global context; outputs tend toward over-smoothing
GAN-Based Models	FFA-Net, GridDehazeNet, TMS-GAN	Generates perceptually convincing textures; enhances visual realism	Training is inherently unstable; lacks explicit physical grounding
Transformer-Based Models	Various ViT and hybrid architectures	Offers full global receptive field; excels in non-uniform haze	Demands high computation and memory; parameter-heavy
Diffusion Models	DDPM, NCSN, SDE-based dehazing	Achieves state-of-the-art perceptual quality; preserves fine details	High inference cost due to iterative sampling; limited physical interpretability

Robustness Challenges and Emerging Solutions

A model can surpass every benchmark, but it will still fail at the moment it leaves the laboratory. This gap - the gap between comprehensive evaluation and real-world generalization - is now widely regarded as one of the biggest obstacles to deploying a dehazing system (Lee et al., 2024). This section focuses on three robustness issues: the mismatch between the training and testing domains, the computational cost of state-of-the-art models, and the large amount of data required for supervised learning. It also reviews emerging strategies, including unsupervised paradigms, semi supervised strategies, and hardware aware design.

Domain Gap and Generalization Issues

The domain gap continues to become a learning based deblurring problem. Models trained on synthetic blur clear pairs often crash on real blurry images. Gui et al. (2023) pointed out that

most publicly available training data are synthesized haze, and there are few real haze images with ground truth. The supervised model scores high in the synthetic test set, but its score drops sharply in the actual input. The root cause is mismatch: the simplified physical model used to synthesize haze does not match the complex degradation in real scenes - uneven haze density, mixed weather, variable lighting, depth dependent effects (Song et al., 2026).

This gap has been measured in several studies. Zheng et al. (2025) tested state-of-the-art deblurring models on real-world images and found that many algorithms with almost perfect synthesis scores severely degraded in practice. This result pushes the field from pure benchmark chasing to generalization.

Several strategies have been proposed to narrow this gap. The domain adaptation method aligns the feature distribution between the synthetic domain and the real domain, allowing the model trained on synthetic data to be generalized to real scenes (Tsai et al., 2025). Data augmentation - physically guided parameter augmentation and relocation - exposes the model to more diverse degradation and improves robustness (Chang et al., 2025). Another approach is to directly embed domain invariant physical constraints, such as atmospheric scattering models, into neural architectures (Su et al., 2025). Recent work has also explored physics guided synthesis to true exfoliation, in order to bridge the gap (Zhou et al., 2025).

Real-Time Processing and Computational Constraints

In many applications, real-time operation is not optional. Autonomous driving, advanced driver assistance, traffic monitoring, and drones all require deblurring modules capable of processing 60 fps or higher resolution videos (Odugu et al., 2026). For computationally intensive models, this is a high requirement (Kankanala et al., 2026).

Transformers and diffusion models are difficult to deploy in real-time. The quadratic complexity of self-attention and the iterative nature of diffusion sampling are not suitable for resource constrained environments (Zhu et al., 2026). Therefore, researchers have turned to hardware acceleration and model compression. Gade et al. (2025) proposed a high-throughput architecture that combines CNN with dark channel priors on FPGA and ASIC platforms. By using on-chip line buffers to eliminate external DRAM access, this design reduces FPGA resources by 85% and increases ASIC area, speed, and power consumption by 92%. Additionally, it increases MSE by 11%, PSNR by 2-30%, and SSIM by 19% under different haze conditions. Another hardware implementation based on saturation driven denoising achieved 70.3 fps at 4K resolution (Odugu et al., 2026).

Lightweight model design has also attracted people's attention. Hazedify (Bhavsar, 2025) first prioritized the simplicity and deployability of consumer hardware, and built a gamma adaptive reconstruction, fast transmission approximation, and stable atmospheric light estimator based on the Dark Channel Prior, achieving real-time denoising without GPU acceleration. HazeTrendNet (Wang & Fan, 2025) utilizes haze concentration trend guidance with only 6.17 million parameters and 56.46 GFLOPs, making it highly suitable for edge deployment in monitoring and autonomous driving. CED-RIDE (Halford et al., 2025) uses only 24659 parameters for real-time smoke exhaust of edge devices.

Unsupervised and Semi-Supervised Learning

Supervised hashing relies on large-scale paired data, which is a major limitation. It has sparked interest in unsupervised and semi supervised methods that can learn from unpaired or unlabelled data and better generalize to real-world scenarios (Gui et al., 2023).

Unsupervised methods do not require paired fuzzy and clear data. They rely on unpaired data, periodic consistency goals, or domain specific assumptions. Cycle Dehaze (Engin et al., 2018) uses enhanced CycleGAN to learn the mapping between fuzzy and clear domains without pairing supervision. ICycleGAN (Sun et al., 2021) embeds an iterative hashing model into CycleGAN and adds detail preservation loss. DW-GAN (Fu et al., 2021) won the NTIRE 2021 non-uniform haze removal challenge by applying discrete wavelet transform within GAN to handle spatially varying haze. YOLY (Li et al., 2021) optimized each image without any training data, decomposing the blurry input into radiation, transmission, and atmospheric light. This can achieve maximum generalization ability, but the inference cost is high. Other unsupervised methods include multi branch networks with high-frequency enhancement (Sun et al., 2024) and contrastive regularization (Wang et al., 2024).

Self-supervised learning has also been explored. Liang et al. (2022) showed that self-supervised pretraining and adaptation can improve the feature representation and generalization ability of deblurring. Xiao et al. (2023) developed a zero-sample dehazing network based on a dark channel prior that does not require external labels. Liang et al. (2025) proposed a self-supervised depth guidance method that uses depth estimation to simulate haze density through a hybrid attention transformer with cross modal fusion.

Semi supervised learning is somewhere in between, using a small, paired set plus a larger unpaired or unlabelled data pool. Li et al. (2019) introduced a semi supervised CNN that has supervised branches on paired data and unsupervised branches constrained by dark channels and gradient priors, improving its real-world generalization ability. The recent semi supervised methods use disentanglement meta knowledge learning (Rupesh et al., 2024) and self-guided disentanglement representation learning (Jia et al., 2024) for more robust feature extraction in the case of limited labels.

Table 3: Comparison of Learning Paradigms for Image Dehazing

Paradigm	Representative Methods	Data Needed	Main Advantage	Main Limitation
Supervised Learning	DehazeNet, FFA-Net, DehazeFormer	Paired hazy-clear pairs	Strong benchmark performance; mature and well-studied	DehazeNet, FFA-Net, DehazeFormer
Unsupervised Learning	Cycle-Dehaze, ICycleGAN, YOLY, DW-GAN	Unpaired or unlabeled data	Eliminates need for paired data; improves domain adaptability	Often yields lower fidelity; training can be unstable
Self-Supervised Learning	Depth-guided, YOLY, zero-shot adaptation	Single test sample or unlabelled data	Maximizes generalization; requires no external training	Expensive per-image optimization cost
Semi-Supervised Learning	Li et al., 2019; Jia et al., 2024; Rupesh et al., 2024	Small paired set + large unpaired pool	Good trade-off between performance and generalization; data-efficient	More intricate training process

There is a trade-off between supervised and semi supervised methods. Semi supervised methods typically have better generalization ability than pure supervised methods, while maintaining competitive overall benchmark performance (Gui et al., 2023). However, unsupervised and semi supervised models often lag behind supervised models on standard synthetic test sets, and unsupervised training based on GAN is unstable. Looking ahead, this field requires stronger domain adaptation, physical priors within unsupervised frameworks, and efficient architectures for edge deployment.

Performance Evaluation and Datasets

More directional algorithms mean a greater demand for benchmarks that allow for fair comparisons. Dehazing is not like many low-level visual problems that can directly capture the truth on the ground. It has poor posture, making it difficult to obtain paired hazy and clear images. This section investigates the datasets and quantitative metrics used in dehazing, and explores their advantages, disadvantages, and relevance to real-world deployment.

Widely Used Datasets

RESIDE (Li et al., 2018) may be the most widely used synthetic benchmark in dehazing. It divides the data into indoor and outdoor scenarios. The indoor training set (ITS) contains 13990 pairs of synthesized hazy and clear images from 1399 indoor images. The Outdoor Training

Set (OTS) consists of 72135 pairs out of 2061 outdoor images. There are three things that explain its popularity: large-scale, diverse scenarios, and standardized evaluation procedures.

The synthetic dataset is large and has ground truth, but they differ from real-world conditions. This has led to several real-world benchmarks. Dense Haze (Ancuti et al., 2019) has 33 pairs of real haze and haze free outdoor images. Haze is generated by professional haze machines to maintain consistency in paired lighting and content. This dataset has dense and uniform haze characteristics and was used for the NTIRE 2019 CVPR haze removal challenge. NH-HAZE (Ancuti et al., 2020) provided 55 pairs of real outdoor images with non-uniform haze, where haze density varies spatially within the scene.

Other benchmarks are targeted towards more specific evaluation contexts. HazeSpace 2M (Rafiq et al., 2026) is a recent large-scale benchmark used for dehazing assessment. For traffic monitoring, HZSC (Chen et al., 2026) provided haze visibility ranking images from 36 different outdoor scenes. These datasets have driven the development of the field, but the gap between synthetic benchmark scores and actual performance remains a serious issue.

Quantitative Evaluation Metrics

Compare the denoised output with the ground truth clear image based on reference metrics. Common examples include Peak Signal to Noise Ratio (PSNR), Structural Similarity Index (SSIM), and CIEDE2000. Non reference indicators do not require ground truth, so they can be used in real hazy scenes without paired clear images. They judge quality by contrast, naturalness of colour, and increased visibility, but they are usually not as reliable as reference-based metrics and are often used as supplements.

There are real limitations to today's evaluation practices. Rafiq et al. (2026) proposed a domain specific composite evaluation framework. Their argument is that current indicators cannot capture all the degradation during the dehazing process in the real world. They also pointed out that the disconnect between benchmark scores and real-world perceived quality is a key obstacle to deployment. Zheng et al. (2025) found that many state-of-the-art models with almost perfect synthesis results exhibit significant degradation on real-world images. This result provides a reason for a more robust evaluation.

Comparative Performance Analysis

Table 4 shows some trends. Based on previous methods such as DCP (He et al., 2010), the score on the composite benchmark is relatively low. This reflects the prior limitations of handcrafting in complex lighting and depth. Deep learning methods always outperform them; At the time of publication, FFA Net (Qin et al., 2020) achieved a PSNR of 36.39 dB on SOTS Indoor. Recently, hybrid models based on Transformer, including EPIGN (Liang & Xu, 2025) and HazeTendeNet (Wang & Fan, 2025), have further improved performance. HazeTrendNet achieves 42.29 dB PSNR on SOTS Indoor with only 6.17 million parameters.

Table 4: Quantitative Performance Comparison of Representative Dehazing Methods on the RESIDE Benchmark

Method	SOTS-Indoor	SOTS-Outdoor	Params (M)	FLOPs (G)
DCP (He et al., 2010)	16.62 / 0.818	19.13 / 0.815	—	—
DehazeNet (Cai et al., 2016)	19.82 / 0.821	24.75 / 0.927	0.009	0.58
AOD-Net (Li et al., 2017)	20.51 / 0.816	24.14 / 0.920	0.002	0.12
GridDehazeNet (Liu et al., 2019)	32.16 / 0.984	30.86 / 0.982	0.956	21.49
MSBDN (Dong et al., 2020)	33.67 / 0.985	33.48 / 0.982	31.35	41.54
FFA-Net (Qin et al., 2020)	36.39 / 0.989	33.57 / 0.984	4.456	287.50
Dehamer (Guo et al., 2022)	36.63 / 0.988	35.18 / 0.986	132.50	48.93
EPIGN (Liang & Xu, 2025)	37.58 / 0.991	35.54 / 0.988	2.024	24.84
HazeTrendNet (Wang & Fan, 2025)	42.29 / 0.997	40.07 / 0.997	6.17	56.46

Note: Results compiled from Wang & Fan (2025) and Liang & Xu (2025). “—” denotes unavailable data. PSNR/SSIM values are reported for SOTS-Indoor and SOTS-Outdoor.

However, strong comprehensive benchmark performance cannot guarantee real-world effectiveness. In dense haze, it is often difficult to train methods on synthetic data. DCP only achieved a peak signal-to-noise ratio of 12.75 dB and an SSIM of 0.443. Although HazeTrendNet performed well in synthetic testing, its PSNR was only 22.14 dB and SSIM was only 0.812. These numbers provide a basis for evaluating the real world and continuing domain adaptation and generalization work.

Conclusion And Future Directions

This review traces how single image hashing evolved from early deep learning methods to today's deep learning. In this process, it covers physical models, algorithms, robustness challenges, and evaluation practices. There are several prominent conclusions.

Summary of Key Findings

The first point is that there have been significant changes in this field over the past two decades. The classic prior based methods - dark channel prior (He et al., 2010), colour fading prior (Zhu et al., 2015), and non-local prior (Berman&Avidan, 2016) - have set theoretical frameworks and practical baselines for dandruff removal. These methods are transparent and have low operating costs, but their performance depends on assumptions that often fail under complex or spatially changing haze.

The second point is that deep learning has changed everything. Advancements in Architecture - Early Convolutional Networks (Cai et al., 2016; Ren et al., 2017), GAN based framework (Qin et al., 2020), Transformer based design (Song et al., 2022); Guo et al. (2023) and the recent diffusion model (Zhou et al., 2025) have steadily improved the overall benchmark performance. Attention and self-attention provide a global receptive field for the model, which is important for non-uniform haze (Zhang et al., 2024). The diffusion model makes the restored image quality closer to human perceptual standards (Zhu et al., 2026).

The third point is that robustness and generalization are the real bottlenecks in deployment. The domain gap between synthetic training data and real hazy scenes remains a fundamental obstacle: models with almost perfect synthetic scores often experience significant degradation on real images (Zheng et al., 2025). This has driven hardware acceleration architecture (Gade et al., 2026; Odugu et al., 2026), lightweight model design (Bhavsar, 2025; Wang & Fan, 2025; Halford et al., 2025), and unsupervised or semi supervised learning to reduce dependence on paired data.

The fourth point is that the evaluation is still fragmented. RESIDE (Li et al., 2018) and other comprehensive benchmarks still dominate quantitative comparisons, despite their poor correlation with real-world performance. The real-world datasets - dense haze (Ancuti et al., 2019), NH Haze (Ancuti et al., 2020), HZSC (Chen et al., 2026), and HazeSpace 2M (Rafiq et al., 2026) - allow for more realistic assessments, but the gap between benchmark indicators and actual utility still exists.

Future Research Directions

Based on the trends and challenges identified in this review, several promising directions for future research have emerged.

Physics based neural networks are worth pursuing. Combining physical priors with data-driven learning can generate high-performance and physically consistent models. Recent studies have shown that embedding domain invariant constraints, such as atmospheric scattering models (Hao et al., 2025) or dark channel priors (Su et al., 2026), into neural architectures can improve robustness. The next step is to find a principled approach to integrating them: a physics-based loss function, interpretable modules, and a hybrid design that combines the advantages of model-based and data-driven methods.

Unsupervised and self-supervised learning can reduce the need for paired data. Supervising deblurring still heavily relies on large-scale paired training data. The methods based on unsupervised paradigms CycleGAN (Engel et al., 2018), zero sample learning (Li et al., 2021), and self-supervised deep guidance (Liang et al., 2025) can improve real-world

generalization without ground trajectory images. What is needed next is an unsupervised framework that maintains perceptual quality and physical consistency, as well as self-supervised goals that utilize image statistics or cross modal information.

Real time and edge deployable systems are important in practical use. Autonomous driving, monitoring, and intelligent transportation require real-time operation on hardware with limited resources. Hardware acceleration architecture (Gade et al., 2026; The latest developments in Odugu et al. (2026) and lightweight model design (Bhavsar, 2025; Wang & Fan, 2025; Halford et al., 2025) indicate that efficiency and quality are not necessarily a trade-off. The next step is neural architecture search and knowledge distillation to shrink the model, as well as domain specific pipelines for edge deployment.

The diffusion model improves the perceptual quality of deblurring. But their computational cost and iterative sampling are obstacles to deployment. Faster sampling, knowledge extraction, and architecture optimization are promising directions for progress. Combining diffusion models with physical priors, such as the physics guided diffusion framework (Xie et al., 2024); Zhou et al. (2025) suggest that perceptual quality can be combined with physical consistency. Domain generalization and adaptation are also urgently needed. This field requires domain adaptation to align feature distributions, physical guidance enhancement to expose the model to various degradation, and adaptive testing time to adjust the model to the target domain without retraining.

A unified evaluation framework is needed. At present, evaluation protocols are decentralized, and benchmark indicators have weak correlation with real-world performance. The recent work on domain specific composite evaluation (Rafiq et al., 2026) is a good start. Next are standardized protocols covering synthesis and real-world testing, indicators that better align with human perception, and datasets covering dense haze, non-uniform haze, nighttime haze, and mixed weather.

In summary, due to advances in physical modelling and deep learning, significant progress has been made in deblurring individual images. However, a powerful, universal, and deployable system still does not exist. Three priorities stand out: narrowing the gap between synthetic benchmarks and real-world practicality, combining physics knowledge with data-driven methods, and designing efficient architectures for edge deployment. Combining physics-based modelling, generative artificial intelligence, and hardware aware design is a promising approach to achieving reliable mine clearance in infrastructure, transportation, and monitoring fields.

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