An Investigative Study on Deep Learning-Based Image Dehazing Techniques

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Abstract: Image dehazing is a complex challenge within the field of computer vision, particularly when dealing with hazy or foggy scenes. Photographs captured in unfavourable weather conditions (such as haze, fog, smog, and mist) often suffer from significant degradation. These deteriorated images pose difficulties for various computer vision applications, including video surveillance, smart transportation, weather forecasting, and remote sensing. The task of mitigating these adverse effects is commonly referred to as image dehazing.In recent years, deep learning (DL) techniques have garnered substantial attention for addressing challenging image dehazing problems. Notably, architectures like Generative Adversarial Networks (GANs) and Convolutional Neural Networks (CNNs) have revolutionized the field. CNNs excel at capturing spatial hierarchies and extracting meaningful features, while GANs leverage adversarial training to enhance the fidelity of dehazed images. By combining feature extraction and reconstruction, these DL models enable the restoration of clarity in hazy scenes.This article provides an extensive analysis of DL-based dehazing methods proposed by various researchers. It covers their performance, datasets used, evaluation metrics, and recent advancements. The goal is to improve the effectiveness and precision of dehazing algorithms, ultimately benefiting a wide range of applications.

Keywords: Dehazing, Deep Learning, CNN, GAN.

1 Introduction

For almost a decade, image dehazing has been a busy field of research. The origin of haze or fog is typically unfavourable weather, and the kind, size, and concentration of the particles all play a role. Unfavourable weather conditions can cause a picture or video to lose contrast and change colour. Variations in colour or contrast have a significant effect on the surveillance system or the object. The technique of scenically enhancing the reduced visibility brought on by meteorological circumstances is known as image dehazing. The primary goal is to recover the scene's brightness from the fuzzy picture. Satellite and underwater image clarity is reduced by fog or haze. The majority of automated systems rely heavily on the definition of the input images; malfunctions that prevent normal operation Daytime and night-time dehazing are the two primary categories of dehazing. For dehazing during the day, there are several dehazed techniques. A linear equation can be used to represent the haze model for day time which is made up of air light along with transmission map. In addition to dehazing during the day, dehazing at night is an important subject. Dehazing in low light conditions is difficult, since the atmospheric light varies throughout the picture. Aside from dehazing throughout the day, the primary cause is lighting from various sources, like street lamps and vehicle lights. Next, the image is subjected to a block effect condition.

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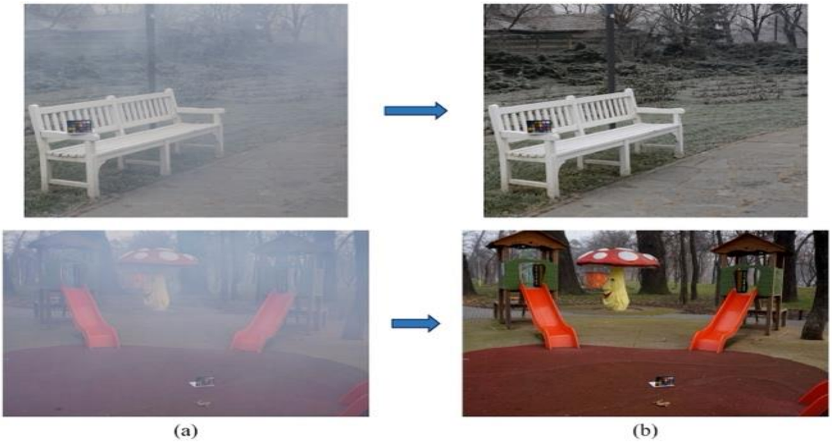

Fig 1: Images with haze and their dehazed images. Source: Dataset O-Haze

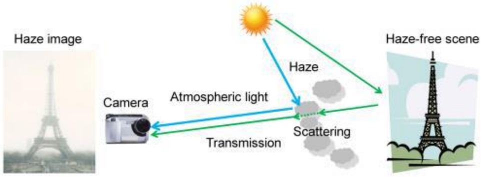

Fig 2: shows the formation of a Hazy image Source: Dataset O-Haze

The fig 2 demonstrates how the image's haze is developing. The particles in the atmosphere attenuate and scatter the light emanating from the item. We refer to this as attenuation. The term "air light" refers to a tiny amount of light that is dispersed from the lighting source and faces the camera. Koschmieder's model is applied to estimate both ambient lighting & the transmission map. The quality of the image is often impacted by airlight and attenuation.

Haze impairs scene sight and influences people's perception of items. It is also possible for thick haze to compromise regular activities like transportation safety. Haze affects computer vision by obstructing objects partially or completely, which lowers image quality and reduces the dependability of high-level vision tasks.

This review paper is arranged as follows: This portion includes a small preface, an overview of various dehazing techniques, a conclusion, and references.

2 Related Works

Subhash Chand Agarwal, Anand Singh Jala[1] have provided an deep analysis understanding in this area; the state of advancement to date and contrasts the most recent works' performance (qualitative and quantitative). This review article provides an in-depth analysis of recent dehazing methods, categorizing them into different groups. It covers popular dehazing techniques, including deep learning-based approaches and restoration-based methods. The paper discusses challenges related to both non-homogeneous and dense haze. Additionally, it shows how the techniques that are dependent on hardware for smart transportation systems.

Jie Gui, et, al [2] provided a thorough analysis of single picture dehazing techniques, including supervised, semi-supervised, and unsupervised. They talked about the physical model, commonly used assessment measures, loss functions, datasets, and network modules. Next, a summary and categorization of the principal contributions of several dehazing algorithms are provided. Experiments using both quantitative and qualitative baseline approaches are also conducted. Lastly, the open problems and difficulties that may stimulate further study are highlighted.Codruta Orniana Ancuti [3] presented the multiple image fusion techniques. It is a method for a dehazing a single image. fusion-based method that uses weights and inputs taken from the fuzzy picture. By applying contrast enhancement and white balancing to the initial fuzzy image, two inputs are produced. During the contrast enhancement process, certain image features could be lost. Therefore, appropriate weight maps are presented. All weight maps are applied to both inputs. Subsequently, the weight maps for both inputs undergo normalisation. For preserving the most important identified features, inputs are finally weighted using particular weight maps. Gaussian pyramid for normalised weight map is computed. Subtracting the extension of the Gaussian pyramid derived from its levels yields the Laplacian pyramid, which is then created from the gaussian pyramid. Eventually, a bottom-up integration of all these levels is achieved.

Lingke Zeng [4] presented a multi scale convolutional neural network to identify distinct & efficient features. 2-networks in particular: coarse and fine scale-networks. By computing the transmission map of the scene using a large-scale network and fine-tuning the transmission-map over the whole image using a fine-scale network, the dehazed result is improved locally.Manjunath. V [5] approach is based on the multiple scattering technique. When combined with a single image dehazing model, this strategy makes dehazing incredibly simple and effective. The algorithm, which is applied to a wider range of photos, is based on local content and is more sensitive than colour. In order to solve this issue, numerous physical models are employed. Particles in the atmospheric layer such as fog, haze, and other particles commonly produce dispersion during rainy weather, which negatively affects imaging.Yu Li [6] presented a model of haze for changing light sources and halos. This model contains air light, a gearbox map, and halos. A halo image is the input. Subsequently, it is separated into images with and without halo using an optimisation problem. We perform advanced processing on the halo-free pictures. The primary responsibility in this method is air light and gearbox map estimation. This approach is simple and economical. Still, haze-free outcomes are not as good as with other approaches.

Yibo Tan [7] Getting rid of the block impact and handling objects that are identical to light in an image is a difficult issue for the dehazing algorithms that are currently in use. A one image haze reduction method based on super pixels and MRF was used to solve this problem. The image's contrast is increased by this markov random field. The superpixels and MRF are used to estimate transmittance. The suggested method properly preserves the edge features. Where artefacts are present, basic linear-iterative-clustering is used to partition the super pixels. The current dehazing approaches have difficulty coping with objects that are identical to light and removing the block effect from images. Using superpixels and a markov random field (MRF), a single -image haze elimination concept was used to solve this problem. The contrast of the image is increased by this markov random field. The MRF and superpixels are used to estimate transmittance. The edge details are successfully preserved by the proposed method. Where there are artefacts, the super pixels are segmented using basic iterative linear clustering. The data term first shows that the superpixel has transmittance. The intensity between the superpixels is indicated by the second neighbour word. Lastly, the possibility that neighbouring pixels will have the same transmittance is indicated by the smooth term. The data term fixes the transmittances that were estimated wrongly. The block effect on the edges is not produced by the Markov random field approach. MRF effectively maintains the barrier.Qingsong Zhu, et, al [8] have introduced is a straightforward yet potent color attenuation principle aimed at clearing haze from a singular hazy image. This novel approach involves constructing a model that is linear to represent the depth of the scene within the foggy picture based on the prior, followed by parameter training via supervised learning techniques. This process effectively recovers depth information. Leveraging the resulting depth map, one can readily estimate transmission and restore scene radiance using The model of atmospheric scattering, thereby efficiently eliminating haze from a single image. Experimental findings show off your superiority of this method over contemporary haze removal algorithms, showcasing improvements in both efficiency and dehazing effectiveness.Xin Fan, et, al [9] have proposed a learning framework was suggested for haze elimination employing a dual-layer Gaussian process regression (GPR). This model, trained on examples, connects input images to depth-dependent transmission directly, while assimilating local image priors to enhance accuracy. Additionally, they devised a method to gather appropriate training pairs automatically, applicable to both synthetic and natural scene images. Their method's efficacy was confirmed through assessments on real and synthetic-hazy images, excelling in scenarios where conventional techniques struggle, such as bright objects and dense haze regions.Bolun Cai introduced DehazeNet, a fully trainable framework designed for estimating medium transmission in hazy images. DehazeNet takes a hazy image as input and generates a medium transmission map, which is then used to produce a haze-free image using an atmospheric scattering model. It employs a deep convolutional neural network architecture, with layers tailored to incorporate established assumptions and priors in image dehazing. Notably, DehazeNet utilizes Max out units for feature extraction, effectively capturing haze-related features. Additionally, it introduces a novel nonlinear activation function called bilateral rectified linear unit, which improves the quality of the resulting haze-free image. Experimental results on standard images demonstrate DehazeNet's superior performance compared to existing techniques, while also emphasizing its efficiency and user-friendliness.

Table 1: Comparison of different Researches done

Sno	Method	Results & Future Scope
1	Deep learning-based approach	1.There is a necessity for a unified approach to assess the quality of dehazing methods, taking into account factors such as the general quality of perception, artifacts, color distortions, lingering haze, and over-enhancement. 2.Most existing methods for fog removal focus on single images, but there are limited methods for removing fog from videos captured with a moving camera; therefore, there is a need for real-time processing methods that can handle high-definition video with little electricity and hardware costs.
2	Supervised, semi-supervised, and unsupervised dehazing techniques	1.The paper aims a thorough analysis of deep-learning based single picture dehazing. 2.The paper categorizes and summarizes the primary benefits of different dehazing algorithms.

3	Fusion-based method using weights and inputs from the fuzzy image	1. The proposed fusion-based strategy for single image dehazing yields accurate haze free results better than intricate existing methods. 2.The method is suitable for real-time applications and demonstrates comparable and even superior outcomes compared to current strategies. 3. The fusion-based approach effectively solves the problem of single image dehazing and is faster than existing strategies, while still producing accurate-results . 4.The approach has been evaluated on a large dataset of photographs that are naturally hazy, further validating its effectiveness.
4	Multi-scale convolutional neural network	1. The suggested algorithm's dehazed findings are nearly identical to the haze-free ground truth photos, suggesting improved transmission map estimate. 2. With respect to PSNR and SSIM, the suggested algorithm outperforms the most advanced dehazing techniques on each image. 3. The usefulness of the suggested algorithm is shown by experimental results on both artificial and real photos. 4. The suggested multi-scale network works effectively and generalizes to real-world scenarios. 5. in this,the proposed mathematical model is not suitable for nighttime hazy images
5	Single image dehazing based on detail technique	1. The paper presents a brand-new idea known as "Color Attenuation Prior." This prior allows researchers to estimate the depth of objects in the scene by assuming how colors are diluted by haze. The atmospheric scattering model in the method then allows it to reconstruct the original scene radiance (haze-free) with depth information. 2. Accuracy: According to the research, the suggested approach performs better than cutting-edge In terms of speed and efficiency, haze removal algorithms and the dehazing impact 3.The method relies on a prior assumption about the behaviour of color in hazy images. This assumption, while generally true for outdoor scenes, might not hold for all scenarios. For instance, images with non-uniform haze distribution or unusual colour content could lead to inaccurate results.
6	1.Model for changing light sources and halos 2.Mapping fog images from RGB space to HSI space 3.Decomposing the luminance channel image using non sub sampled -contourlet transform	1.Enhanced the details of hazy areas in the image while maintaining the overall outline structure. 2.The overall outline structure and edge details of the image are preserved.
7	Single-image haze reduction is based on super-pixels and MRF	1.The proposed method surpasses contemporary image dehazing methods 2.The method achieves better color fidelity and preserves structural boundaries. 3.Existing image dehazing algorithms struggle with objects similar to

		light. Block effect and halo artifacts can still occur in the dehazing results.
8	Color attenuation principle for clearing haze from a singular hazy image	1.Proposed approach superior to cuttting edge haze removal algorithms. 2.Outperforms in terms of efficiency and dehazing effect.
9	Learning framework for haze elimination employing a dual-layer Gaussian process regression (GPR)	1. The suggested method successfully eliminates haze from both artificial and real-world foggy photos. 2. It works especially effectively in areas with a lot of haze and on white or bright items.
10	DehazeNet: Trainable framework for estimating medium transmission	1.DehazeNet outperforms existing methods, demonstrating superior performance.

The above Table 1, represents a comparative study of different image dehazing techniques studied in the literature survey.

Applications based on Image Dehazing

Various methods for improving image clarity have been implemented in practical settings, including medical imaging and outdoor scene enhancement. Recent studies have introduced specialized techniques for medical image enhancement, such as defogging endoscopic videos and removing smoke from laparoscopic images. For instance, Luo et al [11]. devised a strategy for enhancing surgical videos by blending luminance, combining contrast enhancement with rapid visibility restoration to eliminate fog or smoke from endoscopic sequences. Similarly, Wang et al [12]. proposed a method for removing smoke from laparoscopic pictures that transforms the deteriorated picture into smoke and improved segments using a varying method, subsequently employing an augmented Lagrangian technique to eliminate the smoke. While much studies on semantic scene interpretation has focused on Perfect weather conditions [13], efforts have been made to address a broader range of challenges, from light fog to dense fog. One such approach, called curriculum model adaptation (CMAda) [14], employs a fog density estimator and convolutional neural networks to estimate haze in real images based on synthetic fog data. CMAda has proven effective in enhancing visibility in foggy driving scenarios.

Atmospheric scattering Model

The model of atmospheric scattering [15] posits that the haziness in images arises from A combination of transmission loss and Air light. In this context, Air-light encompasses all light rays except for the reflective component captured by the camera's lens. This model views Air light as a contaminant affecting the reflective component of the depicted objects. Transmission loss, on the other hand, is influenced by the separation between the objects and the camera, as well as the atmospheric scattering coefficient. Radiation-induced reflectance loss is indicated by the air scattering coefficient. The light rays that are directly reflected from the objects in the image are referred to as reflectance, and they effectively represent the actual transmission map of the picture. The following equation represents the atmospheric scattering model if 'D' is the damaged image and 'R' is its restored version:

$$P(x) = Q(x)\,tr(x) + Ar\,(1 - tr(x)) \quad (1)$$

where tr(x) stands for 'direct transmission' and 'Ar' is the Airlight of the scene.

The concept of 'direct transmission' can be described using the atmospheric scattering coefficient (**β**), which serves as a parameter controlling the extent of scattering experienced by the rays reflected from an object.

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

where the symbol for "D" is d(x). The accompanying picture 3 illustrates the parameters utilized in the derivation above.

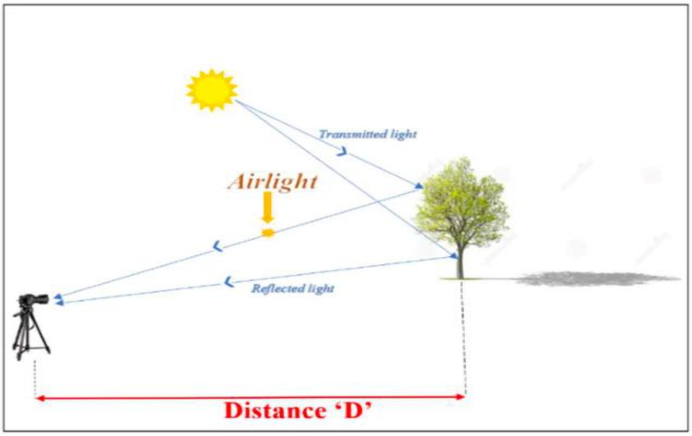

Fig 3: Atmospheric Scattering Model
Source: [Dataset O-Haze]

3 Proposed Methodology

The paper provides an in-depth analysis of several methodologies used in deep learning-based image dehazing, highlighting their performance, datasets utilized, evaluation metrics, and recent advancements. These methodologies are crucial for improving the effectiveness and precision of dehazing algorithms, benefiting various applications such as photography enhancement, autonomous driving, surveillance, and remote sensing. Let's discuss each methodology mentioned in the paper:

Generative Adversarial Networks (GANs)

GANs have gained popularity in image dehazing due to their ability to generate realistic and high-quality images.These models consist of two neural networks: a generator that produces dehazed images from hazy inputs and a discriminator that evaluates the realism of the generated images.Adversarial training encourages the generator to produce dehazed images that are indistinguishable from real haze-free images, leading to improved fidelity and visual quality.

Convolutional Neural Networks (CNNs)

CNNs are widely used in image dehazing due to their capability to capture spatial hierarchies and extract meaningful features from images.These networks consist of multiple layers of convolutional and pooling operations, allowing them to learn hierarchical representations of image features.CNN-based dehazing models leverage deep architectures to learn complex mappings between hazy and haze-free images, enabling them to effectively remove haze and enhance image clarity.

Fusion-based method

Fusion-based methods combine information from the hazy input image with additional cues or priors to generate dehazed images.These methods typically use weighted combinations of features extracted from the hazy image and other sources, such as depth maps, atmospheric light estimation, or prior knowledge about the scene. By integrating multiple sources of information, fusion-based methods aim to improve the accuracy and robustness of dehazing algorithms, particularly in challenging or ambiguous scenarios.

Multi-scale convolutional neural network

Multi-scale CNNs are designed to identify distinct and efficient features at different scales in the input image.These networks often consist of multiple branches or pathways, each processing the input image at a different scale or resolution. By capturing features at multiple scales, multi-scale CNNs can effectively address variations in scene complexity, depth, and haze density, leading to improved dehazing performance.

Color Attenuation Prior

This method estimates the depth of objects in the scene by analyzing how colors are attenuated or diluted by haze.By modeling the relationship between color attenuation and depth, color attenuation priors can effectively estimate the transmission map, which represents the degree of haze in different regions of the image.These priors provide valuable insights into scene geometry and atmospheric conditions, facilitating more accurate and robust image dehazing.

Overall, the methodologies discussed in the paper offer diverse approaches to image dehazing, each with its strengths and limitations. By leveraging deep learning techniques such as GANs, CNNs, fusion-based methods, multi-scale networks, and color attenuation priors, researchers can develop advanced dehazing algorithms capable of producing high-quality, haze-free images for a wide range of applications.

Architecture

It is proposed to combine the strengths of fusion-based methods with the capabilities of GANs and CNNs can lead to a powerful and effective image dehazing methodology. This hybrid approach can leverage the complementary advantages of different techniques to produce high-quality, haze-free images with improved fidelity, realism, and perceptual quality.

A Two-Stage Fusion Dehazing Network (**TSFDNet**) is proposed which combines the capabilities of the three models. This proposed methodology aims to effectively remove haze from images by leveraging the strengths of different approaches. It consists of a two-stage fusion dehazing network (TSFDNet) that incorporates multi-scale feature extraction, hybrid attention mechanisms, and feature fusion to enhance the dehazing effect.

Stage 1: Preliminary Dehazing Sub-Network

Multi-Scale Feature Extraction Block: This block captures haze density features at various scales to provide a comprehensive understanding of the haze effect.
Haze Removal: The network uses the extracted features to perform an initial dehazing, removing a significant portion of the haze.

Stage 2: Refined Dehazing and Detail Compensation Sub-Network
Edge Information Utilization: By focusing on the edges within the image, the network can better preserve details during the dehazing process.
Pixel-Channel Hybrid Attention Residual Modules: These modules help the network pay attention to important features and compensate for any lost details, ensuring the final image retains its quality.

Feature Fusion
Combining Features: The potentially beneficial features from both stages are fused to improve the overall performance of the model.
Final Dehazing: The fused features lead to a refined dehazing output, producing a clear and detailed dehazed image.

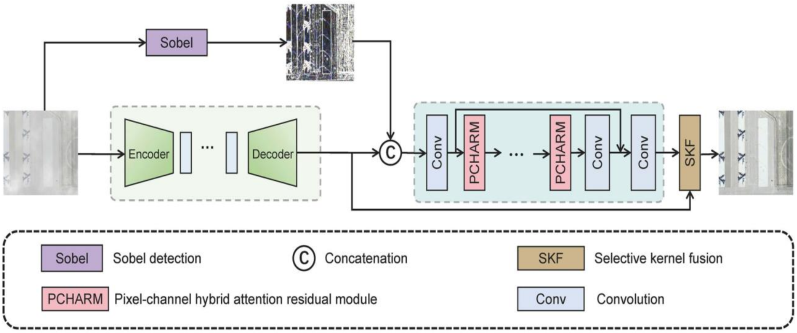

Fig 4: The overall architecture of the proposed TSFDNet

4 Results

This section presents an overview of the datasets and experimental details at first. Then, a comprehensive quantitative and qualitative comparison is conducted with the compared methods. Finally, the effectiveness of the core components of the proposed TSFDNet is verified through ablation experiments.

Methods	PSNR (↑)	SSIM (↑)	FSIM (↑)	FSIMc (↑)
DCP	16.4180	0.7308	0.8754	0.8666
CAP	20.1137	0.8632	0.9357	0.9306
MOF	14.1981	0.6244	0.8447	0.8348
AOD-Net	20.5797	0.8328	0.9095	0.9067
DM^{2}F-Net	29.0326	0.8917	0.9620	0.9615
AECR-Net	29.6923	0.8885	0.9602	0.9591
PSMB-Net	*30.4655*	*0.9296*	*0.9795*	*0.9779*
Ours	**34.7123**	**0.9563**	**0.9851**	**0.9847**

The italicized values represent suboptimal performance, and the bold values represent the best performance

Fig 5: The Quantitative results on the RICE – I dataset

5 Conclusion & Future Work

Many computer vision and image processing applications, such as satellite imagery, video surveillance, underwater photography, and picture compositing, have found usage for dehazing techniques. An abstract view of several techniques for removing haze from a single image that have been offered in the past is presented in this work. This survey looked at several prior/restoration techniques as well as optimisation strategies for multi-scale fusion and improving the quality of fuzzy images. A few studies on haze removal and dehazing techniques are included in this paper.

This study emphasizes the need for better fog removal techniques to address real-world challenges such as non-uniform haze distribution, complex lighting conditions, and scene-specific variations. A methodology also needs to be developed to investigate robustness to noise and artifacts commonly encountered in practical scenarios.

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