Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 45 No. 4 (2024)

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# Review of Deep Learning Based Image Dehazing for Autonomous Vehicle

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***Abstract:-*** Computer vision technology plays an important role in distinguishing the surroundings by autonomous vehicles under adverse weather conditions. The images captured under rainy, foggy, or hazy conditions have reduced contrast and color variation due to the scattering of light. Therefore, deep learning (DL) based techniques are used in image dehazing to detect and remove the haze effect in images without relying on any other models. This paper comprehensively reviews the deep learning-based image dehazing methods used in autonomous vehicles. First discussed the background details of image dehazing and then investigated the DL methods used in image dehazing. Reviewed the benchmark datasets used, and performance matrices evaluated in image dehazing applications and then surveyed the applications of DL in image dehazing. Finally discussed are the potential challenges, significant findings, and future research directions required for further study.

***Keywords****: Image dehazing, Autonomous vehicle, Deep learning, Computer vision, Convolutional Neural Networks, Atmospheric scattering model.*

## 1. Introduction

Blurred conditions caused by natural sensations such as rain and snow, as well as artificial disasters such as urban and forest fires, can severely degrade image quality in photography, surveillance, and similar application's sense of distance [1-2]. This results in poor object exposure, image organization, and image segmentation results [3-4]. The widespread applications of CV in image processing lead to deep learning (DL) approaches. The field of image processing is known as image dehazing [5]. Image dehazing techniques often rely on a foreground-based approach, a statistical method to extract and calculate its dehazing parameter [6], [7]. The deep learning approaches generally provide a good dehazing output under performance-specific blur situations and environments but could not work well for other blur scenes and environments [8-10].

In the past, deep learning-based dehazing mainly relied on Convolutional Neural Networks (CNN). However, in recent years, Vision Transformers (ViTs) have been explored and used for this task [11-13]. Compared to CNNs, VITs typically require a higher amount of training data to achieve competitive performance metrics due to less local inductive bias. This difference arises because ViTs process image bits rather than individual pixels[14, 15].

There are many review papers on dehazing. Here is an updated review of various dehazing approaches on a wide variety of benchmark datasets. However, this existing review does not cover remote sensing and background blur images from airborne mobile platforms such as UAVs and autonomous vehicles [16, 17]. Various dehazing strategies based on deep learning, such as contrast and few-shot dehazing, were surveyed and categorized in a thorough manner [18-20]. Figure 1 shows the workflow for the proposed review.

The organization of the paper is listed as follows, the review objectives are provided in section 2, the background details are included in section 3, the DLbased image dehazing approaches are reviewed in section 4, the datasets used in image dehazing studies are deliberated in section 5, the performance metrics measured in image dehazing approaches are provided in section 6, the performance comparison of DL based methods are provided in section

7, the applications of DL in image dehazing are discussed in section 8, the challenges and opportunities are debated in section 9, the significant outcomes and future research directions are discussed in section 10 and finally section 11 concluded the review.

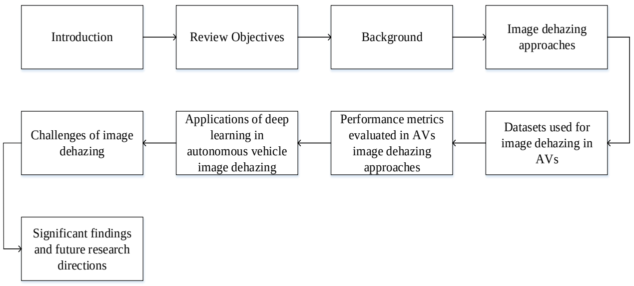


**Figure 1: The workflow of the proposed review**

## 2. Review Objectives

The main aims of this review are discussed as follows,

- To provide enhanced object detection and recognition, image dehazing is needed for AVs under hazy conditions.
- To extract the robust features from the hazy images DL-based techniques are used.
- To provide reliability through safe navigation and collision avoidance
- To validate the performance of DL models benchmark datasets are used, and performance metrics are evaluated.

## 3. Background

Prior models often employed air scattering and the dark channel for picture dehazing [21]. They are essential for generating data to train deep neural networks and design these networks. The atmospheric scattering and the dark channel models help in explaining the process behind fog formation [22].

### A. Atmospheric Scattering Theory

The air scattering concept has long been invoked to account for the hazy pictures. This model can be simply described as follows.

$$C^{z}_{foggy}(d) = E^{z}_{fog-free} P_{r}(d) + H^{z}_{p}\left(1 - P_{r}(d)\right) \tag{1}$$

In this context, $C^{z}_{foggy}$ it denotes the color channel of the captured blurred image, $E^{z}_{fog-free}$ denotes the fog-free image, $H^{z}_{p}$ denotes the atmospheric light, $P_r$ denotes the communication medium, and $d$ denotes the pixel location.This function depends on two strictures: the distance $\chi$ and the scattering coefficient $\alpha$ , as revealed below:

$$P_{r}(d) = a^{-\alpha x(d)} \tag{2}$$

A fog-free condition can be obtained using the following inverse technique picture $E^{z}_{fog-free}$:

$$E^{z}_{fog-free}(d) = \frac{C^{z}_{foggy}(d) - H^{z}_{p}}{P_{r}} + H^{z}_{p} \tag{3}$$

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SID stands for Single image dehazing (SID); it has a complex problem and is necessary to assess two important parameters: $H_p^z$ and $E_{fog-free}^z$ to create a fog-free image.

**B. Dark Channel Previous Model**

When describing air scattering, traditional models often employ a single global scattering coefficient [23].The bottom line is that traditional models aren't effective at reducing fog in challenging environments [24].

These difficulties were addressed by developing a more accurate model of air scattering that incorporates both local and global scattering coefficients [25]. This ideal's formula is provided by,

$$P(d) = C(d)p(d) + E(1 - p(d)) \tag{4}$$

This model $P$ denotes the observed blurred image, $C$ indicates the distorted image, $E$ represents the global ambient light, and $p$ denotes the medium communication.

## 4. Image Dehazing Approaches:

Figure 2 displays the methods used for image dehazing that are based on deep learning.

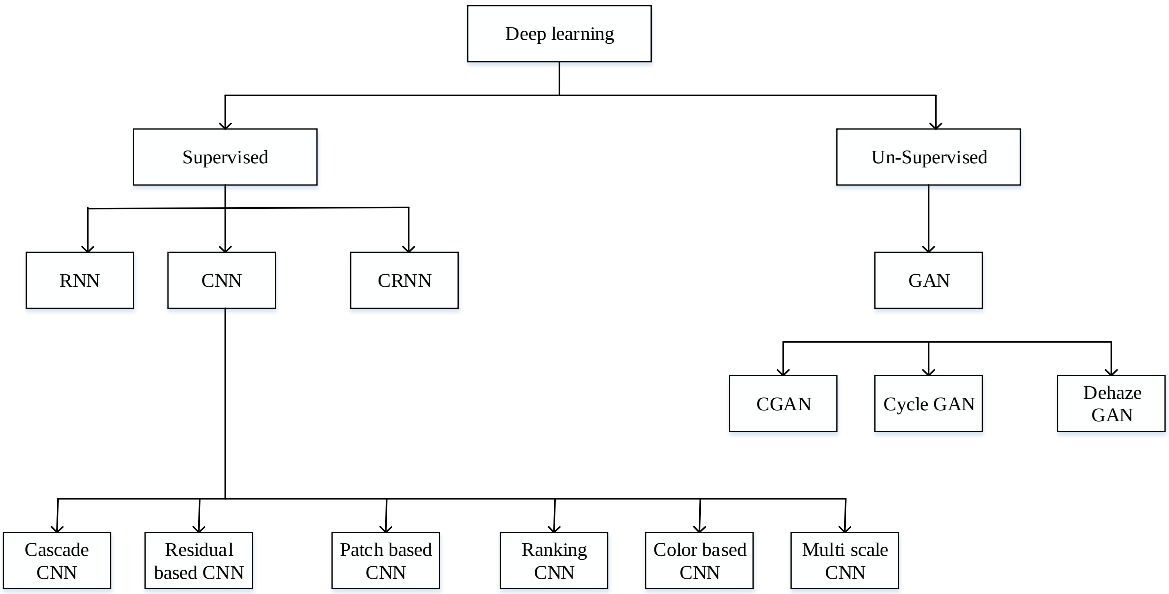



**Figure 2: DL approaches**

For the purpose of single picture dehazing, Dharejo et al. [26] employed a convolutional neural network (CNN) operating in the wavelet domain, which is a hybrid network based on wavelets (local-global combined).Researchers employed a two-dimensional discrete wavelet transform (2-DWT) to break down a single picture sample into frequency sub-bands in order to achieve speedier processing.

Using an encoder-decoder architecture, Frants et al. [27] employed a single-image dehazing network to flawlessly append the quaternion picture representation across the data stream. The QCNN-H framework is used to rigorously assess the performance of quantized convolutional neural networks on a task-specific benchmark, two real-world datasets, and two synthetic datasets.

An effective single-image dehazing method that is based on learning was used in this investigation by Gade et al. [28]. The method includes three main components: dehazing, discrimination, and fine-tuning networks, which together form an end-to-end network model.

The exponential development in deep learning was a dynamic area of research in image dehazing. The resultant output from CNN is often considered noisy even though filters are applied to remove the features from dehazed images. Thus, Xiqin Yuan et al. [29] adopted a feature reduction network (FRNet) in image dehazing to capture and remove the noisy features.

Dehazing images in real time with DL was introduced by Chi Yoon Jeong et al. [30] utilizing an end-to-end network. Therefore, zoomed convolution was implemented to improve picture quality while decreasing processing time. Further zoomed convolution applies a channel attention mechanism to improve the performance.

Object detection in images is normally affected due to foggy weather conditions thus, computer vision-based approaches are developed to reduce the haze effect in images. Pavan Kumar Balla et al. [31] presented a residual CNN (RCNN) model with 14 layers to extract the extent of the haze effect in images. With 4-channel hazy images fed into the 14-layer RCNN, haze-free images are produced as output.

The traditional dehazing methods are inaccurate in predicting the results of complex scenarios. G.P. Suja et al. [32] study integrated DL-based CNN method to learn complex patterns in images and improve the visual quality of images.

Halder et al. [33] adopted a deep neural network model for image de-hazing. To reduce the haze effect in images, atmospheric scattering models based on DNN are applied to images. The comparison of DL-based studies is provided in Table 1.

**Table 1: DL-based studies comparison**

| Author | Method | Dataset | Parameters measured |
|---|---|---|---|
| Dharejo et al. [26] | Wavelet hybrid CNN | RESIDE | PSNR-28.93, SSIM-0.941 |
| Frants et al. [27] | QCNN-H | Real-world dataset | PSNR, SSIM |
| Gade et al. [28] | CNN | RESIDE | PSNR, SSIM |
| Xiqin Yuan et al. [29] | FRNet | RESIDE-IN and OUT, Haze4K, and RS-Haze dataset | PSNR-39.17 and SSIM-0.993 |
| Chi Yoon Jeong et al. [30] | Zoomed convolution | SOTA dataset | PSNR-35.59, SSIM-0.9854, BLIINDS-II-76.88, SSEQ-69.64. |
| Pavan Kumar Balla et al. [31] | RCNN | RESIDE, NYU-Depth V2 and Haze-Realistic dataset | PSNR, SSIM |
| G.P. Suja et al. [32] | CNN | Datasets with diverse hazy scenes are utilized. | PSNR-35.2, SSIM-0.99, MSE-0.001, RMSE-0.01 and perceptual loss-0.04 |
| Halder et al. [33] | DNN | HSTS dataset | MSE= 397.16, PSNR = 23.38, NCC = 0.99, MD = 24.39, NAE = 0.13 |

## 5. Datasets Used for Image Dehazing in AVS

New datasets are the focus of increasing research into deep learning based picture dehazing techniques, with the goal of achieving major strides in the AV area. For both hazy and haze-free photos, two methods are thus offered. One approach is to use the atmospheric scattering model to generate the data in a synthetic method. The second way uses a haze generator to generate haze images from the existing one; thus, the generated haze image datasets include I-haze, O-haze, NH-haze, etc.

### A. I-Haze dataset

A haze machine was used to create hazy photographs in this dataset, which comprises 35 sets of hazy and haze-free interior photos. A Macbeth color chart is also provided to facilitate color tweaking and enhance model performance. The images are taken under simulated lighting conditions [34].

**B. O-haze dataset**

There are 45 sets of outdoor photos in this collection, one set including haze and the other set without. The hazy images are generated by using a cold smoke machine in laboratory settings. Guangzhou University created this dataset by adding fog to the real condition images [35].

**C. Dense haze**

The ISA lab created this dataset, which includes 55 picture sets, some with haze and some without. The images are captured from outside environments, including cities, rural areas, terrain, water bodies, etc.

**D. NH-haze**

This dataset is made obtainable by Peking University based on usual locations, which contains 55 pairs of images captured at different outdoor locations and weather conditions [36].

**E. RESIDE**

A total of 28,417 photos make up the training set of the newly-introduced RESIDE dataset (2019). Of them, 13,990 come from indoor training sets and 14,427 show the outdoors. Unannotated Real-world Hazy Images (URHI), Synthetic Objective Testing Set (SOTS), Real-world Task-driven Testing Set (RTTS), and Hybrid Subjective Testing Set (HSTS) were also members. URHI comprises 4000 hazy images; SOTS consists of 500 pairs of gray images; RTTS includes 4322 tagged images; HSTS dataset includes ten real-world and ten artificial images [37].

**F. BEDDE**

The 208 real-life picture pairs that make up the Benchmark Dataset for Dehazing Evaluation (BEDDE). Each pair included a blurry image, a perfectly matched and crispy reference image captured from 23 different cities [38].

## 6. Performance Metrics Evaluated in AVS Image Dehazing Approaches

The performance of haze removal approaches is evaluated based on the quality of images. The availability of reference images following metrics are evaluated, such as mean square error (MSE) [39], peak signal-to-noise ratio (PSNR) [40], and structural similarity index metric (SSIM) [41]. When the reference image is not available, the removal of haze is a difficult task; the metrics considered for comparison include the mean of the image, entropy, Average Gradient (AG), and mean of local standard deviation.

**A. Mean square error (MSE)**

MSE measures how similar or distorted the two images are given as follows,

$$MSE = \frac{1}{hxw}\sum_{a=1}^{h}\sum_{b=1}^{w}\left(G(a,b) - H(a,b)\right)^2 \tag{5}$$

**B. Peak signal-to-noise ratio (PSNR)**

PSNR is evaluated using MSE given as follows,

$$PSNR = 10\log_{10}\left[\frac{(2^n - 1)^2}{MSE}\right] \tag{6}$$

**C. Structural similarity index metric (SSIM)**

SSIM is assessed using the following criteria: the relationship between structural information and visual perception in humans,

$$SSIM(G,H) = \frac{2\mu_g\mu_h + K_1}{\mu^2{}_g + \mu^2{}_h + K_1}\frac{2\sigma_{gh} + K_2}{\sigma_g^2 + \sigma_h^2 + K_2} \tag{7}$$

**D. Natural Image Quality Evaluator (NIQE)**

NIQE is used to measure the naturalness of images by comparing the statistical features with real images given as follows [42],

$$NIQE = V_1 * F_1 + V_2 * F_2 + V_3 * F_3 + ...... + V_n * F_n \tag{8}$$

$$F_n = E[c_n] + \beta * \sigma_n \tag{9}$$

**E. Visibility index (VI)**

VI measures the quality of the images that are hazed and dehazed by comparing the image with the reference image. The similarity amongst the haze and haze-free images is done by measuring the transmissions and gradients given as follows,

$$VI = \frac{\sum_{P=\alpha} G_m(P).[S_T(P)]^{\beta} T_q(P)}{\sum_{P=\alpha} T_q(P)} \tag{10}$$

$$S_T(P) = \frac{2I_1(P).I_2(P) + K_1}{I^2{}_1(P). + I^2{}_2(P) + K_1} \tag{11}$$

$$G_m(P) = \frac{2g_1(P).g_2(P) + K_2}{g^2{}_1(P). + g^2{}_2(P) + K_2} \tag{12}$$

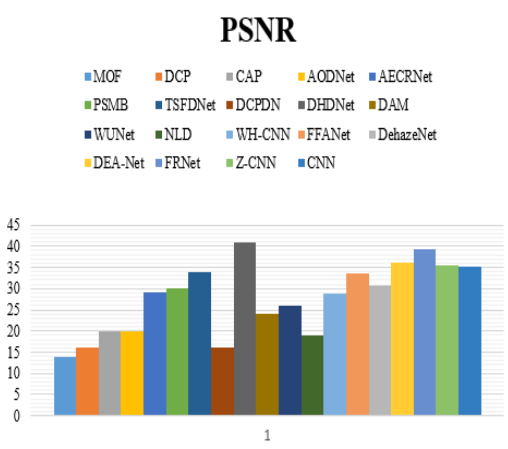
**F. Realness index (RI)**

The realness index is evaluated using the following equation,

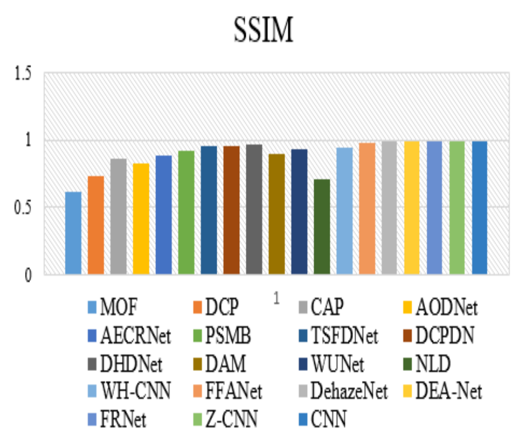
$$RI = \frac{\sum_{P=\alpha} C_m(P).[X_c(P)]^{\beta} V_M(P)}{\sum_{P=\alpha} V_M(P)} \tag{13}$$

## 7. Performance Comparison Of Dl-Based Methods

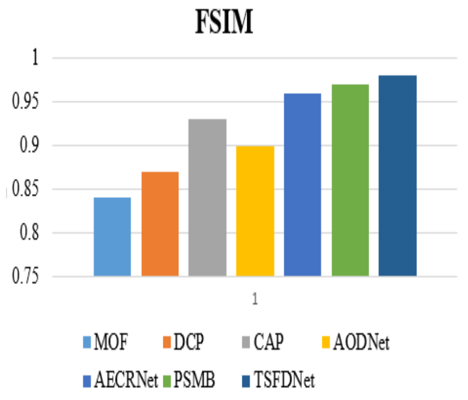
The performances of DL-based studies are compared in this section based on various performance parameters like PSNR, SSIM, FSIM, FSIMc, SSEQ, latency, etc. The performances are compared with DL-based studies like Densely connected pyramid dehazing network (DCPDN), Dark Channel Prior (DCP), multiscale CNN, Feature fusion and attention networks (FFANet), all-in-one dehazing networks (AODNet), etc. [43-45].



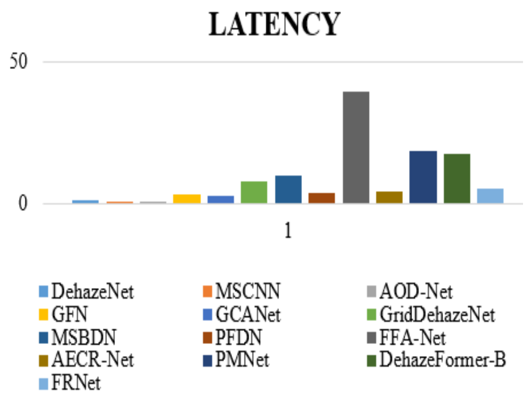

(a) PSNR



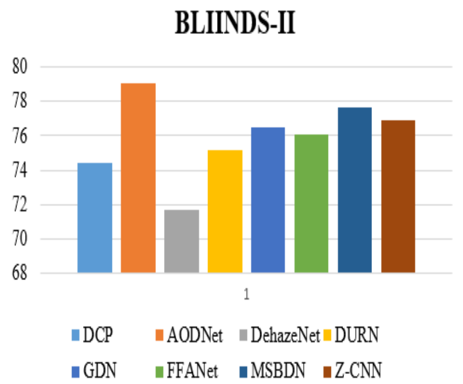

(b) SSIM



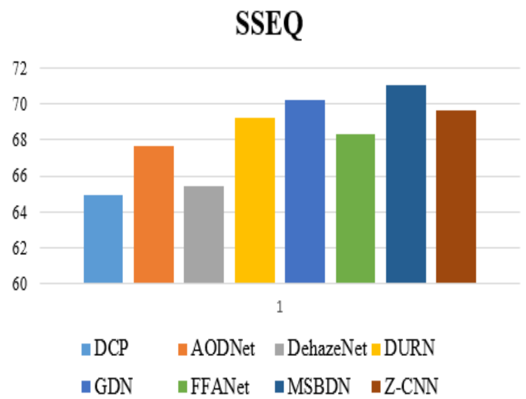

(c) FSIM



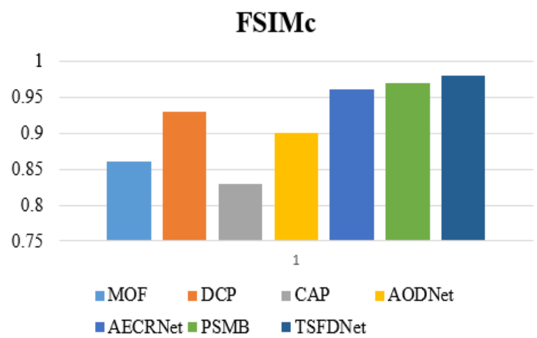

(d) Latency




(e) BLIINDS-II




(f) SSEQ




(g) FSIMc

**Figure 3 (a) – (g): The Performances measured for DL-based studies**

Figure 3 shows the performances measured by different DL-based models. The PSNR graph measures the quantity of noises introduced during the processing of images. Higher PSNR represents better image reconstruction quality with reduced noise. PSNR evaluates the effectiveness of the denoising algorithm in removing the noise. SSIM measures the similarity between images based on similarity, contrast, and structure. Blind Image Integrity and Novelty Detection System – II (BLIINDS-II) measures the various types of tampering and verifies the integrity of images. FSIM also measured the similarity between images, which was more perceptual than PSNR and SSIM. Spatial-spectral entropy-based quality (SSEQ) measurement was used to measure the spectral and spatial quality of images. Evaluating the SSEQ measures the image degradation quality. FSIMc measures the feature similarity index of color images, which is an extension of FSIM.

## 8. Applications of Deep Learning in Autonomous Vehicle Image Dehazing

### A. Application of DL for object detection on road

Haze removal is mandatory in autonomous vehicles to identify the objects on the road. As a result, in order to estimate the transmission map, Sivaji et al. [46] utilized an encoder-decoder architecture that included deep learning. The results are validated using the NYU depth dataset, FRIDA, and RESIDE dataset, respectively.

### B. Application of DL for traffic sign detection

Autonomous vehicle navigation technology has shown significant advancements. In order to identify and detect traffic signs, Radha Rani et al. [47] introduced a convolutional neural network architecture that is based on deep learning. The research was conducted using the CURE-TSD, which stands for Carleton University Retinal Eye-Traffic Sign Dataset.

### C. Application of DL for vehicle type and color classification

The haze removal technology prevents accidents by selecting an ideal path for autonomous driving. JongBae Kim et al. [48] introduced YOLO-based ResNet-50 CNN architecture for detecting the vehicles.

## 9. Challenges of Image Dehazing

The following are some of the many difficulties that remain despite the fact that supervised, semi-supervised, and unsupervised approaches have improved performance in autonomous vehicle picture dehazing tasks,

- The atmospheric scattering model (ASM) is considered to be most appropriate for the haze creation process. The usage of more effective ASM will reduce the dim effect on image dehazing.
- Training in dehazing models requires a sufficient amount of haze and haze-free images. However, collecting real-world images is time-consuming and laborious.
- The haze formed by ASM does not exhibit similar characteristics to real haze. Hence real haze synthesis algorithms are proposed to overcome the domain shift problem.
- In computer vision tasks, dehazing is considered a pre-processing task in object detection. Thus, dehazed images must be of high quality in order to provide further processing.
- The balance between the performance measured, interpretation time, and the quantity of parameters is necessary. The dehazed image should have high PSNR, SSIM, etc.
- The perceptual loss is often evaluated using the pre-trained models to improve the image quality. The normal L1/L2 loss mainly focuses on pixel-wise differences, while perceptual loss preserves the edges and textures.
- Dehazing methods find application in numerous computer vision tasks, including picture segmentation and object detection.
- The DL model removes haze independently of any other model. Knowledge based model enhances the generalization ability of the model. Thus, using a knowledge based model with DL based dehazing method is worth verifying.

## 10. Significant Findings and Future Research Directions

- The DL algorithms in image dehazing made significant findings in object detection like road lane detection, pedestrian detection and traffic sign recognition.
- In adverse weather conditions DL models help to learn robust features from hazy images.
- Developing a lightweight model that operates in real-time is critical. Thus, research is needed to accelerate hardware with deep learning architectures.

- For autonomous driving under adversarial weather environments like snow, rain, and fog is necessary to enhance the robustness of dehazing models.
- Integration of DL techniques with sensor data such as LIDAR RADAR increases the overall perception capabilities of autonomous vehicles.
- Developing explainable AI-based DL models helps to understand how the models make decisions.

## 11. Conclusion

This review provided a comprehensive review of image dehazing with a focus on autonomous vehicle driving under adverse weather conditions. The review surveyed the background details, approaches used in image dehazing, and their DL applications. Also evaluated and compared the performances of different methods based on the datasets used and parameters measured. The review also identifies open problems, research gaps, and future directions, including the need for diverse real-world haze datasets, efficient algorithms, and the integration of domain-specific knowledge into learning-based frameworks. This review provided a foundation for understanding the current methods in image dehazing and charting future research directions. The demand for high-quality images necessciate the need for has created a demand for high-quality images that are free from haze or fog. New techniques and improvements to old methods are the focus of the increasingly important field of dehazing. The development of advanced dehazing techniques is a crucial research area with significant practical implications in today's world.

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