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A Review on Deep Learning-based approaches for Image Dehazing

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Abstract

Images captured in unpredictable weather conditions frequently suffer from significant degradation. The scattering and absorption of airborne particles in the atmosphere effect on image quality such as poor visibility, low contrast, and color distortions. The problem of image degradation is addressed by many computer vision applications in unpredictable weather conditions as these conditions diminish the clarity of the visual scene due to loss of image details. The learning-based image dehazing approaches play an imperative role to eliminate haze and enhance the quality of haze-free image. This paper presents a review of different learning-based image dehazing approaches which employ different techniques to approximate atmospheric light and transmission map to restore a haze-free image with image details and color fidelity.

Keywords: Image dehazing; Image degradation; Image quality; Weather; Transmission map; Atmospheric light.

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Introduction

Single image dehazing is an advanced computational technique utilized to recover visibility and improve the excellence of hazy images [1] as shown in Fig. 1. The aim of single image dehazing is to calculate the underlying scene radiance and eliminate the unwanted atmospheric effect caused by scattering and absorption of light due to particles in the atmosphere such as fog, smoke, dust [2]. The atmospheric degradation diminishes the color saturation and contrast in the captured images, making it difficult for automated systems and human viewers to see important details [3]. The assessment of transmission map and the atmospheric light is included by the dehazing process. The spatially diverse haze density and degradation in various regions of the image is indicated by the transmission map. The dominant light in the scene is denoted by the atmospheric light, which is owing to dispersing of light by the tiny particles [4]. Recently, several algorithms and methods have been suggested for single image dehazing, employing various approaches like dark channel prior (DCP) [5], color attenuation [6], and image fusion [7]. These methods often employ optimization algorithms, advanced image processing techniques, and machine learning models to accomplish delightful dehazing results. Single image dehazing has achieved important attention owing to its practical applications in fields, including surveillance, autonomous vehicles, and outdoor imaging, where it is important to get clear and visually attractive images even in bad weather conditions [8]. Many research papers on image dehazing have been presented in [9-12]. The comparison of five algorithms based on physical scattering model for image dehazing is described in [9]. Various defogging approaches based on enhancement and restoration are explored in [10][11]. Different visibility enhancement methods introduced for both uniform and non-uniform fog conditions are presented in [12]. In this paper, a review is conducted on various deep learning-based image dehazing approaches. These approaches will enable readers to comprehend the effectiveness of each approach and contribute to the development of advanced dehazing approaches.

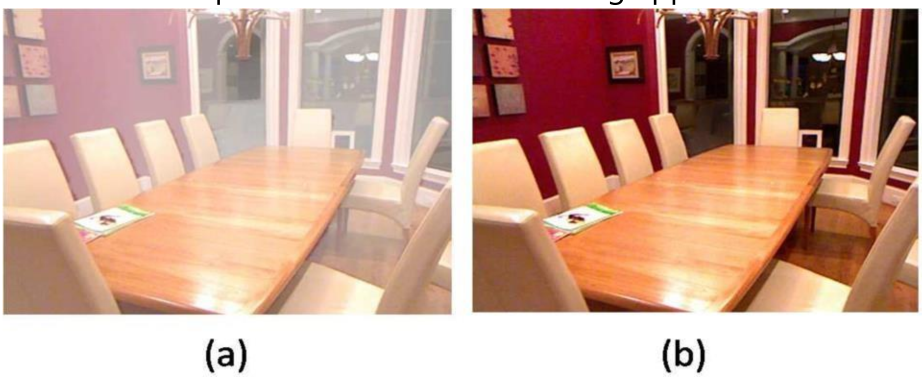

Fig. 1 (a) Hazy image, (b) Haze-free image

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Image Dehazing Approaches

The study of different research papers related to image dehazing for last six years is described in this section. Various researchers and scholars have proposed different approaches to analyze transmission map and atmospheric light and made their contributions using different techniques for image dehazing. This section is divided into five sub sections based on the different techniques and network structures for single image dehazing. It includes end-to-end approaches, attention based approaches, fusion based approaches, attention and fusion based approaches, and U-Net based approaches.

End-to-End approaches

The enhanced version of the CycleGAN framework for single image dehazing entitled Cycle-Dehaze was presented by D. Engin *et al.* [13]. To enhance the dehazing performance, several modifications to an end-to-end CycleGAN [14] architecture are developed. The approach does not necessitate the pairing of hazy and haze-free images for training and testing. Instead, it employs CycleGAN to obtain the style transfer from hazy images to dehazed images. Besides, the suggested approach does not rely on assessment of the variables related to the atmospheric scattering model. Cycle-Dehaze improves the texture information recovery and generates a visually superior dehazed image by integrating a perceptual loss function into the existing CycleGAN framework as illustrated in Fig. 2. Cycle-Dehaze requires significant processing power and extensive parameter tuning to produce haze-free images. This factor makes the approach less robust and may require domain expertise to accomplish optimal results.

Fig. 2 Qualitative results of the Cycle-Dehaze and CycleGAN approaches on I-Haze and O-Haze datasets. From left to right, the first column pair shows the hazy images, the second and third column pair shows the outcome of CycleGAN and Cycle-Dehaze approaches and the fourth column pair shows the ground truth image.

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A generic model-agnostic convolutional neural network for single image dehazing was introduced by Z. Liu *et al.* [15]. The network structure applies the downsampling and upsampling operations to extract different features and produces an estimation of the desired outcome using transformation. The network employs paired hazy and haze-free images of ITS and OTS datasets and mean square error (MSE) loss function to train the approach in fully supervised manner. It assists to produce visually pleasing haze-free images. The network eliminates haze, enhances image details and accomplishes better performance in terms of dehazing quality. The generic model-agnostic approach facilitates network to handle different hazy scenarios without explicitly modeling the atmospheric scattering process.

H. H. Yang *et al.* [16] suggested network for single image dehazing named Y-Net. The network combines multi-scale features, allowing for better representation of haze-related details and context. It supports the wavelet transform to extract structural information which assists in preserving significant image details during the dehazing process. The wavelet SSIM loss function is utilized for training the network where it employs a series of discrete wavelet transformations to segregate the image into patches of varying sizes, each characterized by various frequencies and scales as shown in Fig. 3. Y-Net is evaluated on the RESIDE dataset and compared against existing image dehazing approaches. The experimental findings show that the network accomplishes greater performance using both the qualitative and quantitative metrics.

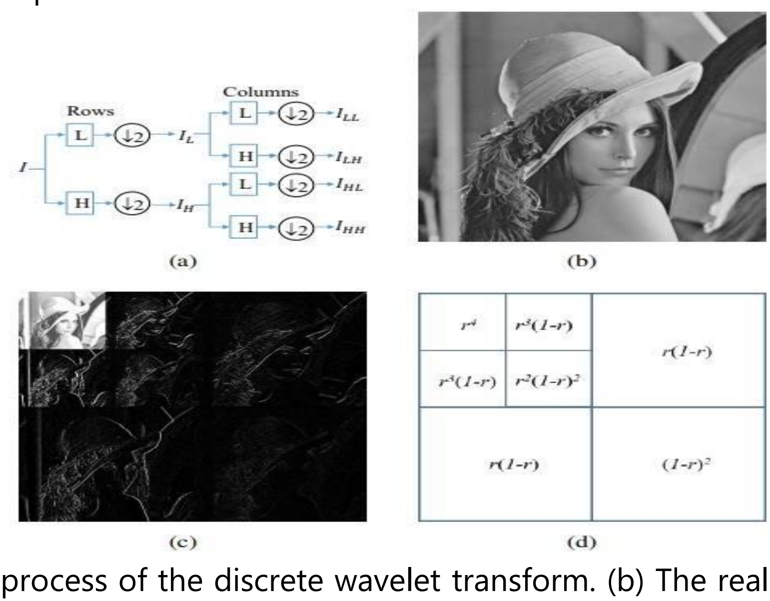

Fig. 3 (a) The process of the discrete wavelet transform. (b) The real image. (c) The outcome obtained from applying the discrete wavelet transform twice. (d) The ratios pertaining to various patches.

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Y. Shao *et al.* [17] suggested domain adaptation method to tackle the single image dehazing problem where the training and testing data come from different domains. The image translation module and two dehazing modules are comprised by the domain adaptation structure. To establish a connection between synthetic and real domains, the bidirectional translation network is employed effectively enabling the translation of images between the two domains. The results obtained from translation of two synthetic hazy images are shown in Fig. 4. Subsequently, the images are utilized to train these two image dehazing networks before and after translation, while enforcing a consistency constraint. The real hazy images into the dehazing training process are integrated during this phase, utilizing the characteristics of clear images to enhance the domain adaptively. While training both the image translation and dehazing networks, the enhanced outcomes are achieved by the approach.

Fig. 4 The results obtained from translation of two synthetic hazy images. From left to right (a-b), (a) Synthetic hazy image, (b) Translated image.

A. Singh *et al.* [18] described single image dehazing approach which handles various types of challenging haze scenarios such as dense haze and non-homogeneous haze. The approach uses a back projected pyramid network (BPPN) architecture that contains different blocks. The pyramid convolution technique is developed to acquire spatial features of various levels. The iterative U-Net block learns complex and distinct haze features without loss of the structural information. The four contemporary challenging datasets of diverse haze scenarios are utilized to optimize the performance. The network is trained employing the incorporation of MSE loss, content loss, adversarial loss, and structural similarity loss. The suggested approach is assessed on the challenging datasets and compared with other dehazing approaches. Experimental findings show that the BPPN accomplishes competitive dehazing performance across different types of haze scenarios.

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Attention based approaches

Y. Lee *et al.* [19] proposed a novel approach for image dehazing. In this approach, the benefits of a U-Net architecture with contextualized attention mechanisms are combined to enhance the quality of haze-free images. The contextualized attentive U-Net model combines the parallel dilated convolution module and the squeeze-and-excitation modules that demonstrate outstanding performance in image segmentation tasks. The encoder-decoder network structure captures the contextual and attentive features of the input hazy image and reconstructs the dehazed image. The contextualized attention mechanism enables the network to pay attention on important image regions during the dehazing process. With the incorporation of contextual information, the network understands the global scene features and makes informed decisions when removing haze. RESIDE dataset is utilized for training the proposed approach. The training process includes mean square error and perceptual loss to calculate the inconsistency between the predicted and ground truth haze-free images. The approach is evaluated on synthetic and real world images and compares it with other algorithms. The experimental findings show that the proposed approach achieves better dehazing performance in terms of subjective and objective metrics. The contextualized attentive U-Net effectively diminishes haze and improves the visibility of fine details in hazy images.

An end-to-end single image dehazing network named AED-Net was proposed by S. A. Hovhannisyan *et al.* [20]. The network recovers essential scene information without depending on atmospheric scattering model, external information, or various images of same scene. To improve the ability of network, the region-aware modified Gamma correction (RAMGC) is integrated to refine edges and distorted colors as shown in Fig. 5. The four loss functions such as smooth L1 loss, MS-SSIM loss, perceptual loss, and adversarial loss are utilized to compute the numerical disparity between the dehazed results and ground truth images. For experimental findings, three datasets namely NH-HAZE2, I-Haze, O-Haze are utilized to train and assess the network. The AED-Net shows promising findings in terms of image dehazing quality, outperforming numerous existing dehazing algorithms. The effectiveness of algorithm makes it appropriate for various real-world applications requiring single image dehazing.

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Fig. 5 The efficiency of the region-aware modified Gamma correction (RAMGC)

The approach employs a combination of generative adversarial networks and an attention mechanism for improving hazy images was proposed by Y. Ma *et al.* [21]. Hazy images frequently endure from diminished visibility and color distortion, making them less visually attractive. The generative adversarial networks consist of a generator and a discriminator network, which is utilized to address these issues. The approach does not entail paired datasets and does not depend on atmospheric scattering model during the haze-removing process. It integrates channel attention and domain attention mechanisms into the generator network that allows the model to concentrate on significant regions of the image to improve significant image details and textures while suppressing noise and artifacts. Dense blocks are employed to augment the depth of the network and enhance its ability for feature extraction. The generator network recovers the background details during dehazing process, while the discriminator network differentiates between the generated and real clear images. Cycle-consistency loss is utilized to reduce the discrepancy between the hazy images and their reconstructed counterparts. The model gradually enhances its ability to dehaze hazy images effectively by optimizing the generative adversarial network. Experimental results show the superiority of the proposed approach in terms of both visual quality and objective metrics as compared with several existing dehazing approaches.

An end-to-end deep learning-based approach for real-time single image dehazing was presented by C. Y. Jeong *et al.* [22]. A zoomed convolution group is developed for reducing the processing time of model without compromising the excellence of recovered image. To improve the dehazing performance, efficient channel attention mechanisms are incorporated in the network. The L1 loss is employed for model training. For experimental results, the RESIDE dataset is employed to train and evaluate the dehazing performance of model. The approach accomplishes better dehazing results while managing real-time processing speed, making it suitable for applications that require efficient and fast image dehazing.

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Fusion based approaches

The novel fusion based approach for single image dehazing was suggested by W. Ren *et al*. [23]. The network leverages both the local and global information and acquires new strategy based on fusion to improve the dehazing performance. The network obtains three inputs from the hazy image employing encoder-decoder structure. The encoder captures the contextual information of the input image, which is then employed by the decoder to calculate the individual contributions of each input towards accomplishing the ultimate deblurring outcome, resulting in a confidence map at the pixel level. The input images are gated and merged by employing the confidence map, resulting in the haze-free image as shown in Fig. 6. Gated fusion network requires substantial processing power and memory resources. It may fail to generate satisfactory outcomes in variations of weather and lighting conditions, and haze densities.

Fig. 6 The efficiency of the gated fusion network (GFN)

The approach for image dehazing and deraining is proposed by D. Chen *et al.* [24], which utilizes a smoothed dilation technique to eliminate grid artifacts caused by the dilated convolution. The features from various levels are fused employing gated subnetworks. The image is improved by collecting information from neighboring regions and fusing features from various levels. Mean square error loss function is utilized to train the network with RESIDE dehazing benchmark which contains synthetic images. Experimental results demonstrate that GCANet accomplishes outstanding performance in single image dehazing. This CNN based approach still possesses some limitations. The image possesses the less contextual information. As the dilation rate rises, the information from the nearest elements of the convolution kernel becomes highly varied leading to grid artifacts in the haze-free results. Furthermore, this approach is not suitable to generate highly detailed information.

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The deep fusion approach for single image dehazing was introduced by Z. Deng *et al.* [25], which combines several dehazing models to separate layers to improve the quality of hazy image. It comprises three stages to produce the final dehazed image. Initially, the attentional feature integration module is formulated to improve the incorporation of features at diverse convolution neural network layers, and produce attentional multi-level integrated features. Subsequently, these features are employed to produce a haze-free output using an atmospheric scattering model and four haze-layer separation models. These outcomes are then combined to generate the final dehazed image. In order to access the dehazing performance, the network is compared with various image dehazing approaches using two synthetic and real-world benchmark datasets. Experimental findings prove that the suggested approach accomplishes outstanding dehazing performance. It generates dehazed results with the improved image details and diminished artifacts.

A multi-scale approach with dense feature fusion was proposed by J. Pan *et al.* [26] that leverages both local and global information for effective dehazing. The proposed approach employs two principles such as boosting and error feedback to solve the dehazing problem. With the incorporation of boosting strategy, the network design is effective to recover the dehazed image. To enhance the network performance, a dense feature fusion module integrates back-projection technique in the network. This fusion assists to capture multi-scale details and improves the representation power of the network. Experimental findings on different datasets exhibit that the network accomplishes good performance in terms of dehazing quality, while comparing to state-of-the-art approaches. The network eliminates haze while preserving image details and generates visually pleasing results. The boosting strategy and dense feature fusion module with back-projection technique contribute to the overall success of the proposed approach.

The U-Net architecture for image dehazing was proposed by G. Fan *et al.* [27]. The proposed network structure leverages depth information to improve the dehazing process. It combines multi-scale depth maps at various stages employing encoder-decoder structure with skip connections. The network captures both local and global cues, enables more precise and comprehensive dehazing while fusing depth information at multiple scales. The negative SSIM loss function is utilized to train the network. The synthetic image dataset, NYUv2 depth dataset and Make3D dataset are used to verify the approach. It ensures that haze-free images preserve both visual and depth information. The experimental findings illustrate that the network attains greater dehazing performance by incorporating the multi-scale

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depth information which removes haze, improves visibility, and generates high quality haze-free images.

Single image dehazing using multi-scale approach was proposed by Z. Chen *et al.* [28], which integrates both global and local features at various scales effectively. It improves hazy images that are suffered from color distortion, reduced contrast, and loss of fine details. The approach comprises two feature extraction modules and one deep fusion module. The global features are computed in the global feature extraction module which captures the overall scene transmission and atmospheric light. Multi-scales are considered to handle object sizes and multiple levels of haze. A deep fusion module is utilized to combine the global and local features through skip connections, where the local features portray the image contents. The fusion strategy integrates the complementary information from both types of features, improving the overall dehazing performance. To train the network, mean square error loss function is utilized to compute the difference between the haze-free image and ground truth image. For experimental results, artificially synthesized foggy images are used to train and evaluate the proposed approach. Experimental findings demonstrate that the proposed approach accomplishes significant improvements in terms of color fidelity, visibility, and preservation of fine details when compared to other dehazing algorithms.

J. Xu *et al.* [29] presented the innovative approach for single image dehazing which integrates the transformer and convolution neural network architectures. For improving the dehazing capability, the network captures both the global and local features using transformer-convolution hybrid layer. The adaptive fusion mechanism accomplishes a trainable merging of the output findings from both the swin-transformer and the optional convolution blocks. The five subsets of the RESIDE dataset are employed to train the network and L1 loss function is employed to ensure the generation of visually pleasing haze-free images. The experimental findings illustrate that the suggested approach accomplishes superior performance compared to existing dehazing approaches. It effectively eliminates haze, enhances image visibility, and preserves image details. Moreover, the integration of transformer and CNN architectures provides a synergistic effect, improving the efficiency of the dehazing approach.

Attention and Fusion based approaches

The GridDehazeNet for single image dehazing was presented by X. Liu *et al.* [30]. The network does not depend on atmospheric scattering model. It comprises three modules such as pre-processing module, backbone module, and post-processing

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module. The pre-processing module produces relevant features in its learned inputs, surpassing the limited potential of manually selected pre-processing techniques as shown in Fig. 7. The structure utilized for the backbone network is GridNet [31], which integrates a new technique to estimate the multi-scales employing a grid network and attention mechanism. This method effectively alleviates the common bottleneck issue faced by the conventional multi-scale methods. The post-processing module assists in minimizing artifacts from final output. Extensive experimental findings exhibit that the suggested approach accomplishes greater performance in terms of dehazing quality, color fidelity, brightness maintenance and outperforms existing methods on the large scale synthetic dataset. Furthermore, the network sometimes generates dark artifacts in some smooth areas.

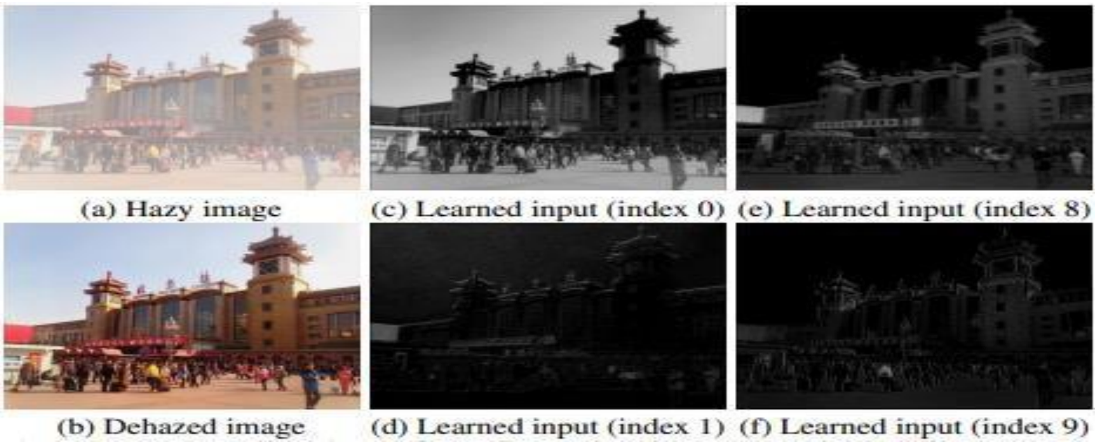

Fig. 7 The Judgment of Hazy image, dehazed image, and multiple learned inputs

An attention-based deep learning approach named FFA-Net was suggested by X. Qin *et al.* [32], that effectively eliminates haze from images by incorporating feature fusion and attention mechanisms. The network structure comprises three components such as Feature attention, block structure, and attention-based feature fusion. Various features and pixels are treated unequally by feature attention, enabling increased flexibility in handling diverse information types. The local residual learning and feature attention are incorporated by block structure. Through local residual learning, less significant information can be bypassed employing several local residual connections. This enables the network to concentrate more on significant information. The attention-based feature fusion employs feature attention module at various levels, through which the weights of the features are adaptively learned assigning greater importance to the significant features. Simple L1 loss function is utilized to train the network with RESIDE dehazing benchmark that contains synthetic hazy images. Experimental results

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demonstrate that FFA-Net accomplishes outstanding performance in single image dehazing. The attention-based feature fusion allows the network to eliminate haze while preserving image details and producing visually attractive results.

A novel approach titled "Hierarchical Feature Fusion with Mixed Convolution Attention for Single Image Dehazing" was proposed by X. Zhang *et al.* [33]. The approach comprises an end-to-end network structure with skip connections to extract multi-level features using a feature extraction block. The mixed convolution attention mechanism is utilized to lessen redundancy among features, adaptively emphasize important features while squashing inappropriate information, assisting effective feature fusion. The deep semantic loss, perceptual loss, MSE loss, and smooth L1 loss are utilized to compute the statistical disparity between the haze-removed results and real dehazed images. The synthetic and real-world datasets, namely RESIDE, I-Haze, and O-Haze are utilized to train and test the approach for experimental results. Experimental assessments on benchmark datasets exhibit that the proposed approach accomplishes superior performance in terms of dehazing quality and objective evaluation metrics. The dehazed images preserve important details and produce more visually realistic results. The mixed convolution attention and hierarchical feature fusion contribute to improving visibility and eliminating haze efficiently, assisting the potential of the approach for single image dehazing applications.

A novel approach named as "Multi-stream Fusion Network With Generalized Smooth L1 Loss for Single Image Dehazing" was suggested by X. Zhu *et al.* [34]. The information of multi-streams is utilized by the network to improve the dehazing process. The network structure combines different components like an encoder-decoder structure, attention mechanisms, and skip connections, to capture and refine significant features at various scales. A generalized smooth L1 loss function is designed for training and addressing the network dehazing challenges. The robust and accurate dehazing results are promoted by incorporating the advantages of smooth L1 and L2 loss functions. The synthetic and realistic image dehazing datasets are employed to train and test the approach. The suggested approach attains better dehazing performance employing qualitative and quantitative evaluation metrics on benchmark datasets. It removes haze effectively from images and improves visibility, examining its potential for real-world applications.

A two-stage approach for single image dehazing employing an encoder-decoder network structure was introduced by X. Li *et al.* [35], that leverages the Swin-

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Transformer model to effectively recover haze-free images from hazy inputs. The approach comprises two stages. In the first stage, a transformer-cnn codec is developed to extract and merge both local and global features. An inter-block supervision mechanism reduces the loss of feature information resulting from upsampling and downsampling processes, thereby enriching the features. In the next stage, the local features are extracted by the original resolution block following the process of interaction and feature fusion. Furthermore, the combination of shallow and deep features is facilitated by the integration of fusion attention mechanism between the stages, thereby enhancing the learning competence of the network. The network is trained employing joint loss function. RESIDE, I-Haze, and O-Haze benchmark datasets are employed for training and evaluating the proposed approach. Experimental findings illustrate that the dehazing performance of proposed approach is greater as compared to various other approaches.

The single image dehazing approach was suggested by S. Memon *et al.* [36]. The approach integrates multi-stream features at three different resolution levels. The attention mechanism is utilized to adaptively emphasize important features while squashing inappropriate features. Deep semantic loss, smooth L1 loss, and perceptual loss are utilized to compute the statistical variation between the dehazed results and real images. For experimental findings, RESIDE and externelcvpr are employed to train and assess the approach. The suggested approach gets improved performance in terms of qualitative and quantitative evaluation metrics on synthetic and real-world datasets. The approach effectively removes haze from images, improves visibility and retains images with sharp textural and structural details.

U-Net based approaches

Pavan A *et al.* [37] suggested a novel approach to eliminate haze from image named LCA-Net. The LCA-Net architecture integrates the benefits of convolutional neural networks and autoencoders for effective dehazing. The autoencoder design enables the network to learn a compact representation of input image, while convolution layers allow the extraction of the significant features. An encoder-decoder network structure of the LCA-Net squeezes the hazy image and recovers the dehazed image from the latent representation. The network is trained on a custom dataset employing the mean square error loss function. It accomplishes greater performance compared to other dehazing approaches which is demonstrated by the experimental assessments on benchmark datasets.

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Le-Anh Tran *et al.* [38]presented an approach for single image dehazing which employs the transmission map extracted by adopting DCP as additional input to the network. The approach employs encoder-decoder network architecture (U-Net), spatial pyramid pooling module, and swish activation function to accomplish better performance. The high-level features from the input hazy image are extracted and analyzed by the encoder and an output haze-free image is generated by decoder. To train the network, a combination of MSE loss, perceptual loss, and adversarial loss are utilized to compute the difference between the dehazed outputs and the equivalent haze-free images. For experimental findings, the four benchmark datasets of hazy images such as Dense-Haze, I-Haze, O-Haze, and NH-Haze are utilized to train and evaluate the approach. Experimental findings show that the suggested approach enhances the visibility of hazy images, leading to improved image quality and details as shown in Fig. 8.

Fig. 8 Visualization of the dehazing outcomes achieved on synthetic images, where each pair comprises of a hazy image on the left and its corresponding dehazed image on the right.

Performance Evaluation on Synthetic Image Datasets

The performance of various image dehazing approaches is evaluated on the synthetic image datasets as shown in Table 1. The different loss functions are employed to train the networks that examine the inconsistency between the dehazed results and ground truth haze-free images. The quantitative results on the indoor and outdoor images are considered to measure the efficiency of each approach. With the incorporation of deep semantic loss in [33], the outcomes of proposed network are impressive. The deep semantic loss assists model optimization and enhances the dehazing performance on indoor and outdoor synthetic images. The dehazed images preserve significant details and generate more visually attractive results than other dehazed approaches.

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Table 1. Quantitative results with loss functions of various dehazing approaches on synthetic images

Approach	**Loss Functions** Mean square error Loss (MSE), Smooth L1 Loss (L1), Perceptual Loss (Perc), Deep semantic Loss (DS), Structural similarity index measure Loss (SSIM), Content Loss (Cont), Adversarial Loss (Adver), Cycle-consistency Loss (CC)								**Metrics**			
									Indoor		**Outdoor**	
	MSE	**L1**	**Perc**	**DS**	**SSIM**	**Cont**	**Adver**	**CC**	**PSNR**	**SSIM**	**PSNR**	**SSIM**
Cycle-Dehaze [13]			✓					✓	18.03	0.80	19.92	0.64
GMAN [15]	✓								27.94	0.897	26.00	0.936
Y-Net [16]					✓				---	---	26.61	0.947
Domain Adaptation [17]	✓						✓	✓	---	---	27.76	0.93
BPPN [18]	✓				✓	✓	✓		22.56	0.8994	24.27	0.8919
DSEU [19]	✓		✓						23.57	0.917	28.31	0.955
AED-Net [20]		✓	✓		✓		✓		20.75	0.872	25.56	0.845
A-CycleGAN [21]								✓	26.428	0.886	27.476	0.947
Real-time dehazing [22]		✓							35.59	0.9854	---	---
GFN [23]	✓						✓		22.30	0.8800	28.29	0.9621
GCANet [24]	✓								30.23	0.9800	---	---
DM^{2}F-Net [25]		✓							34.29	0.9844	29.37	0.9464
MSBDN [26]	✓								28.01	0.9109	27.96	0.9465
MSDFN [27]					✓				30.88	0.9965	33.73	0.998
Multi-scale single image dehazing [28]	✓								26.90	0.9651	21.79	0.9048
TCFDN [29]		✓							37.62	0.9910	---	---
GridDehazeNet [30]		✓	✓						32.16	0.9836	30.86	0.9819
FFA-Net [32]		✓							36.39	0.9886	33.57	0.9840
Hierarchical Feature Fusion Network [33]	✓	✓	✓	✓					35.21	0.9954	34.98	0.9920
MSFNet [34]		✓							34.74	0.9895	32.10	0.9849
Two-stage single image dehazing network [35]					✓				30.84	0.9628	36.33	0.9836
AMSFF-Net [36]		✓	✓	✓					34.87	0.9899	32.23	0.9854
LCA-Net [37]	✓								18.23	0.7808	23.37	0.8763
EDN-GTM [38]	✓		✓				✓		22.90	0.8270	23.46	0.8198

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Conclusion

This paper presents a review on deep learning-based image dehazing approaches. The performance of various approaches is assessed by evaluating the quantitative results using loss functions on synthetic images. The hierarchical feature fusion network accomplishes the superior performance than other dehazing approaches. The haze-free image preserves important details and produces more visually realistic results. The mixed convolution attention and hierarchical feature fusion contribute to improving visibility and eliminating haze efficiently. Further, the advancements in deep learning-based approaches have improved the quality of haze-free images. The exploration of various network architectures, attention mechanisms and incorporation of generative adversarial networks have led to distinguished progress in handling intricate scenes and challenging haze conditions. The continued research in this field embraces great promise to further improve the performance of single image dehazing approaches.

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