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Image Dehazing using GMAN

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Abstract. *The most frequent environmental factor that affects image quality and image analysis is fog. A coherent generative approach to image organization is suggested in this study. We require the construction of a fully convolutional neural network in order to recognize the haze pattern in the input photo and restore a clear, fog-free image. The suggested method is agnostic because it doesn't take into account air scattering models. Surprisingly, even SOTS outdoor images created using atmospheric scattering models outperform current state-of-the-art image decluttering techniques. Many modern apps use visual data analysis to find patterns and make decisions. Intelligence and control systems are some instances where clear pictures are crucial for precise outcomes and dependable performance. Environmentally generated distortions, the most frequent haze and fog, could, however, have a considerable impact on such systems. Therefore, the challenge of recovering high-quality images from their fuzzy equivalents has received attention in the vision community. The dehaze problem is the common name for that issue. This work proposes a dehazeNN that simply focuses on creating a blur-free version of the input picture, offering a novel and more flexible approach to the dehaze problem. The dehaze problem is the common name for that issue. This work proposes a dehazeNN that simply focuses on creating a blur-free version of the input picture, offering a novel and more flexible approach to the dehaze problem. It constructs an encode and decode architecture using the most recent developments in deep learning in order to recover the clear image. While entirely removing the estimation problem. The method might also be able to spot intricate haze patterns that the atmospheric scattering model missed, which were present in the training data. A convolutional neural network called the Generic Model-Agnostic Convolutional Neural Network (GMAN) has been proposed for the elimination of haze and the restoration of clear images. An end-to-end deep learning system for photo denoising uses encoder-decoder networks.*

Keywords: *Image dehazing, deep learning, Convolutional Neural network*

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I. INTRODUCTION

Many modern apps use visual data analysis to find patterns and make decisions. Intelligent monitoring, tracking, and controlling the systems can require sharpening pictures for accurate results and reliable Images. We take advantage of the latest method in machine learning to build encode/decode architectures trained to recover sharp images while completely eliminating parameter estimation problems instantly [1]. The proposed method may also be able to detect complex haze patterns that were missed by the atmospheric scattering model but were present in the training data. The use of haze-generating models has wide applications in the fields of computer vision and image processing. This model is often used to develop images in adverse weather conditions. Atmospheric particles range in size from 1 to 10 µm, and the presence of these particles in aerosols affects image quality. The quantity of particles in the atmosphere is influenced by the weather. Calculating measurements of the particles responsible for the visual qualities has taken a lot of work.[2].

Therefore, simple weather conditions are divided into two categories: constant and dynamic. For degraded weather images, mainstream image processing applications give mediocre results. As a result, dehaze algorithms are becoming increasingly important in various applications such as aerial photography, object detection, image retrieval, and object analysis. Atmospheric acquisition deviations have also been observed from severe meteorological conditions consisting of haze, fog, haze, smoke from the outdoor landscape or beautiful decomposition of other media, resulting in several problems, such as automated monitoring systems. Will occur. outdoor identification system [3]. Digital images taken outdoors in scenic environments are effectively polluted by the haze that degrades the information being transmitted. Haze is a natural phenomenon that obscures the landscape, narrows vision, or changes color. Image dehazing is a technique that is gaining popularity for restoring images of the natural world that have degraded due to low visibility weather, dust, and other factors.

The advancements in autonomous systems and platforms have increased the requirement for low-complexity, high-performing dehazing solutions. While contemporary learning-based picture dehazing systems usually add complexity at the expense of dehazing performance, which has recently improved, the use of prior-based approaches persists despite their poorer performance.[4]. A frame dehaze using color attenuation priority based on haze lines. In this article, we propose a new frame-by-frame deblurring method for synthetic and real blurry images. The removing non-local image haze to limit visibility and reduce image contrast in outdoor photography. Degradation is pixel-by-pixel and depends on the distance of the scene point from the camera. The model DehazeNet is used Removing haze from a single image is a difficult task. Many constraints and priorities are used in existing approaches to provide a realistic haze removal solution. To achieve haze removal, it is essential to estimate the average transmittance map of the blurred input image. This model fails in places where slightly inaccurate air lights lead to poor performance.

The paper is structured in such a manner: Section 1 contains the abstract of the project, and section 2: Contains the introduction of the model. Section 3 contains the literature Survey of the relative work for image dehazing for several types of research. Section 4 Includes System Architecture and design. Section 5 proposed methodology Section 6 includes results and discussion, and section 7 concludes all the work.

II. RELATED WORK

The GMAN proposed in this article explores new approaches to solving the problem of haze removal. GMAN learned to take blurry structures in pictures and get clear structures using the fully convolutional architecture of the encoder/ decoder without using an atmospheric scattering model. GMAN is an end-to-end generative network that employs encoder-decoder architectures with a down- and up-sampling factor of 2. Using blocks with 64 channels of convolution, its initial two layers are constructed. Following them are two-step down sampling layers that encode the input image into a 56 56 128 volume. Moreover, it avoids estimating the deemed superfluous parameters A and t. The CNN's (potential for GMAN) experimental findings proved its ability to produce images devoid of fog and showed that it could correct several typical mistakes made by state approaches, such as B. dark colors and excessively sharp edges. Also, the architecture of CNN (generic GMAN) may open up new avenues for investigation into generic image recovery in the future. Indeed, we anticipate that the network will generalize as a result of training and design optimization. The current work not be better to propose a better solution to the haze removal problem but is also a step forward in developing a picture restore model [5].

Yang, G and Evans A.N. [1] Improved Single Frame Organizing Method for (Radar cross-section) RCS – Frame Organizing Handles the Deteriorating Effects of Bad Weather, Dust, and Other Factors on Photos in Nature is a method that is becoming more popular. The development of autonomous systems and platforms has resulted in improved performance of dehaze solutions. We require an autonomous system.

Qianru Wang [13] proposed a frame dehaze using color attenuation priority based on haze lines. Pro artificial and actual fuzzy photos, we provide a new frame-by-frame deblurring technique in this article. The constant scattering coefficient has been proposed to be replaced by a dynamic scattering coefficient, an exponential function of picture depth. According to experimental findings, the deblurred images produced by the suggested algorithm are more transparent and realistic than those produced by the previous color attenuation. The haze effect can be effectively improved by the suggested algorithm. In the presence of extremely thick haze particles, the issue in this model is useless.

Bolun Cai [2] introduced DehazeNet. Removing haze from a single image is a difficult task. Many constraints and priorities are used in existing approaches to provide a realistic haze removal solution. To achieve haze removal, it is essential to estimate the average transmittance map of the blurred input image. This model fails in places where slightly inaccurate air lights lead to poor performance.

Dana Berman [16] proposed removing non-local image haze to limit visibility and reduce image contrast in outdoor photography. Degradation is pixel-by-pixel and depends on the distance of the scene point from the camera. This dependence is expressed as a transmission coefficient, which controls the attenuation of the scene and the amount of haze for each pixel. This model fails in places where the air light is much brighter than the scene.

These models face so many challenges as they fall in places where the air light is very bright; these models always require an autonomous system for doing the experiments and are sometimes ineffective in places where there are thick haze particles. So, to solve all these problems, we proposed a model image dehazing using GMAN.

III. PROPOSED METHODOLOGY

Since frame fog removal is an inappropriate task, a (DotNetNuke)DNN based on convolution, Continuous, and deconvolution models is designed and trained to take the blurred picture and restore the fog-free picture.

Deblurring method: Haze turns a coloured image into a whitish one and can result in loss of image detail and reduced parallax. Similarly, haze poses problems for various applications, including targeted direct monitoring and indirect detection, tracking and measurement. Clean up your images to remove haze from your photos, improve your view of the scene, and enhance the overall visual effect[5]. Haze removal is the biggest challenge associated with mathematical ambiguity. However, image organization is essential for computer vision applications. As a result, most researchers have attempted to tackle these problematic tasks using various dehaze algorithms. Image Enhancement, Image Fusion, and Image Restoration are three categories of cleanup methods. There are two categories of single-image restoration. Single-image dehaze, which requires only one image as input, and multi-image dehaze, which requires two, three, or more images of the same POI. Both methods fall into different categories. Haze removal algorithms that take only one image as input can classify an image into three main types: Prior probability or hypothesis-based algorithms. This method removes the haze from the image while evaluating the haze image parameters of the model and yields satisfactory results [6]. In their technique two sources of information were obtained from the first authentic picture weight by three weight maps (luminance, saturation, and enhancement) to obtain a multiscale Blended in combination to remove haze effects. This method has recently attracted the interest of researchers..

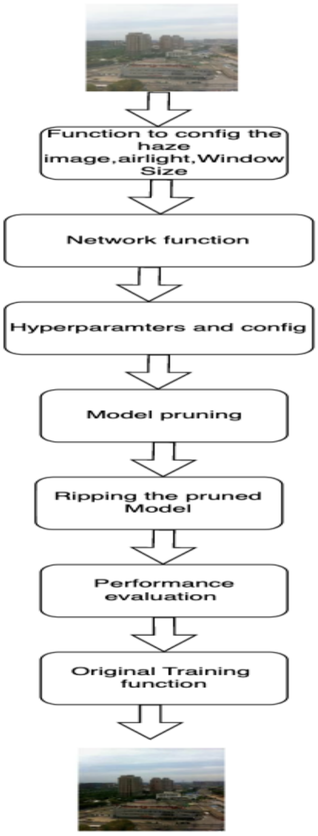

Fig. 1. Flow of the proposed GMAN model

Conv2D is frequently used to detect features, such as in the encoder part of an autoencoder model, and it may result in the input shape of your input model shrinking. Contrarily, Conv2DTranspose is employed to create features, such as those found in the decoder portion of an autoencoder model for creating images. While Conv2D may make your input larger and is used to identify features in an image, Conv2DTranspose may make your input smaller and be used to create these features.

Loading of the image includes loading the image in the form of tensors, a function to get the path of the individual image by adding folders like clear image, hazy image, and hazy clear image and loading the tensor image data in batches. This function includes shaping the image and window size, normalizing the filter of the image, also calculating the weighting function by using rows, columns, and num filters, and pre-compute the constants that are later needed in the optimisation steps. This employs an encoder-decoder-based end-to-end generative method to address the dehazing problem. The first two layers that an input picture encounter contain convolution blocks with 64 channels. They are followed by two downsampling blocks (encoders) with stride 2. The encoded picture then came into a level of four leftover blocks. Each block contains a shortcut link (same as ResNets)[7]. This leftover layer contributes to understanding the hazy structure. Following these, the upsampling or deconvolutional (decoder) layer reconstructs the results of the residual layers. The input image (global residual layer) is combined with the final two layers (convolutional blocks) to produce a dazed image from the upsampled feature map—this scene's overall residual layer aids in capturing the boundary properties of objects at various depths. The encoder component of the architecture helps to reduce the image's dimension before supplying the downsampled image to the residual layer to recover the image's features. The decoder component will then learn and recreate the lost data from the blur-free image. They were pruning the network from the pre-trained network. In ripping the pruned model, we must remove the wrappers added to the network. Performance evaluation includes importing the required modules and checking if the weights are pruned or not correctly, checking all the parameters window size, comparing the sizes and adequately checking the folder path of the image. We have used naturally hazed images taken from our own campus instead of taking a day there is a problem with the size of the image, then resizing it according to the parameters. They are calculating the boundary size as a final training constraint. Based on the original training function, we refine the estimate of the transmission [8].

A complete convolutional neural network has been proposed convolution Neural Network (CNN). It was used to remove fogging from the input image. This is an end-to-end generative network with a 2-sample down and upsampling encoder/decoder structure[9]. The top two layers consist of 64-channel convolution modules. This is followed by a two-level downsampling layer that encodes the input image into a 56x56x128 volume. After encoding, the image is placed in a continuous layer. The continuous layer consists of four continue blocks, each with an association link. The subsequent unfolding layer samples the output of the continuous layer and remakes the new 224 224 64 volume for subsequent convolution, marking the transition from encoding to decoding.

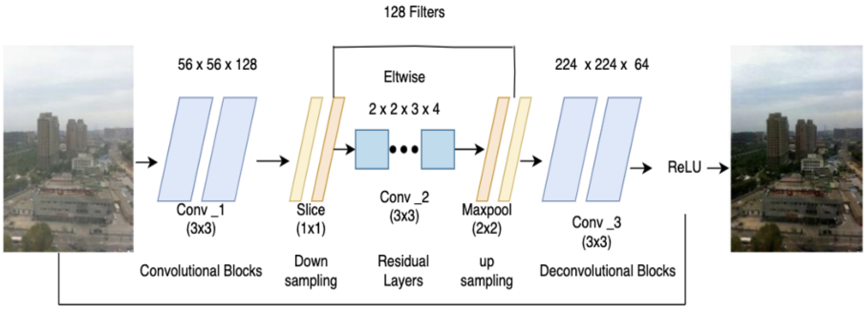

Fig. 2. Proposed architecture of GMAN model

A well-known encoder/decoder design used to address the denoising problem is the basis for the proposed GMAN architecture. It consists of three components: decoder, hidden layer and encoder. This architecture enables in-depth network training while reducing the size of the data. Since haze is a type of error, the encoded output is downsampled and sent to the continuous layer to recover crucial properties. The network discards error data while preserving the best aspects of the original image. Throughout the decoding phase, the decoder component is expected to develop functionality. Reconstruct missing data from fog-free images considering the statistical distribution of the input data.[10]

This network employs relative learning at both the local and global levels. A local residual layer is constructed using the residual blocks from the hidden layer immediately after downsampling. For easy training, we use the virtual and empirically proven capacity of the residual block[11]. Capturing Blurry Structure Recognition Moreover, residual learning is observed in the whole architecture of the model GMAN. The first input picture is passed to the sum operator and the final convo layer's final picture to produce the single global continuous block. A well-known two-component loss function is used to train the proposed GMAN. The first determines how well the results match the real-life situation and help to make a pleasing picture. The most popular method for proving an algorithm's efficacy is to compute the difference between the output image and the source image using the (Peak Signal to Noise Ratio) PSNR. MSd is therefore chosen as the first component of the LMSE (Linear Mean Square Error). Perceptual Loss In many well-known picture restoration issues, MSE loss is employed to evaluate the resulting image's quality. The loss, nevertheless, may not necessarily provide a solid indicator of the visual impact. Conv2D and Conv2DTranspose routines were employed during creation. [12]

The first is the GMAN network, which has 3 channels in the final output layer and 64 filters altogether (excluding the encoding layers, which have 128). The Parallel Network (PN), which is a convolutional network with all of the dilated layers. This includes 64 filters, with the exception of the final layer, which has three channels and is modeled after GMAN[13]. How to custom train a model is the most important thing I discovered. In general, forecasting appears exciting, but this is the actual training methodology. We have a training loop and a validation loop for every epoch. The training loss is then calculated using the gradients, which were computed using the training data. The output (using the display img function) and validation loss are analyzed using the gradients computed in that epoch utilizing validation data in the validation loop. Lastly, we reset the loss measures and store the model (weights, variables, etc.) from that epoch. The kernel weights are not initialized at zero; instead, random normal initialization produces superior results. To reduce overfitting, an L2 regularizer with a weight decay of 1e-4 is also utilized. Not every layer has the same kernel initialization, so keep that in mind[14].

IV. RESULTS AND DISCUSSIONS

In terms of performance, the proposed GMAN outperforms many state-of-the-art technologies. It outperforms all its competitors. An outdoor data set is considered. In addition, as shown in the figure, GMAN prevents object edges from being too sharp and image tints from being too dark. On the other hand, GMAN performs well in regions of high-depth values in the target image but performs poorly in regions of moderate depth. This is due to the dynamic method, which attenuates the light intensity of the defogged image and causes color distortion in areas with high depth values (such as the sky). As a result, the model GMAN can address issues and produce a clearer picture. We also tested the network using an indoor dataset. This achievement is not very noticeable, ranking only after DehazeNet, (Gated Fusion Network) GFN and (All-in-One Dehazing Network) AOD-Net. The great potential of model-independent dehaze approaches can already be seen in indoor data sets. Networks, GFN ranks first for (Structural Similarity Index) SSIM and second for PSNR, putting him almost on par with DehazeNet in the first place. Our preliminary results show that by integrating and generalizing the underlying concepts of GMAN, the Outperforms outdoor (Synthetic Objective Testing Set) SOTS dataset and indoor. Follow-up investigations will clarify this issue. They are training the Model successfully by uploading clear and hazy images (dataset from Kaggle).Once the model is trained, we can use the model by passing in our test image dataset called hazy_test_images Uploaded hazy_test_images to the trained model and implementing dehazing on these test images.

4.1 Running time comparison

In the proposed model, 50 photos from TestSet to run on the MacBook Pro with all models. Table 1 displays the overall average running time per image for each model. Although the algorithm's speed is not the fastest, it may be utilized for real-time dehazing and provides the best dehazing effects. As a result, when the algorithm is taken into account completely, video defogging may be an application. The running time of all the models is shown in table 1 [15].

Table 1. Runtime Comparison

Models	**Run Time**
DCP	0.92
DEHAZENET	0.51
MSCNN	0.47
NIN-DEHAZENET	0.39
GMAN(Proposed Model)	**0.38**

4.2 PSNR value comparison

Utilizing the Peak Signal-to-Noise Ratio, the proposed algorithm is evaluated against the most advanced dehazing techniques (PSNR). Table 2 reveals that the strategy which has been suggested performs better than others in terms of PSNR [15].

Table 2. PSNR value comparison

Models	**PSNR VALUE**
DCP	17.81
DEHAZENET	18.03
MSCNN	18.25
NIN-DEHAZENET	18.48
GMAN(Proposed Model)	**20.53**

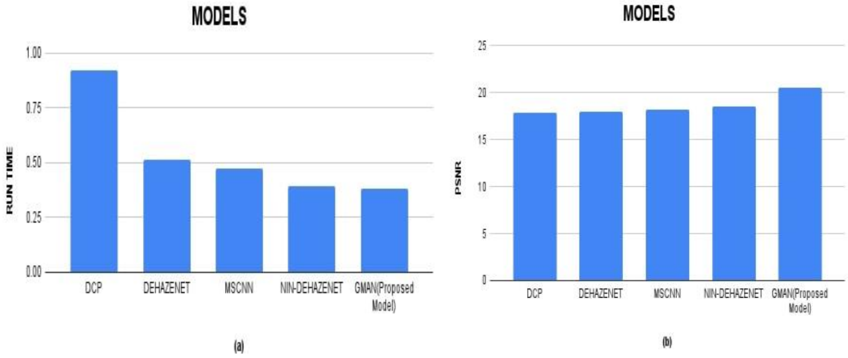

Fig. 3. (a) Runtime Comparison **(b)**PSNR value comparison

The proposed GMAN in this study explores a novel strategy for the dehaze problem. Because to its encoder-decoder completely convolutional design, GMAN learns to capture haze structures in photographs and restore the clear ones without requiring the atmosphere scattering model. The ability of GMAN to produce images free of haze and to avoid some of the common downsides of cutting-edge approaches, such as color darkening and excessive edge sharpening, have been proved through experimental results. Furthermore, the general architecture of GMAN might provide as a starting point for future research on general picture restoration. Our network should be able to generalize to capture other types of visual noise and distortions with practice and a few design tweaks. The present operates in this manner[16].

V. CONCLUSION

GMAN's ability to produce fog-free images while avoiding some of the shortcomings of state technologies, such as B. Experimentally proven to darken colors and over-sharpen edges. Additionally, GMAN generic architecture may serve as a starting point for future research on generic image recovery. Indeed, with training and some design modifications, we expect the network to be able to generalize to a wide range of visual noise and distortions. In this regard, current research not only provides more effective haze removal solutions but also advances the development of general image restoration techniques. In this work, GMAN investigates a new approach to the haze removal problem. Due to its fully convolutional encoder/decoder design, GMAN is capable of capturing haze structures in images and restoring well-defined structures without computing the parameters A and t(x) according to atmospheric scattering models, which are considered unnecessary. Learn. It also retains GMAN's ability to produce fog-free images confirmed by experimental results and to avoid some common shortcomings of modern techniques, such as B. Dark colors and overly sharp. The primary takeaways from this work are a GMAN architecture, research into the dehazing domain, and advice on how to handle inputs where both the features and the labels both are images. Further research will be done to enhance the performance of the suggested model and combine it with the object detection component utilizing deep sort to dehaze the traffic video as well.

REFERENCES

[1]. Yang, G., Evans, A.N. Improved single image dehazing methods for resource-constrained platforms. J Real-Time Image Proc 18, (2021)2511–2525

[2]. B. Cai, X. Xu, K. Jia, C. Qing and D. Tao, "DehazeNet: An End-to-End System for Single Image Haze Removal," in IEEE Transactions on Image Processing, (2016) 5187-5198

[3]. H. Tang, Z. Li, R. Zhong, J. Zhang and X. Fang, "Sky-Preserved Image Dehazing and Enhancement for Outdoor Scenes," 2021 IEEE 4th International Conference on Electronics Technology (ICET), Chengdu, China, (2021)1266-1271

[4]. S. Tang and Z. Meng, "Positive-and-Negative Learning for Single Image Dehazing," 2022 7th International Conference on Intelligent Computing and Signal Processing (ICSP), Xi'an, China, pp. (2022) 1879-1883

[5]. Q. Shu, C. Wu, Z. Xiao and R. W. Liu, "Variational Regularized Transmission Refinement for Image Dehazing," 2019 IEEE International Conference on Image Processing (ICIP), Taipei, Taiwan, (2019) 2781-2785

[6]. H. Zhang, J. Li, L. Li, Y. Li, Q. Zhao and Y. You, "Single image dehazing based on detail loss compensation and degradation," 2011 4th International Congress on Image and Signal Processing, Shanghai, China, (2011) 807-811,

[7]. X. Ren, C. Tang, B. Wang, H. Su and X. Li, "Single Image with Large Sky Area Dehazing Based on Structure-texture Decomposition," 2020 IEEE 6th International Conference on Computer and Communications (ICCC), Chengdu, China, (2020) 415-419

[8]. C. -H. Yeh, C. -H. Huang, L. -W. Kang and M. -H. Lin, "Single Image Dehazing via Deep Learning-based Image Restoration," 2018 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC), Honolulu, HI, USA (2018) 1609-1615

[9]. Y. Liu, S. Rong, X. Cao, T. Li and B. He, "Underwater Image Dehazing Using the Color Space Dimensionality Reduction Prior," 2020 IEEE International Conference on Image Processing (ICIP), Abu Dhabi, United Arab Emirates, (2020) 1013-1017

[10]. X. Min et al., "Quality Evaluation of Image Dehazing Methods Using Synthetic Hazy Images," in IEEE Transactions on Multimedia, vol. 21, no. 9, (2019) 2319-2333

[11]. Wang, Wencheng & Yuan, Xiaohui. Recent advances in image dehazing. IEEE/CAA Journal of Automatica Sinica. 4, (2017) 410-436

[12]. Y. Huang and X. Chen, "Single Remote Sensing Image Dehazing Using a Dual-Step Cascaded Residual Dense Network," 2021 IEEE International Conference on Image Processing (ICIP), Anchorage, AK, USA, (2021) 3852-3856

[13]. Q. Wang, L. Zhao, G. Tang, H. Zhao and X. Zhang, "Single-Image Dehazing Using Color Attenuation Prior Based on Haze-Lines," 2019 IEEE International Conference on Big Data (Big Data), Los Angeles, CA, USA, (2019) 5080-5087

[14]. M. Zheng, G. Qi, Z. Zhu, Y. Li, H. Wei and Y. Liu, "Image Dehazing by an Artificial Image Fusion Method Based on Adaptive Structure Decomposition," in IEEE Sensors Journal, vol. 20, no. 14, (2020) 8062-8072

[15]. X. -M. Dong, X. -Y. Hu, S. -L. Peng and D. -C. Wang, "Single color image dehazing using sparse priors," 2010 IEEE International Conference on Image Processing, Hong Kong, China, (2010). 3593-3596

[16]. Y. Kudo and A. Kubota, "Image dehazing method by fusing weighted near-infrared image," 2018 International Workshop on Advanced Image Technology (IWAIT), Chiang Mai, Thailand, (2018) 1-2

[17]. Berman, Dana & Treibitz, Tali & Avidan, Shai. . Non-local Image Dehazing.(2016) 1674-1682