International Journal of Inventive Engineering and Sciences (IJIES)
ISSN: 2319-9598 (Online), Volume-11 Issue-11, November 2024

Single Image Dehaze using Deep Learning with Beetle Swarm Optimization Algorithm

R. Prakash Kumar, Manja Naik. N

Abstract: ***Particles present in the atmosphere the captured light is deviated into scattering due to this, haze is captured by camera. The process of removal of haze in an image is called De-hazing. Dehazing is a challenging task in computer vision and surveillance applications. Deep learning methods have been developed and shown encouraging results. However, these approaches have significant impact on how well these approach work. In this paper we introduce an innovative deep learning as Beetle Swarm Optimization (BSO) algorithm for single image dehazing. BSO is a nature inspired optimization algorithm that uses beetle's social behavior as model to get the best response. The dehazing model performs more effectively after the parameters of deep learning network optimized using BSO. The experimental results indicate well how our method works at eliminating haze from single images. Benchmark data sets are used to access the suggested strategy. In this paper the proposed method is evaluated in terms of Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE) and Structural Similarity Index (SSI) also our method produces dehazed images with high contrast and colour accuracy as well as more visually pleasing shots. The proposed method which has applications in surveillance, remote sensing and self-driving cars provides a dependable and efficient solution to dehaze a single image.***

Keywords**:** ***Dehazing, Atmospheric Light, Convolution Neural Networks.***

I. INTRODUCTION

Image dehazing is the process of removing an image of atmospheric haze or fog to improve its clarity and attractive appearance. The scattering of light by particles, water droplets, and other air particles results in haze, which lowers the contrast and colour accuracy of the image. In aerial surveillance and outdoor images, when there is a considerable distance between the camera and the object of interest, this occurrence is prevalent. Dehazing in an image seeks to determine the scene radiance from the observed image and reduce the haze component. Due of the non-linear and intricate nature of the haze formation process, this is a difficult task.

Manuscript received on 24 January 2024 | Revised Manuscript received on 13 March 2024 | Manuscript Accepted on 15 November 2024 | Manuscript published on 30 November 2024.
*****Correspondence Author(s)

R. Prakash Kumar*, Research Scholar, Department of Electronics and Communication Engineering, UBDTCE, VTU, Davangere (Karnataka), India. Email ID: prajkash.rachmagdu@gmail.com, ORCID ID: 0000-0002-7528-2837

Dr. Manja Naik.N, Professor, Department of Electronics and Communication Engineering, UBDTCE, VTU, Davangere (Karnataka), India. Email ID: manjubdt2009@gmail.com, ORCID ID: 0000-0001-6886-1606

Conventional dehazing techniques have limitations in challenging situations because they rely on hand-made models of air scattering and radiance assumptions. The physical modelling of the creation of haze in an image is best represented as [1][2], One way to characterize the physical modelling [3] is

$$f(y) = W(y) \cdot e^{\beta d[y]} + \mathrm{Al}\left(1 - e^{\beta d(y)}\right) \ldots \quad (1)$$

$$m(y) = e^{\beta d(y)} \ldots \quad (2)$$

Where f(y) is the captured Image Al is Atmospheric light w(y) is scene radiance and m(y) is transmission map. The additive component Al(1-$e^{\beta d(y)}$) is the air light in eq (1). In areas of the image where there is a lot of haze, the transmission map is almost nil. As a result, the scattered light Al(1-m(y)) is about equal to A, resulting in very little information about the clear image, and the clear image J is almost totally attenuated.

The objective of this effort is to recover a representation of the environment J(x) as seen through a clear, haze-free medium. The image is more closely approximated to the appearance of the original scene thanks to physical model-based restoration procedures. Complex conditions enable better image processing, which leads to the storage of more whole picture data. Although several promising systems have been developed, they are based on speculative assumptions and need many Images formation-related components. These options are rarely accessible. Because the scene's circumstances are unknown, establishing a foreground won't be effective; instead, a more reliable strategy must be established. In this research paper provides a novel approach to improve the current deep web-based dehazing techniques.

The mapping between hazy and dehazed photographs has been learned from large datasets in recent years using deep learning-based algorithms, which have demonstrated promising results in image dehazing. These methods employ convolutional neural networks to evaluate scene brightness and eliminate the haze component from the input image. (CNNs). Deep learning-based algorithms perform better, as shown by the peak PSNR, MSE and SSIM.

Image dehazing is necessary for many computer vision applications, including remote sensing, surveillance, autonomous driving, and medical imaging. The ability to remove haze from photographs can improve customers' perceptions of images as a whole and improve the precision and dependability of image-based algorithms.

II. RELATED WORKS

Researchers have previously experimented with a variety of approaches to lessen the effects of haze on the image are removed by enhancement and physical based models [3]. As CNN perform so well on high-level vision tasks including image interpretation, deblurring, and image categorization, among others, researchers have increasingly focused on deep learning, particularly CNN, to study how well it fulfils the goal of haze removal. Deep learning-based methods are invariably superior to traditional approaches when deep features rather than surface-level characteristics are utilized.

Shengdong Zhang [4] addressed removing the haze in an image by estimation m(y) and w(y).The transmission map m(y) can be calculated by using a deep CNN. It consists of multiple layers and a training strategy to estimate the transmission map of a hazy image.

Masud An-Nur Islam Fahim [5] proposed an End-to-End CNN-based dehazing approach that aims to improve the performance of single image dehazing. The proposed approach uses multi-scale features and residual connections to enhance the representation capability of CNN and to capture both local and global information of the input image.

Ebtesam Mohameed Alharbi [6] proposed a Research on Single Image Dehazing Algorithms It is a combination of CNN with Dark Channel Prior (DCP) , which is used to estimate the transmission map. The transmission map is a measure of how much the light is attenuated by the haze in the scene By estimating the depth map and transmission map, which allows for the generation of a clear and high-quality image.

He Zhang [7] proposed a Joint Transmission Map Estimation and Dehazing using Deep Networks it consists of two stages one is transmission map estimation and other is dehazing. In the first stage, the train CNN to estimate the m(y) from the hazy input image. In the second stage, dehazing is performed using a simple atmospheric scattering model that considers the estimated transmission map and the intensity of the haze in the image.

Wenqi Ren [8] given some modifications to the architecture of the network and the training process, which they claim improve the quality of the dehazed images. Quality of the image can be improved by using residual network and Guided filter to refine m(y) obtain a clear iamge

Wei Ren [9] haze can be removed by using Unsupervised Generative Adversarial Network (GAN). GAN network consists of generator and discriminator network , Generator maps the hazy to clear image , discriminator differentiate between the hazy and clear image .the GAN is trained by using unsupervised learning and it will minimize error between haze and clear image.

Hongyuan Zhu [10] haze can be removed by using Compositional Adversarial Network (CAN) to decompose the hazy image into its intrinsic components, including the transmission map, atmospheric light, and clear image. This method also includes a fusion module that combines the intrinsic components obtained from the CAN to obtain the final dehazed image.

JINJIANG L [11] proposed a Image Dehazing Using Residual-Based Deep CNN suggests that traditional methods for dehazing images may not be able to effectively handle complex haze scenarios, and that deep learning techniques can provide a promising solution to this problem

Boyi Li [12] proposed a method All-in-One Dehazing Network combines the advantages of both global and local features by using a multi-scale and multi-level network architecture. Specifically, the network consists of two parts: a feature extraction network and a dehazing network. The feature extraction network extracts multi-scale and multi-level features from the input image, while the dehazing network estimates the transmission map and removes the haze from the image.

TISONG LIANG [13] haze in an image can be removed by using feedback mechanism.it consists of progressive network and dehazing process. Progressive network refines dehazing process by training series of CNN. The intermediate transmission map and dehazed image are then fed back into the network as input for the next stage, allowing the network to gradually refine.

A. Objectives of Proposed Method

The main objectives of this approach are to improve the visibility of hazy images and to achieve this in a computationally efficient and effective manner. By combining deep learning and optimization techniques.

Improve Image Visibility: The primary objective of single image dehazing using deep learning with BSO algorithm is to improve the visibility of hazy images.

Achieve State-of-the-Art Results: By combining deep learning and optimization techniques, the algorithm aims to outperform existing methods for dehazing images.

Enhance Computational Efficiency: In addition to improving image visibility, the algorithm also aims to enhance computational efficiency. This is achieved by using the beetle swarm optimization algorithm to optimize the parameters of the deep learning model, which can lead to faster and more accurate results compared to other optimization methods. By enhancing computational efficiency, the algorithm can be applied to larger datasets and can process images more quickly, making it more practical for real-world applications [20, 28, 29].

III. PROPOSED METHOD

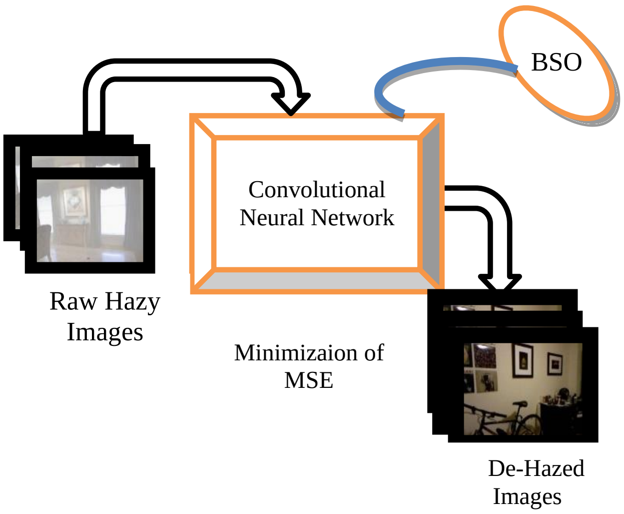
The proposed model is shown in Fig 1., consists of (i)Acquisition of an Image (ii) Dehazing Image model (iii) tuning the Hyperparameters by BSO algorithm.

Acquisition of an Image: The first phase is the acquisition of a hazy image that needs to be dehazed. Images are acquired by using Standard Data set Sot.

Image dehazing model: The second phase is the image dehazing model, which uses a Deep Learning architecture such as a Convolutional Neural Network (CNN) to learn the mapping between the hazy image and the corresponding dehazed image. The Deep Learning model is trained using a dataset of hazy and corresponding dehazed images.

Retrieval Number: 100.1/ijies.C980713030224
DOI: 10.35940/ijies.C9807.11111124
Journal Website: www.ijies.org

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)



[Fig.1: Proposed Model Architecture]

Hyperparameter tuning by optimization: The third phase is hyperparameter tuning, which involves optimizing the parameters of the Deep Learning model to improve its performance in dehazing hazy images. In this phase, the Beetle Swarm Optimization Algorithm is used to search the hyperparameter space and find the optimal values for the Deep Learning model parameters.

The Beetle Swarm Optimization Algorithm (BSO) is a population-based optimization algorithm that mimics the behavior of beetles in finding the optimal solution to a problem.

The block diagram of CNN: It consists of the following layers as shown fig 2.

Input layer: The input layer receives the input image.

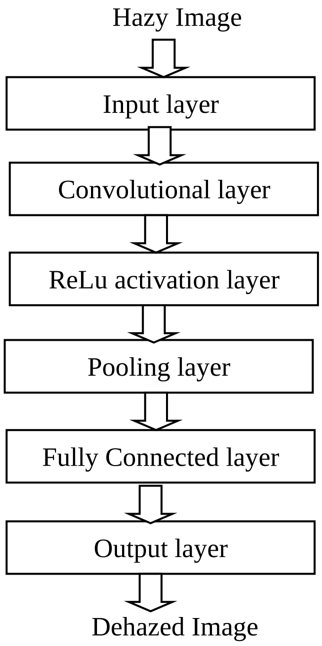
Convolution layer: The convolution layer performs convolution operation on the input image using a set of learnable filters. Each filter extracts a specific feature from the input image.

ReLU activation layer: The ReLU (Rectified Linear Unit) activation layer applies the ReLU activation function to the output of the convolution layer. This introduces non-linearity into the network and helps in learning complex features.

Max Pooling layer: The pooling layer reduces the spatial dimension of the output of the ReLU activation layer. It achieves this by taking the maximum or average value of a group of adjacent pixels.

Fully connected layer: The fully connected layer connects all the neurons from the previous layer to every neuron in the current layer. It performs a weighted sum of the outputs from the previous layer and applies a non-linear activation function.

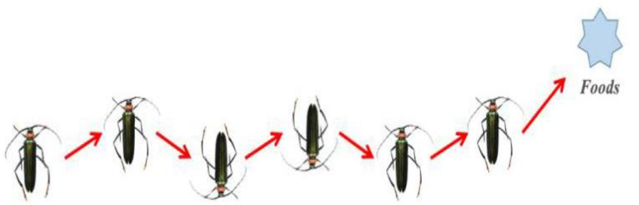
Output layer: The output layer produces the final output of the CNN, which can be a classification or regression result depending on the application.



[Fig.2: Block Diagram of Convolutional Neural Network]

Beetle Swarm Optimization [14][15] is a population-based optimization algorithm inspired by the foraging behavior of beetles. It is a nature-inspired algorithm that mimics the collective intelligence of a group of beetles to search for an for food as shown in fig 3 optimal solution to a problem

$$Y_Y = Y + l * \vec{d}$$
$$Y_Y = Y + l * \vec{d}$$



[Fig.3: Feeding Behavior of Beetles]

An single beetle is located at point Y= (Y1, Y2,……YS) in the S-dimensional i.e. beetle location is given by

$$\vec{S} = \frac{\text{rands}(S,1)}{\|\text{rands}(S,1)\|}$$

Based on a comparison of the potency of an odor by the left and right antennae, the revised adjustment approach for the beetle's future exploration location is as follows:

$$Y_{t+1} = Y_t + \delta_t * \vec{s} * \text{sign}[f(Y_r) - f(Y_0)]$$

where t stands for the algorithm's current iteration count, f(.) for the fitness function, and t for the exploration step at the rth iteration with a typical value of 0.95, stands for the step decay factor, and sign (.) stands for the sign function. The step and sign functions are defined specifically as follows:

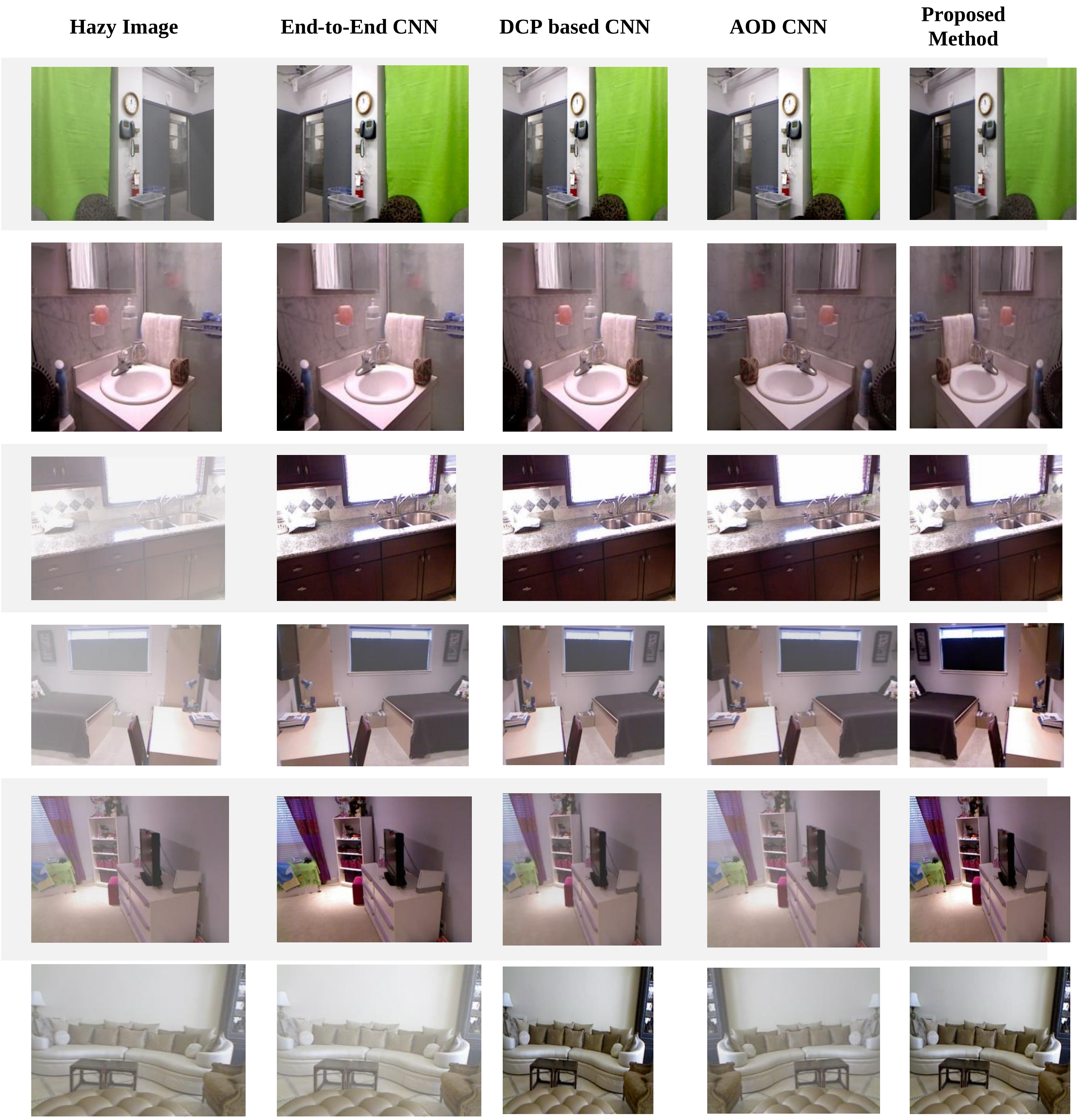
Retrieval Number: 100.1/ijies.C980713030224
DOI: 10.35940/ijies.C9807.11111124
Journal Website: www.ijies.org

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

$$\mathrm{sign}(Y) = \begin{cases} -1, & Y < 0 \\ 1, & Y \geq 0 \end{cases}$$

IV. RESULT AND DISCUSSION

In this part, we will evaluate the performance of the proposed model using SOT data sets that include both artificial and actual foggy images. First, we evaluate three traditional prior-based approaches such as End-to-End CNN [5], DCP-based CNN [6] and AOD CNN [7]. In the proposed setup, the patch of image size is 128x 128 x 3, with 3 representing the number of channels, and the batch size is fixed at 4. In comparison, our approach is evaluated against 3 novel approaches as shown in fig.4.



[Fig.4: Simulation Results of Different Types of Dehazing Methods]

The proposed model uses BSO optimization during the training phase, and both learning rates are set at 0. 001.To boost the network's resilience, we first train the module for 23 epochs with 1% Gaussian noise added to the suggested results.

The provided model achieves improvements in performance over End-to-End CNN of 7.6%, DCP-based CNN of 12.1% enhancement, and PSNR, SSI, and MSE results of 14% when the maximum difference of the suggested Deep CNN is considered [21,22,23][25][26][27].

Retrieval Number: 100.1/ijies.C980713030224
DOI: 10.35940/ijies.C9807.11111124
Journal Website: www.ijies.org

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

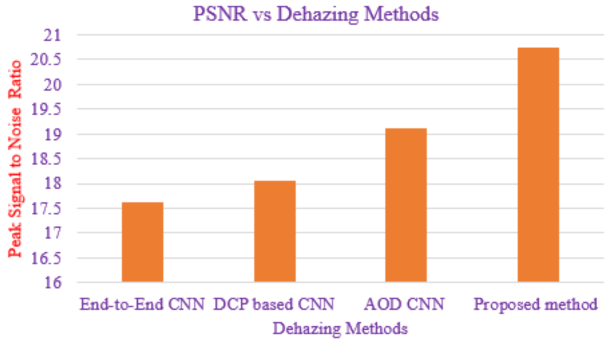
International Journal of Inventive Engineering and Sciences (IJIES)
ISSN: 2319-9598 (Online), Volume-11 Issue-11, November 2024

As a result, the proposed image dehazing model using BSO optimized -Deep CNN method has been used.

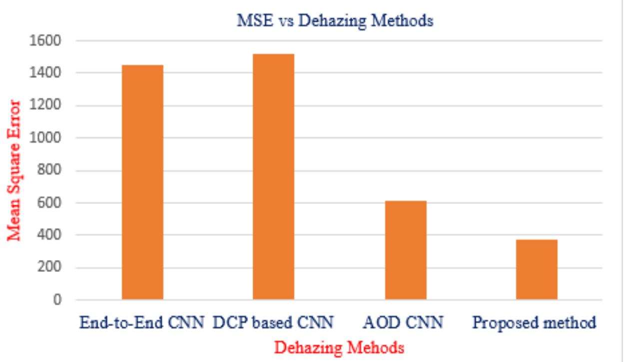
Table I: PSNR MSE and SSIM Values on SOTS (Indoor)

Dehazing Methods	SOTS (Indoor) Data Set		
	Psnr	Mse	Ssi
End-to-End CNN	17.62	1450.5	0.623
DCP based CNN	18.05	1523.1	0.7364
AOD CNN	19125	616.5	0.7825
Proposed method	20.737	371.7	0.821

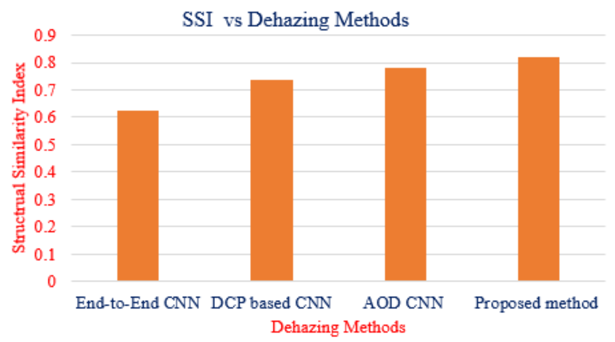
In comparison, our approach is evaluated against 3 novel approaches. As shown in Table.1 The dehazed image performance can be evaluated by using PSNR, MSE and SSIM. The PSNR index of the proposed approach has the benefit of Showthat the dehazing result is less impacted by noise and that the findings are often understandable. At the same time the SSI findings show that our technique performs better at the edge detail and Tarel [16] which are almost equivalent to [21] and [24] method.



[Fig.5: Various Dehazing Techniques Compared to the Proposed Image Dehazing Model for Peak Signal to Noise Ratio (PSNR)]



[Fig.6: Shows Various Dehazing Techniques Compared to the Proposed Image Dehazing Model for Minimum Square Error (MSE)]



[Fig.7: Various Dehazing Techniques Compared to the Proposed Image Dehazing Model for Structural Similarity Index (SSI)]

Figure 5,6,7 shows the outcomes of the SOTS test results. The suggested method performs better at picture dehazing than End-to-End CNN [5], DCP-based CNN [6], and AOD CNN [7]. End-to-End CNN still delivers greater quality with quicker performance benefits despite Dehaze net [17,18, 19] and AOD Net having far deeper convolution layers than the recommended methodology, proving the method's effectiveness with less convolution. But our approach delivers a better visual and quantitative output (Table 1).

V. CONCLUSION

Single image dehaze using Deep learning with Beetle Swarm Optimization Algorithm is a promising approach for image dehazing. This algorithm combines the power of deep learning with the efficiency of BSO algorithm to optimize the weights and biases of the CNN model for image dehazing. The BSO algorithm effectively explores the parameter space of the CNN model to find the optimal values that minimize the loss function. The local search and global search operations help the algorithm to explore the search space effectively and converge towards the global optimum.

The results obtained by this algorithm are promising and show that it can effectively dehaze images. The algorithm can handle different types of hazy images and can produce high-quality dehazed images with better visibility and contrast. However, the algorithm is computationally intensive and requires a large amount of time and resources to run. Therefore, further research is needed to optimize the algorithm's performance and reduce its computational cost.

DECLARATION STATEMENT

After aggregating input from all authors, I must verify the accuracy of the following information as the article's author.

- **Conflicts of Interest/ Competing Interests:** Based on my understanding, this article has no conflicts of interest.
- **Funding Support:** This article has not been sponsored or funded by any organization or agency. The independence of this research is a crucial factor in affirming its impartiality, as it has been conducted without any external sway.
- **Ethical Approval and Consent to Participate:** The data provided in this article is exempt from the requirement for ethical approval or participant consent.
- **Data Access Statement and Material Availability:** The adequate resources of this article are publicly accessible.
- **Authors Contributions:** The authorship of this article is contributed equally to all participating individuals.

REFERENCES

1. S. G. Narasimhan and S. K. Nayar, “Contrast restoration of weather degraded images,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 25, no. 6, pp. 713–724, 2003, doi: 10.1109/TPAMI.2003.1201821. https://doi.org/10.1109/TPAMI.2003.1201821
2. S. G. Narasimhan and S. K. Nayar, “Chromatic framework for vision in bad weather,” Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit., vol. 1, pp. 598–605, 2000, doi: 10.1109/cvpr.2000.855874. https://doi.org/10.1109/CVPR.2000.855874

3. R. Prakash Kumar and N. Manja Naik, “A Review on Efficient state-of-The-Art Image Dehazing Techniques,” ICISTSD 2022 - 3rd Int. Conf. Innov. Sci. Technol. Sustain. Dev., no. 2, pp. 115–121, 2022, doi: 10.1109/ICISTSD55159.2022.10010424. https://doi.org/10.1109/ICISTSD55159.2022.10010424
4. C. A. Hartanto and L. Rahadianti, Single image dehazing using deep learning, vol. 5, no. 1. Springer International Publishing, 2021. doi: 10.30630/joiv.5.1.431. https://doi.org/10.30630/joiv.5.1.431
5. M. A. N. I. Fahim and H. Y. Jung, “Single image dehazing using end-to-end deep-dehaze network,” ACM Int. Conf. Proceeding Ser., pp. 158–163, 2020, doi: 10.1145/3426020.3426058. https://doi.org/10.1145/3426020.3426058
6. S. Lee, S. Yun, J. H. Nam, C. S. Won, and S. W. Jung, “A review on dark channel prior based image dehazing algorithms,” Eurasip J. Image Video Process., vol. 2016, no. 1, pp. 1–23, 2016, doi: 10.1186/s13640-016-0104-y. https://doi.org/10.1186/s13640-016-0104-y
7. H. Zhang, V. Sindagi, and V. M. Patel, “Joint Transmission Map Estimation and Dehazing Using Deep Networks,” IEEE Trans. Circuits Syst. Video Technol., vol. 30, no. 7, pp. 1975–1986, 2020, doi: 10.1109/TCSVT.2019.2912145. https://doi.org/10.1109/TCSVT.2019.2912145
8. G. Veerappan and C. Suresh Gnana Dhas, “Survey of optimistic power aware routing protocols in mobile datacenter networks,” ARPN J. Eng. Appl. Sci., vol. 10, no. 12, pp. 5406–5412, 2015, doi: 10.1007/978-3-319-46475-6. https://doi.org/10.1007/978-3-319-46475-6
9. W. Ren, L. Zhou, and J. Chen, “Unsupervised single image dehazing with generative adversarial network,” Multimed. Syst., no. 0123456789, pp. 18–20, 2022, doi: 10.1007/s00530-021-00852-z. https://doi.org/10.1007/s00530-021-00852-z
10. H. Zhu et al., “Single-Image Dehazing via Compositional Adversarial Network,” IEEE Trans. Cybern., vol. 51, no. 2, pp. 829–838, 2021, doi: 10.1109/TCYB.2019.2955092. https://doi.org/10.1109/TCYB.2019.2955092
11. J. Li, G. Li, and H. Fan, “Image Dehazing Using Residual-Based Deep CNN,” IEEE Access, vol. 6, pp. 26831–26842, 2018, doi: 10.1109/ACCESS.2018.2833888. https://doi.org/10.1109/ACCESS.2018.2833888
12. B. Li, X. Peng, Z. Wang, J. Xu, and D. Feng, “AOD-Net: All-in-One Dehazing Network,” Proc. IEEE Int. Conf. Comput. Vis., vol. 2017-Octob, pp. 4780–4788, 2017, doi: 10.1109/ICCV.2017.511. https://doi.org/10.1109/ICCV.2017.511
13. T. Liang, Z. Li, Y. Ren, Q. Mao, and W. Zhou, “A Progressive Single-Image Dehazing Network with Feedback Mechanism,” IEEE Access, vol. 9, pp. 158091–158097, 2021, doi: 10.1109/ACCESS.2021.3130468. https://doi.org/10.1109/ACCESS.2021.3130468
14. T. Wang, L. Yang, and Q. Liu, “Beetle swarm optimization algorithm: Theory and application,” Filomat, vol. 34, no. 15, pp. 5121–5137, 2020, doi: 10.2298/FIL2015121W. https://doi.org/10.2298/FIL2015121W
15. K. A. Kumar and R. Boda, “A Multi-Objective Randomly Updated Beetle Swarm and Multi-Verse Optimization for Brain Tumor Segmentation and Classification,” Comput. J., vol. 65, no. 4, pp. 1029–1052, 2022, doi: 10.1093/comjnl/bxab171. https://doi.org/10.1093/comjnl/bxab171
16. L. Zhou, K. Chen, H. Dong, S. Chi and Z. Chen, "An Improved Beetle Swarm Optimization Algorithm for the Intelligent Navigation Control of Autonomous Sailing Robots," in IEEE Access, vol. 9, pp. 5296-5311, 2021, doi: 10.1109/ACCESS.2020.3047816. https://doi.org/10.1109/ACCESS.2020.3047816
17. Hsieh, Cheng-Hsiung, Ze-Yu Chen, and Yi-Hung Chang. "Using Whale Optimization Algorithm and Haze Level Information in a Model-Based Image Dehazing Algorithm." Sensors 23.2 (2023): 815. https://doi.org/10.3390/s23020815
18. H. Zhang, V. Sindagi and V. M. Patel, "Joint Transmission Map Estimation and Dehazing Using Deep Networks," in IEEE Transactions on Circuits and Systems for Video Technology, vol. 30, no. 7, pp. 1975-1986, July 2020, doi: . https://doi.org/10.1109/TCSVT.2019.2912145
19. L. Li et al., "Semi-Supervised Image Dehazing," in IEEE Transactions on Image Processing, vol. 29, pp. 2766-2779, 2020, doi: 10.1109/TIP.2019.2952690. https://doi.org/10.1109/TIP.2019.2952690
20. P. Wang, G. Li and Y. Gao, "A Compensation Method for Random Error of Gyroscopes Based on Support Vector Machine and Beetle Antennae Search Algorithm," 2021 International Conference on Computer, Control and Robotics (ICCCR), Shanghai, China, 2021, pp. 283-287, doi: . https://doi.org/10.1109/ICCCR49711.2021.9349411
21. Rui Wang, Jinming Li, "A New Improved Beetle Swarm Optimization Algorithm", Proceedings of 2021 Chinese Intelligent Systems Conference, vol.805, pp.663, 2022. https://doi.org/10.1007/978-981-16-6320-8_67
22. Xin Cui, Cong Wang, Dongwei Ren, Yunjin Chen, Pengfei Zhu, "Semi-Supervised Image Deraining Using Knowledge Distillation", IEEE Transactions on Circuits and Systems for Video Technology, vol.32, no.12, pp.8327-8341, 2022. https://doi.org/10.1109/TCSVT.2022.3190516
23. Chuheng Chen, Juping Liu, Kai Chen, Mingye Ju, "Single Image Dehazing Method Based on Gradient Matrix and Ternary Parameter Search", 2021 13th International Conference on Wireless Communications and Signal Processing (WCSP), pp.1-5, 2021. https://doi.org/10.1109/WCSP52459.2021.9613598
24. Sameer Malik, Rajiv Soundararajan, "Semi-Supervised Learning for Low-light Image Restoration through Quality Assisted Pseudo-Labeling", 2023 IEEE/CVF Winter Conference on Applications of Computer Vision (WACV), pp.4094-4103, 2023. https://doi.org/10.1109/WACV56688.2023.00409
25. Saradha, Dr. S., Priyanandhini, Mangayarkarasi, S., & Sreekala, T. (2019). Single Image Dehazing using Transmission Estimation. In International Journal of Innovative Technology and Exploring Engineering (Vol. 8, Issue 10, pp. 2852–2857). https://doi.org/10.35940/ijitee.j9606.0881019
26. John, J., & Davies, S. (2019). Image Dehazing Based on Physical Model and Gray Projection. In International Journal of Engineering and Advanced Technology (Vol. 9, Issue 1s3, pp. 241–245). https://doi.org/10.35940/ijeat.a1046.1291s319
27. Shrivastava, A. K., & Jain, Dr. S. (2019). A Robust Technique to Remove Fog from Single Image. In International Journal of Recent Technology and Engineering (IJRTE) (Vol. 8, Issue 2, pp. 3124–3130). https://doi.org/10.35940/ijrte.b2758.078219
28. Nagar, K., & Chawla, M. P. S. (2023). A Survey on Various Approaches for Support Vector Machine Based Engineering Applications. In International Journal of Emerging Science and Engineering (Vol. 11, Issue 11, pp. 6–11). https://doi.org/10.35940/ijese.k2555.10111123
29. Sistla, S. (2022). Predicting Diabetes u sing SVM Implemented by Machine Learning. In International Journal of Soft Computing and Engineering (Vol. 12, Issue 2, pp. 16–18). https://doi.org/10.35940/ijsce.b3557.0512222

AUTHORS PROFILE

R. Prakash Kumar, Research scholar in UBDTCE, VTU in the department of ECE also working as Senior Assistant Professor in the department of Electronics and Communication Engineering at CVR college of engineering, Hyderabad He has .Completed Masters in Digital Systems and Computer Electronic in 2010 at JNTU College of Engineering at Hyderabad. His areas of research include signal, Image processing, Machine learning and Communication.

Dr. Manja Naik.N, presently working as Professor in Department of ECE in UBDTCE, VTU,Davangere, Karnataka. He has received M. Tech fromVTU,Karnataka and Ph.D. in 2017 from VTU,Belgavi. His areas of interest include Image video and signal processing. He has more than 20 years of experience in teaching and research. He has published 20 national and international journal articles and 3 patents.