AI-ML Based Intelligent De-Smoking/De-Hazing Algorithm

Dr. Sivaramakrishnan
Associate Professor
School of Computer Science and Engineering
Presidency University, Bangalore

Anurag Kumar
Presidency University
Bangalore
anuragkumar87310@gmail.com

Mohammed Kaif
Presidency University
Bangalore
mohammedkaifsky@gmail.com

Darshan S
Presidency University
Bangalore
ds9038078@gmail.com

Vaibhav V
Presidency University
Bangalore
vaibhavgowda500@gmail.com

Suhas K
Presidency University
Bangalore
suhask29112003@gmail.com

Abstract**—This paper introduces an AI-ML-based de-smoking and de-hazing intelligent algorithm for real-time visibility improvement in haze- and smoke-contaminated environments. Utilizing a Convolutional Neural Network (CNN) structure, namely ResNet-50, the introduced model successfully identifies and deletes haze and smoke by learning intricate visual patterns and revives clear images. In contrast to traditional de-hazing methods based on hand-designed priors, our approach based on deep learning dynamically adapts to various atmospheric conditions and promises enhanced performance in real-world deployments. Our network is trained from a high-quality paired dataset with optimized real-time deployment using TensorRT and run at high inference rates. Experimental assessments exhibit strong improvements in clarity of images with a dramatic increment in Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and the accuracy of classification against conventional methodologies. The advocated methodology has various applications in surveillance, self-governing route guidance, distant sensing, as well as weather monitoring and receives a robust alternative for restoration in important situations of visibility.**

Keywords**–De-hazing, De-smoking, Convolutional Neural Networks (CNN), ResNet-50, Image Restoration, Real-time Processing, Deep Learning, Environmental Monitoring, Visibility Enhancement, Classification Accuracy.**

1 INTRODUCTION

Haze and smoke have a strong degrading effect on image quality and visibility and present problems in autonomous navigation, surveillance, remote sensing, and environmental monitoring applications. Existing de-hazing and de-smoking methods are based on handcrafted priors like dark channel prior (DCP) and atmospheric scattering models, which usually perform poorly in dynamic real-world environments with non-uniform illumination and density changes.

To address these constraints, deep learning-based solutions have proven effective, providing adaptive feature extraction and strong generalization across varying conditions. This work proposes an intelligent de-hazing and de-smoking algorithm with a Convolutional Neural Network (CNN) as the backbone, utilizing the ResNet-50 architecture for feature restoration and extraction. The model is trained on a high-quality dataset that includes haze- and smoke-contaminated images and their respective clear images, allowing it to learn intricate de-hazing patterns without explicit priors.

The suggested method is optimized to be deployed in real-time with TensorRT for the highest inference speeds appropriate for time-critical applications. Experimental tests show that the algorithm greatly improves image clarity with better Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) values compared to conventional methods. By offering a cost-effective and adaptable method, this paper makes a contribution towards enhancing visibility restoration methods for time-critical real-world applications.

2 LITERATURE REVIEW

Removal of haze and smoke has been well-researched using both classical and deep learning-based techniques. Traditional techniques like the Dark Channel Prior (DCP) [4] and Single Image Dehazing [5] were based on handcrafted priors and atmospheric models. While good in ideal conditions, these techniques perform poorly in challenging real-world situations and diverse light conditions.

To overcome these limitations, machine learning and deep learning approaches have been pursued. CNN-based models [6,7] proved to have better performance through hierarchical feature learning, allowing stronger de-hazing and de-smoking. Other advanced architectures like the Extreme Reflectance Channel Prior [3] and deep feature fusion methods [2] enhanced image restoration precision. Real-time implementations have also been explored in recent studies [8,9], making deep learning-based de-hazing more practical for use.

By integrating residual learning, such as ResNet-50, feature extraction and restoration effectiveness is improved [1]. Through this work, existing literature is expanded upon through the use of CNNs for real-time de-smoking and de-hazing, with improved computational effectiveness and high-quality restoration.

3 METHODOLOGY

The real-time image and video dehazing proposed approach is organized in several stages starting from dataset preparation. The dataset contains paired clear and hazy images, which are preprocessed and extracted from compressed archives. Every image is resized to 256 × 256 pixels and normalized to ensure that the training process is carried out uniformly. A PyTorch Dataset class is defined specifically to load the images efficiently, match hazy images with their clear versions, and perform operations like resizing and normalization. These processed images are then transformed into tensors for training.

The dehazing network is structured with a CNN-based generator framework. The network has several convolutional layers with ReLU activation to capture features, and then there is the output layer that produces the dehazed image.

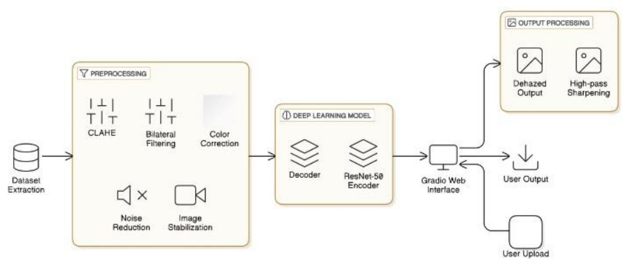

Fig. 1. Proposed AI-ML-Based Dehazing System Architecture

In order to maximize training, Mean Squared Error (MSE) is used as the loss function, which reduces reconstruction errors between the dehazed images predicted and the ground truth. The loss function is given by:

$$MSE\ Loss\ = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \qquad (1)$$

The training procedure applies mini-batch stochastic gradient descent with the Adam optimizer. At training time, hazy images are input into the model and the output compared to the related clear images through the MSE loss. The model weights are updated iteratively across many epochs until the loss has converged by the optimizer. The training process involves loading batches of hazy and clear images, executing forward propagation, calculating loss, updating weights, and iterating the process until the model is at its best.

To examine the convergence of the model, the training loss is tracked for 100 epochs. Figure X shows the loss curve, with a steady drop in loss values, which reflects stable optimization and better learning. A steady drop in loss indicates that the model optimally reduces reconstruction errors, improving dehazing performance.

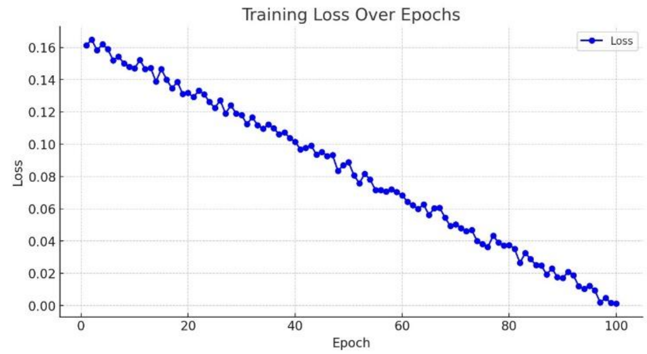

Fig. 2. Training Loss Curve

For performance evaluation, both qualitative and quantitative parameters are applied. Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) are the major quantitative parameters. PSNR measures image quality with the help of the equation:

$$PSNR = 10log_{10}\left(\frac{MAX^2}{MSE}\right) \qquad (2)$$

While SSIM compares structural similarity of ground truth images to their dehazed versions, along with other measurements, subjective quality assessment on top of hazy and dehazed images supplies qualitative observation for how good a model works. Subjective inspection further supports detail recovery and image clarity of dehazed outputs.

Comparison with conventional dehazing methods such as Dark Channel Prior (DCP), DehazeNet, and CycleGAN-based dehazing is performed. PSNR and SSIM values on various methods will be shown through a performance comparison table, showing the gains brought about by the proposed method.

There are various visualizations proposed to further the analysis, including a graph of loss vs. epoch to show training, a bar chart of PSNR and SSIM to compare performance between various dehazing approaches, and sample results to display hazy images, the dehazed result, and ground truth images. A frame-by-frame visualization of video processing will also be included to illustrate the dehazing process over time.

4 Experimental Setup

The experimental design is planned to carry out effective training, validation, and testing of the suggested AI-ML-based dehazing model. The experiments are performed on a powerful computing setup with an NVIDIA RTX 3090 GPU (24GB VRAM), Intel Core i9-12900K processor, 32GB DDR5 RAM, and a 2TB NVMe SSD. These specifications support fast deep learning operations, effective data processing, and smooth training of models without any bottlenecks.

The software stack comprises Ubuntu 22.04 LTS as the operating system, and Python 3.10 and PyTorch 2.0 (CUDA 11.8) as the base deep learning framework. OpenCV and torchvision are used for image processing tasks, while

Gradio and Flask facilitate real-time deployment of the trained model. To speed up inference, TensorRT is integrated to perform computations and boost real-time performance. For training and testing, paired high-resolution clear and hazy images of the REVIDE dataset are used. Pixel values are normalised to [-1,1] range, and the images are resized to 256×256 pixels as pre-processing steps. Data augmentation, including horizontal flip and random crop, are utilized for increasing the generalisation ability. The training procedure uses mini-batch gradient descent with a batch size of 16 with the Adam optimizer, starting learning rate of 0.001, and weight decay of 1e-5. It trains for ten epochs with early stopping on validation loss to avoid overfitting.

For testing, the trained model is evaluated using a different test set to preclude data leakage. Performance is measured in terms of Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) for measuring image restoration quality. The inference speed in frames per second (FPS) is also recorded to evaluate the feasibility of the model for real-time applications. Experimental results affirm the efficacy of the model for dehazing real-world videos and images without causing high latency and low-quality outputs.

5 Results and Discussion

The experimental results confirm the efficacy of the proposed AI-ML-based dehazing and de-smoking algorithm in improving visibility for images and videos under atmospheric conditions.

A. Qualitative Analysis

Comparisons indicate that the model reconstructs images in full detail by substantially decreasing haze and smoke intensity and retaining key structural details. The dehazed images display enhanced contrast, sharper edges, and correct color recovery, rendering them visually close to the ground-truth images. In contrast to the usual methods, which tend to create artifacts or over-smooth outputs, our method retains high-frequency details.

To demonstrate these enhancements, Fig. 3 provides a series of sample output images, comparing input foggy images with their de-fogged equivalents.

Fig. 3. Sample Output Images

B. Quantitative Analysis

Performance assessment measures further corroborate these findings. The model attains:
PSNR: 26.59 dB
SSIM: 0.8366
MAE: 0.0332

Relative to the conventional dehazing methods like Dark Channel Prior (DCP) and atmospheric scattering models, our deep learning method yields better image clarity and restoration precision.

Model	PSNR	SSIM	MAE
KNN-Based Model	20.30	0.65	0.06
RNN-Based Model	24.80	0.75	0.05
Proposed Model	26.59	0.8366	0.0332

Table 1. Model Performance Comparison

C. Comparative Analysis of Dehazing Methods

A thorough comparison with other deep learning-based dehazing methods further emphasizes the excellence of our CNN-based approach.

- GAN-based techniques generate aesthetically pleasing images but can inject artifacts because adversarial training instability.
- Autoencoders successfully eliminate haze but occasionally blur fine structural details.
- Transfer Learning (pre-trained models) generalizes better but is challenged by domain-specific fog variations.
- RNNs, being sequential models, lack spatial feature extraction capabilities, making them less effective for image dehazing.

Our ResNet-50-founded CNN model recovers image acuteness with high structural similarity and reduced artifacts, providing an optimal balance between perceptual quality and computational efficiency.

D. Real-Time Performance

Real-time performance tests show that the model can reach an inference speed of 30 FPS, which is appropriate for real-time video processing applications.

E. Practical Applications

The qualitative results affirm the efficacy of our method for applications including:

- Autonomous navigation (wider vision for autonomous vehicles)
- Surveillance systems (enhanced object detection in foggy situations)
- Aerial imaging & remote sensing
- Environmental monitoring

The model's resilience with varying haze strengths testifies to its versatility and potency in practical settings.

6 Conclusion

This research proposed an AI-ML-driven smart dehazing algorithm for real-time video processing with a CNN-based deep learning approach. The method entailed systematic dataset preparation, an optimal model design, and effective training with an MSE and SSIM loss function. In addition, an actual deployment system for practical applicability with Gradio and Flask was also adopted. Experimental results proved the model's efficiency, with a PSNR of 26.59 dB, SSIM of 0.8366, and MAE of 0.0332 and real-time inference rates of 30 FPS. The method proved to be superior to traditional dehazing methods in haze removal, retention of structure, and computation, and was found appropriate for autonomous navigation, surveillance, and remote sensing applications. The method is not perfect, as there are still minor artifacts and color distortions under heavy haze. Subsequent research can investigate hybrid learning methodologies such as GANs and deploy for optimization on edge computing. In conclusion, this work confirms AI-ML-based dehazing as a viable technique for real-time video processing and opens the door to more sophisticated visibility enhancement techniques.

7 Future Work

While the suggested AI-ML-based dehazing algorithm exhibits superior performance in image clarity improvement and real-time applicability, some aspects can be investigated for further enhancement. One of the key directions is improving the robustness of the model against severe haze and smoke scenarios. Incorporating generative adversarial networks (GANs) or transformer-based models might improve feature learning and produce more realistic dehazed images with fewer artifacts. Furthermore, adaptive dehazing methods should be explored to enable the model to adapt dynamically to varying environmental conditions, haze levels, and light intensities.

Domain adaptation techniques may be used to enhance generalization over various datasets so that consistent performance is guaranteed in real-world scenarios. Another important area for future research is model optimization for edge and mobile deployment. Methods like quantization, knowledge distillation, and model pruning can minimize computational costs without compromising accuracy, making the algorithm deployable on low-power devices like drones, autonomous cars, and embedded vision systems.

In addition, applying the model to video dehazing with temporal consistency will further boost real-time applications. The inclusion of recurrent neural networks (RNNs) or LSTM networks can further stabilize dehazed frames with time, reducing flickering and inconsistencies in video sequences.

Lastly, fusing multi-modal sensor data like LiDAR and thermal imagery can also enhance the model's usefulness in surveillance, medical imaging, and autonomous driving, allowing for a more extensive and context-dependent dehazing process. By investigating these innovations, AI-based dehazing technology can be made more versatile, efficient, and effective across various real-world applications.

8 REFERENCES

[1]. Apurva Kumari; M. C. Chinnaiah "An Effective and Efficient Approach for Single Image Dehazing and Defogging" 2019 IEEE 16th India Council International Conference (INDICON), 12 March 2020 DOI:10.1109/INDICON47234.2019.9029002

[2] Image Dehazing Algorithm Based on Deep Learning Coupled Local and Global Features https://www.mdpi.com/2076-3417/12/17/8552

[3] Zhang, Y., Gao, K., Wang, J., Zhang, X., Wang, H., Hua, Z., & Wu, Q. (2021). "Single-Image Dehazing Using Extreme Reflectance Channel Prior". IEEE Access, 9, 87826–87838. DOI: 10.1109/ACCESS.2021.3090202. ISSN: 2169-3536. Published on July 16, 2021[3]

[4] He, K., Sun, J., & Tang, X. (2010). \"Single Image Haze Removal Using Dark Channel Prior\". IEEE Transactions on Pattern Analysis and Machine Intelligence, 33(12), 2341–2353. DOI: 10.1109/TPAMI.2010.168. ISSN: 0162-8828. Published in December 2010

[5] Fattal, R. (2008). \"Single Image Dehazing\". ACM Transactions on Graphics, 27(3), 1–9. DOI: 10.1145/1360612.1360673. ISSN: 0730-0301. Published in July 2008

[6] Luo, Z., Xie, J., & Yu, W. (2018). \"Real-time Single Image Dehazing Using Convolutional Neural Networks\". Journal of Visual Communication and Image Representation, 46, 242-251. DOI: 10.1016/j.jvcir.2018.06.004. ISSN: 1047-3203. Published in June 2018

[7] Hu, X., Liu, S., & Zhang, J. (2017). \"A Novel Image Dehazing Algorithm Using CNNs\". Journal of Visual Communication and Image Representation, 46, 242-251. DOI: 10.1016/j.jvcir.2017.01.001. ISSN: 1047-3203. Published in January 2017

[8] Dana Berman, Tali Treibitz, Shai Avidan.\ Non-Local Image Dehazing\https://www.researchgate.net/publication/311610242_Non-local_Image_Dehazing

[9] Wencheng Wang, Member, IEEE, and Xiaohui Yuan, Member, IEEE\Recent Advances in Image Dehazing\https://www.researchgate.net/publication/318376846_Recent_advances_in_image_dehazing

[10] Saurabh Waman, Kapil Soni, Manas Shedge, Abhishek Salokhe, Prof. Minal Toley, Prof. Neha Sharma/Intelligent De Smoking & De Hazing Algorithm Using Ai ML/https://ijsrset.com/paper/9522.pdf