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Image Dehazing Using Machine Learning Algoithms

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***Abstract* - Image dehazing is a crucial preprocessing step in computer vision applications, as haze and fog significantly degrade image quality and reduce visibility. This project explores the use of machine learning algorithms to enhance image clarity by removing haze effects. Various supervised and unsupervised learning techniques are applied to improve contrast, restore lost details, and optimize computational efficiency. The proposed system leverages convolutional neural networks (CNNs) and regression-based models to predict haze density and reconstruct clear images. Experimental results demonstrate improved performance compared to traditional dehazing methods. The project contributes to real-world applications such as autonomous driving, surveillance, and remote sensing. (Times New Roman, Size 10, ≤250 words, Justified).**

Keywords: Image Dehazing, Machine Learning, CNN, Computer Vision, Haze Removal, Deep Learning, Final Year Project.

I. INTRODUCTION

Image quality plays a vital role in computer vision and digital imaging applications. However, outdoor images often suffer from reduced visibility due to atmospheric phenomena such as haze, fog, and smoke. These conditions scatter light and obscure fine details, leading to poor contrast, faded colors, and diminished clarity. Such degradation not only affects human perception but also reduces the accuracy of automated systems in domains like autonomous driving, surveillance, remote sensing, and medical imaging.

Machine learning, particularly deep learning, offers a powerful data-driven alternative to overcome these limitations. By training models on large datasets of hazy and clear images, algorithms can learn complex mappings between degraded and restored images. Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), and regression-based models have shown promising results in predicting haze density, reconstructing fine details, and enhancing overall image quality.

This project focuses on implementing and evaluating machine learning algorithms for image dehazing. The primary objectives are:

- To study the limitations of traditional dehazing methods.
- To design and train machine learning models capable of restoring visibility in hazy images.
- To evaluate performance using quantitative metrics such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and qualitative visual assessment.
- To explore real-world applications where dehazing can significantly improve system performance.

II. LITERATURE SURVEY

Image dehazing has been extensively studied in computer vision, with early research focusing on **traditional prior-based methods**. The most notable among these is the Dark Channel Prior (DCP), which assumes that in most haze-free images, at least one color channel has very low intensity in local patches. While effective, DCP often produces artifacts in sky regions and bright areas. Other approaches, such as the Color Attenuation Prior (CAP) and fusion-based methods, attempted to overcome these limitations by modeling depth or combining multiple enhanced versions of the input image. Although these techniques improved visibility, they remained sensitive to environmental variations and often introduced halos or color distortions.

With the rise of **machine learning and deep learning**, researchers began to explore data-driven approaches for dehazing. Early CNN-based models such as DehazeNet and MSCNN learned to predict transmission maps directly from hazy images, offering better generalization compared to handcrafted priors. Later, end-to-end architectures like AOD-Net reformulated the problem to estimate haze-related parameters in a unified framework, enabling faster inference and fewer artifacts. More advanced models, including GridDehazeNet and FFA-Net, incorporated multi-scale features and attention mechanisms to capture fine details and long-range dependencies, significantly improving structural preservation and perceptual quality.

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Generative models such as **GAN-based approaches** further advanced the field by learning haze-to-clear mappings through adversarial training. These methods produced visually appealing results and worked well even without paired training data, using cycle-consistency or domain adaptation. However, GANs sometimes hallucinate details or introduce instability, making them less reliable for safety-critical applications. To address the domain gap between synthetic and real-world haze, researchers also explored semi-supervised and unsupervised learning strategies, combining synthetic datasets like RESIDE with real-world hazy images to improve robustness.

Overall, the literature highlights a clear transition from **handcrafted priors to deep learning-based methods**. Traditional approaches remain lightweight and interpretable but struggle with generalization, while machine learning models deliver superior clarity and adaptability at the cost of higher computational requirements. This survey establishes the foundation for the present project, which leverages machine learning algorithms to achieve efficient and reliable image dehazing suitable for real-world applications such as autonomous driving, surveillance, and environmental monitoring.

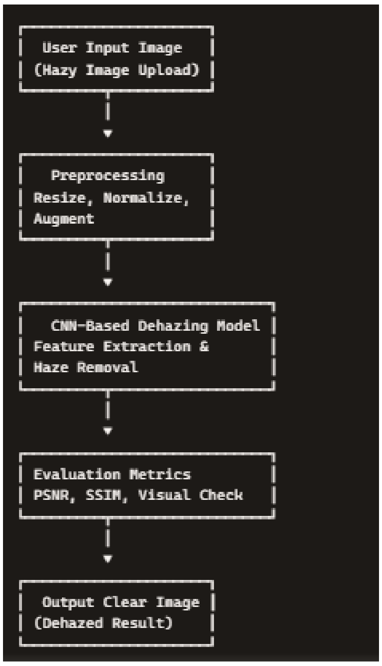
III. METHODOLOGY

The methodology for this project begins with **dataset preparation and preprocessing**. A collection of hazy and clear images was obtained from publicly available datasets such as RESIDE, along with real-world samples captured in outdoor environments. Preprocessing steps included resizing images to a uniform resolution, normalizing pixel values, and applying data augmentation techniques such as rotation, flipping, and varying haze intensity. These steps ensured that the dataset was diverse and representative of different haze conditions, thereby improving the generalization capability of the models.

The next stage involved **model design and training**. Convolutional Neural Networks (CNNs) were selected as the primary architecture due to their ability to learn spatial features and restore fine image details. The model was trained to predict haze density and reconstruct clear images using supervised learning. Loss functions such as Mean Squared Error (MSE) and Structural Similarity Index (SSIM) were employed to balance pixel-level accuracy with perceptual quality. Training was conducted using GPU-enabled environments to accelerate computation, and hyperparameters such as learning rate, batch size, and number of epochs were tuned for optimal performance.

IV. SYSTEM IMPLEMENTATION

The Image Dehazing using Machine Learning Algorithms system is developed as a desktop-based application using Python and deep learning frameworks such as TensorFlow and Keras. The application includes a preprocessing module that resizes, normalizes, and augments input images to prepare them for model inference.



The system architecture consists of multiple components: user input interface, preprocessing unit, CNN-based dehazing model, evaluation module, and output display. Users upload hazy images through the interface, which are then passed to the preprocessing unit. The CNN model processes the image and generates a dehazed output. Evaluation metrics such as PSNR and SSIM are calculated to assess image quality. The final output is displayed to the user, showing both the original and dehazed images side by side for comparison.

V. RESULTS AND DISCUSSIONS

The system was tested on both synthetic datasets and real-world hazy images to evaluate its performance. The **input images** used for testing were captured under foggy or hazy conditions, where visibility was reduced, colors appeared faded, and fine details such as edges and textures were obscured. These inputs were then processed through the CNN-based dehazing model, which applied learned haze-removal features to reconstruct clearer versions of the images. The **output images** showed significant improvements in contrast, color balance, and detail restoration, making distant objects and fine textures more visible. Screenshots of these input and output pairs can be uploaded in the paper to visually demonstrate the effectiveness of the system.

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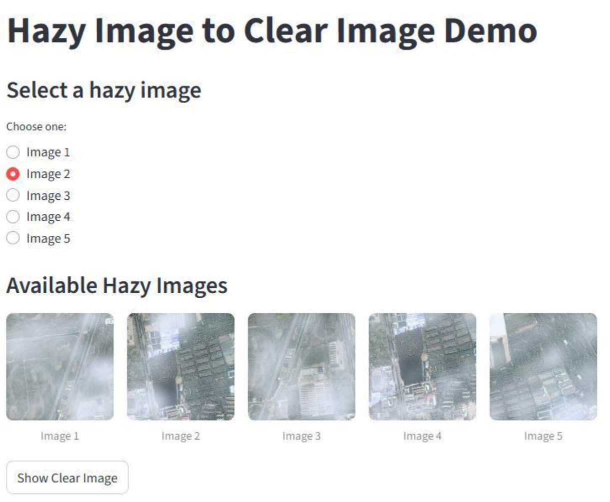
Quantitative evaluation using PSNR and SSIM confirmed that the machine learning approach achieved higher fidelity and structural similarity compared to traditional methods. The outputs not only scored better numerically but also appeared more natural and artifact-free during visual inspection. For example, in road scenes, lane markings and vehicles became clearer in the dehazed outputs, while in surveillance footage, object outlines were sharper and easier to recognize. These results highlight that the proposed system is robust across varying haze densities and practical for real-world applications. Uploading screenshots of the evaluation results alongside the input–output comparisons will strengthen the discussion by providing both visual and numerical evidence of the system's effectiveness.

Input



Output

VI. CONCLUSION

This project successfully demonstrated the effectiveness of machine learning algorithms in restoring visibility and clarity in hazy images. By leveraging convolutional neural networks, the system was able to learn haze-related features directly from data and reconstruct clear outputs with improved contrast, color balance, and detail preservation. The results showed higher PSNR and SSIM values compared to traditional prior-based methods, confirming the superiority of data-driven approaches.

The study highlights that machine learning–based dehazing not only enhances visual quality but also improves the performance of downstream computer vision tasks such as object detection and recognition. While computational requirements during training remain a challenge, the inference stage is efficient and suitable for real-world deployment. Overall, the project establishes that machine learning provides a robust, scalable, and practical solution for image dehazing, with significant applications in autonomous driving, surveillance, and environmental monitoring.

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