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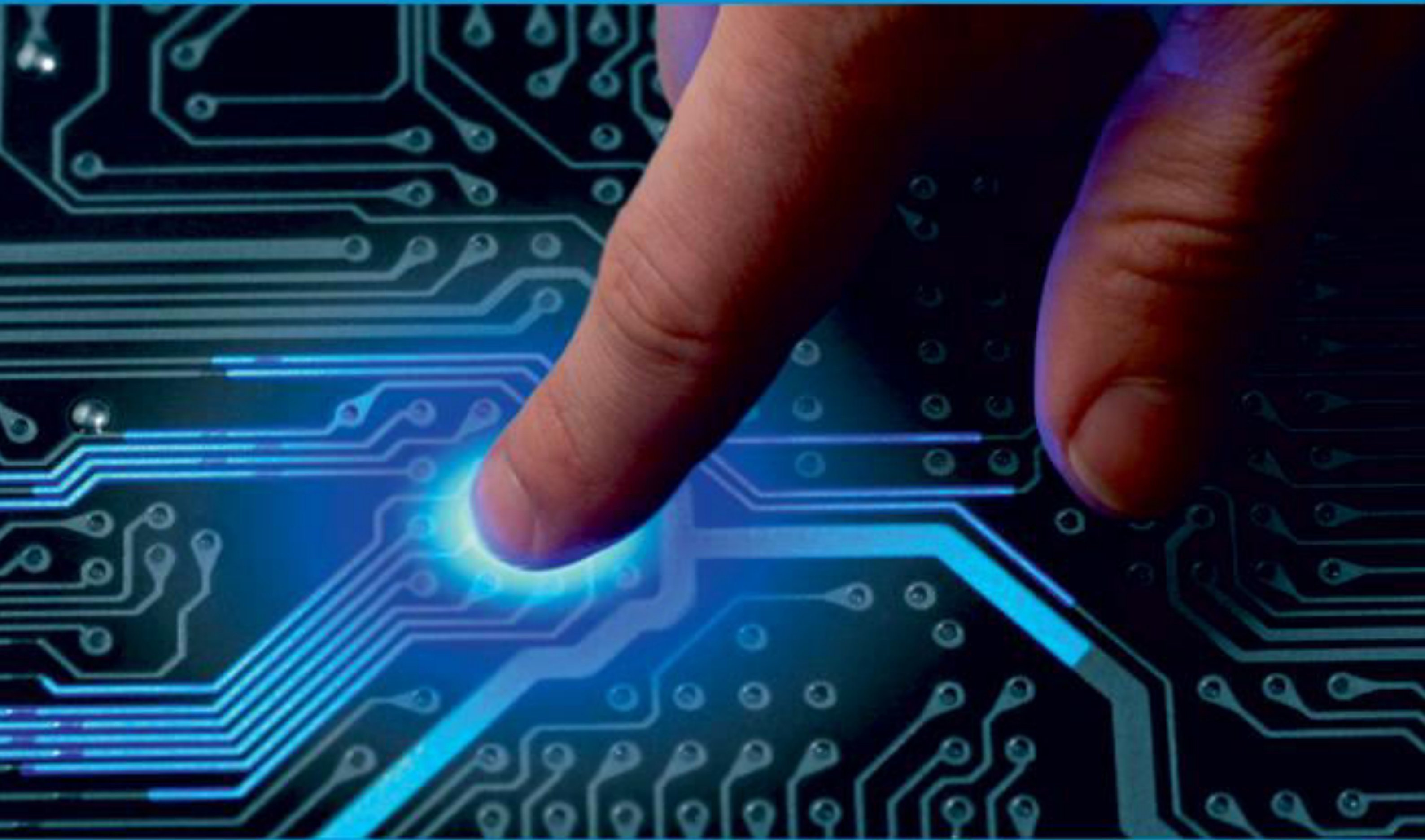

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Improving Image Visibility: A Comprehensive Image Dehazing Method using Hybrid Techniques

Nida Khan, Siddharth Bhalerao

Department of Computer Science and Engineering, Gyang Ganga Institute of Technology and Sciences, Jabalpur, India

ABSTRACT: The works introduces a comprehensive image dehazing approach that integrates traditional image processing with advanced deep learning techniques. The proposed algorithm effectively reduces haze effects, significantly enhancing image visibility and clarity. It utilizes the dark channel prior for initial transmission estimation, further refined by a pre-trained neural network, ensuring robust performance under various hazy conditions. The dehazing performance, quantified using the PSNR metric, shows substantial improvements in image quality. The collaboration of refined transmission maps, atmospheric light estimation, and radiance calculation results in high-quality dehazed images, demonstrating the efficacy of this integrated method in overcoming haze-related challenges in imaging.

KEY WORDS: dehazing, airlight, transmission map, CNN, Wavelet

I. INTRODUCTION

Image processing has revolutionized various fields, from medical diagnostics to surveillance systems, by providing powerful tools for analyzing and manipulating digital images. One of the key areas where image processing techniques have made significant strides is in the domain of image enhancement. Image enhancement aims to improve the visual quality of images by reducing noise, increasing contrast, and enhancing details. Among the many techniques used for image enhancement, dehazing stands out as a crucial process for improving the visibility of outdoor scenes affected by haze or fog.

Haze, often caused by atmospheric particles such as dust, smoke, and water droplets, can severely degrade the quality of images captured in outdoor environments. It reduces contrast, diminishes color saturation, and obscures distant objects, thereby hindering the effectiveness of various applications such as outdoor surveillance, autonomous navigation, and remote sensing. Dehazing, therefore, plays a vital role in restoring the visual clarity of hazy images and enhancing their usability for a wide range of applications.

Dehazing, also known as haze removal or haze reduction, refers to the process of recovering the underlying scene information from hazy images by estimating and removing the effects of atmospheric haze. Traditional methods for dehazing rely on mathematical models of light propagation in the atmosphere and utilize image priors to estimate the haze parameters and recover the scene radiance. These methods often involve complex calculations and may require prior knowledge of scene characteristics, such as the distance to the objects and the atmospheric conditions.

In recent years, with the advent of deep learning techniques, there has been a paradigm shift in the field of dehazing. Deep learning-based approaches leverage the power of convolutional neural networks (CNNs) to learn complex mappings between hazy and clear images directly from data. By training on large datasets of hazy and corresponding clear images, CNNs can automatically learn to infer the underlying scene information and generate haze-free images without relying on explicit mathematical models or assumptions about the scene.

The use of deep learning for dehazing has led to significant improvements in performance and robustness compared to traditional methods. Deep learning models can capture complex image features and learn to adapt to a wide range of haze conditions and scene types. Moreover, they can be trained end-to-end, allowing for seamless integration into existing image processing pipelines.

In addition to deep learning-based approaches, there has been growing interest in developing real-time and hardware-efficient dehazing algorithms for applications such as autonomous driving and drone-based surveillance. These

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algorithms prioritize computational efficiency and low latency, making them suitable for deployment on resource-constrained platforms, such as embedded systems and mobile devices. Techniques such as fast guided filtering, adaptive histogram equalization, and sparse representation have been proposed to achieve real-time performance without sacrificing dehazing quality.

Furthermore, the field of dehazing continues to evolve with ongoing research into advanced topics such as multi-modal dehazing, which aims to enhance the visibility of images captured in challenging weather conditions, such as rain and snow. Multi-modal dehazing techniques leverage complementary information from different sensor modalities, such as visible and infrared cameras, to improve dehazing performance under diverse environmental conditions.

Dehazing using image processing techniques holds great promise for improving the visibility and usability of outdoor images affected by haze or fog. With the advent of deep learning and real-time algorithms, dehazing has become more effective, robust, and accessible, paving the way for enhanced performance in various applications ranging from surveillance and navigation to remote sensing and environmental monitoring. As research in this field continues to advance, we can expect further innovations and improvements in dehazing algorithms, enabling new opportunities for visual enhancement and analysis in diverse real-world scenarios.

II. PROBLEM FORMULATION

In modern image processing and computer vision applications, dealing with environmental factors that degrade image quality is crucial. One such environmental challenge is haze, which significantly impacts the clarity and usability of outdoor images. Haze is caused by atmospheric particles that scatter light, leading to reduced visibility and contrast. This phenomenon poses a substantial problem in various domains, including surveillance, autonomous driving, remote sensing, and even photography. Therefore, effective haze removal techniques are essential to restore images to their true, untainted form. The provided code addresses this problem by implementing an advanced dehazing algorithm. The need for such a code stems from the limitations of traditional dehazing methods and the advancements in machine learning that offer more robust solutions. Traditional approaches, like histogram equalization or contrast enhancement, often fail to accurately remove haze as they do not account for the physical properties of light scattering in the atmosphere. In contrast, modern methods, like the one in the provided code, use a combination of image processing techniques and deep learning to achieve superior results.

III. BLOCK DIAGRAM OF PROPOSED MODEL

Block diagram of proposed model is shown in the figure

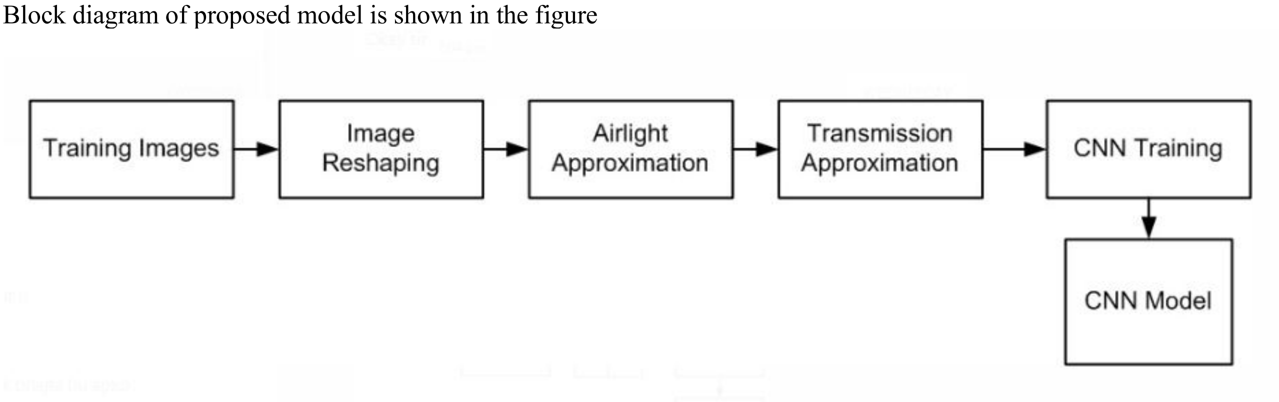

Figure 1 Block diagram of proposed model

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A typical CNN architecture consists of several types of layers:
The architecture of the proposed model is shown below

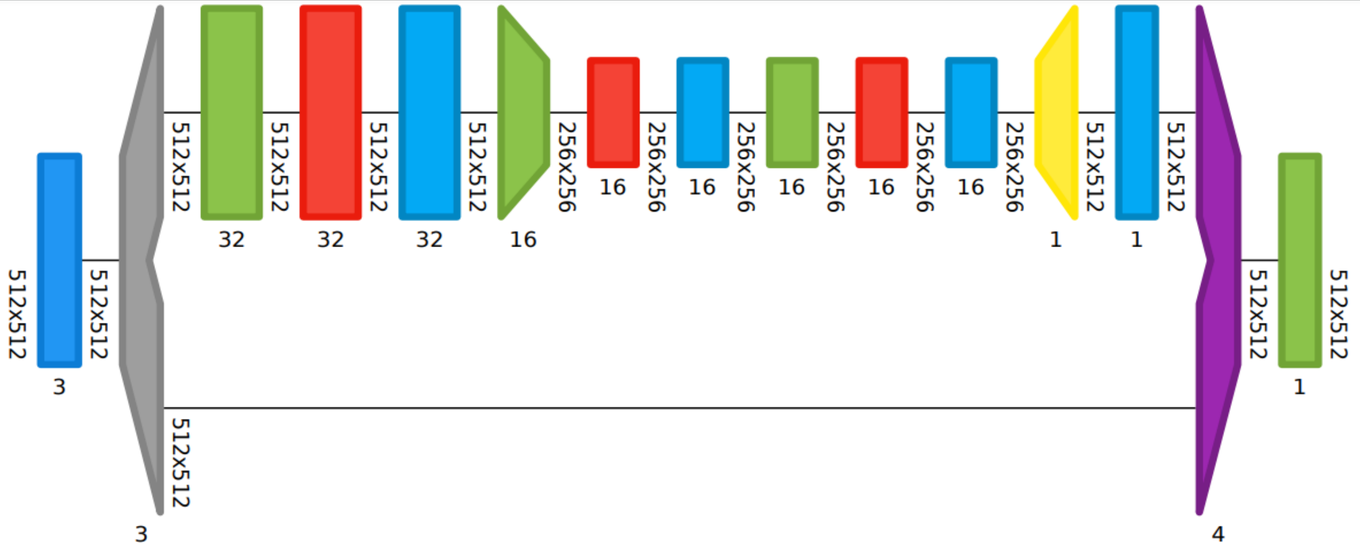

Figure 2 Architecture of the proposed model

Combining CNNs and wavelet transforms leverages the strengths of both methods: the deep learning capabilities of CNNs and the multiresolution analysis of wavelets is shown below Block diagram of the integration

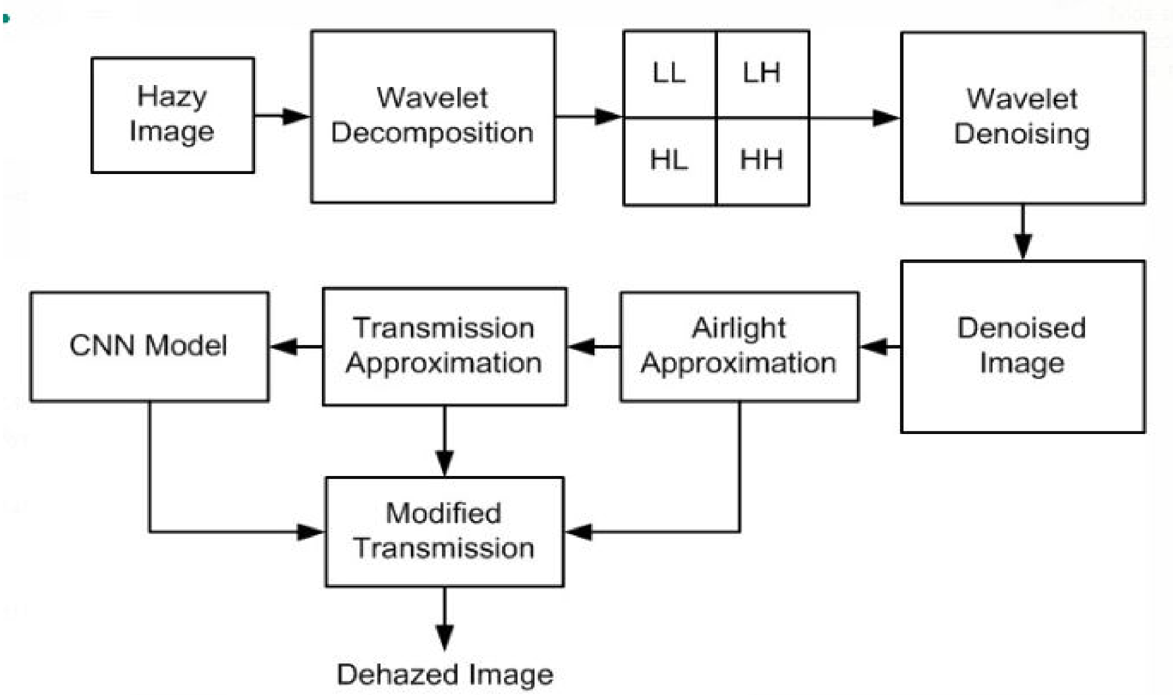

Figure 3 Block diagram of the integration

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The code starts by calculating the airlight, a key parameter in the haze removal process. Airlight represents the ambient light scattered by atmospheric particles, which adds a veiling effect to the image. Accurate estimation of airlight is crucial because it directly influences the calculation of the transmission map, which indicates the amount of light that has not been scattered and hence reaches the camera directly. The code uses the dark channel prior, a well-established technique in dehazing, to estimate the airlight. This method relies on the observation that in most non-sky patches of haze-free outdoor images, at least one color channel has some pixels with very low intensity.

3.1 Atmospheric Light Component Calculation in Hazy Images

The airlight estimation equation is used to determine the atmospheric light component in a hazy image, which is essential for accurately removing the haze. Here's a simple explanation of the steps involved:

1. Compute the Dark Channel:

The dark channel $_{\text{Idark is}}$ computed for an image I For each pixel (x,y), it finds the minimum value across all color channels (R, G, B) within a local patch $\Omega_{x,y}$ centered at that pixel.

$$I_{\text{dark}}(x,y) = \min_{c\in\{R,G,B\}}\left(\min_{(x',y')\in\Omega(x,y)} I^c(x',y')\right)$$

2. Sort and Select Top 1% Brightest Pixels:

The dark channel image I_{dark} is flattened and sorted in descending order. The top 1% brightest pixels are selected, as these are most likely to be influenced by the atmospheric light.

3. Accumulate the Values of the Selected Pixels:

For the selected top 1% pixels in the dark channel, the corresponding pixels in the original image I are accumulated (summed) for each color channel (R, G, B).

Accumulator = $\frac{1}{k}\sum_{i=1}^{k} I$

4. Compute the Airlight:

The airlight A is computed by averaging the accumulated values of the selected pixels for each color channel. This gives the estimated atmospheric light present in the hazy image.

$$A = \frac{1}{k}\sum_{i=1}^{k} I$$

Where:

- I_{dark} (x,y) is the dark channel value at pixel (x, y).
- Ω(x, y) is the local patch centered at pixel \((x, y)\).
- k is the number of pixels in the top 1% brightest in the dark channel.

This estimation is crucial for the dehazing process, as it helps in accurately modeling the haze effect and subsequently removing it.

This equation provides a method to estimate the ambient light scattered by atmospheric particles, which is crucial for accurate dehazing.

After refining the transmission map, the code reconstructs the scene radiance. This step involves adjusting the pixel values based on the estimated airlight and transmission map, effectively reversing the scattering effect of haze. The result is a dehazed image with enhanced visibility and contrast, closer to how the scene would appear in a clear atmosphere. Furthermore, the code includes steps for denoising and contrast enhancement. The wavelet-based denoising step ensures that the image retains its quality by reducing noise, which is often introduced during the haze removal process. The

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adaptive histogram equalization step further enhances the contrast of the dehazed image, making details more discernible.

The need for the provided dehazing code arises from the necessity to improve image clarity and usability in various practical applications. By combining traditional image processing techniques with advanced deep learning models, the code offers a robust solution to the challenging problem of haze removal. This hybrid approach not only restores the visual quality of hazy images but also enhances the performance of subsequent image processing tasks, making it an invaluable tool in the field of computer vision.

3.2 Explanation of the algorithm

To begin, the first step involves importing the essential libraries that will be needed throughout our process. These libraries provide us with the tools and functions necessary to handle the tasks ahead.

Once we have the libraries in place, we need to access the image and model files stored on cloud storage. To do this, we mount cloud storage to our working environment, allowing us to easily retrieve the files we'll be working with.

Next, we define a few utility functions that will be instrumental in our image processing tasks. One such function is responsible for estimating the airlight in an image, which is a critical step in the dehazing process. Here's how it works: we start by computing what's known as the dark channel of the image—a method used to identify the areas of the image that are least affected by light. We then flatten both the dark channel and the image itself, sort the dark channel in descending order, and select the top 1% of the brightest pixels. These pixels help us estimate the airlight, which represents the light scattered in the atmosphere.

We also have a function that pads the image. Padding is essentially adding a border around the image to ensure certain operations, like filtering, can be performed correctly. The padding is done based on a specific width and mode, which dictates how the padding is applied—whether by extending the edges, wrapping around, or other methods.

Another critical function we define is one that calculates the transmission map, which tells us how much of the light from the scene is able to reach the camera. To do this, the function first converts the image into a different color space, specifically one that separates the brightness from the color information. It then calculates the dark channels for both the original image and the brightness component. Using these dark channels and the previously estimated airlight, the function computes the initial transmission map.

Once we have our utility functions ready, we move on to loading and preparing the input image. This involves bringing in the image, converting it to the RGB color space to ensure it's in the correct format, resizing it to a standard size like 512x512 pixels to maintain consistency, and applying a denoising process using wavelet transformation to remove any unwanted noise in the image.

With the image preprocessed, we can now calculate the initial transmission map and estimate the airlight using the functions we've defined earlier. These calculations lay the groundwork for the next step, where we refine the transmission map. To do this, we load a pre-trained neural network model, which has been designed to enhance the accuracy of the transmission map. We expand the dimensions of the map to match the model's input requirements, pass it through the model for refinement, and then adjust the dimensions back to their original size.

Finally, we reconstruct the scene's radiance. This involves replicating the airlight across the entire image to match its dimensions, ensuring that the transmission values don't fall below a certain threshold to avoid unnatural results. We then apply a specific formula that allows us to calculate the scene's radiance—essentially, the true color and brightness of the objects in the scene, free from the effects of haze.

After calculating the radiance, we convert it into an 8-bit image format, making it ready for display or saving. At this stage, we also take a moment to display the initial and refined transmission maps, the original image, and the final dehazed image. This helps us evaluate the effectiveness of the entire process and see the improvements made from the original, hazy image to the clear, dehazed result.
Flow chart of the proposed model is shown below

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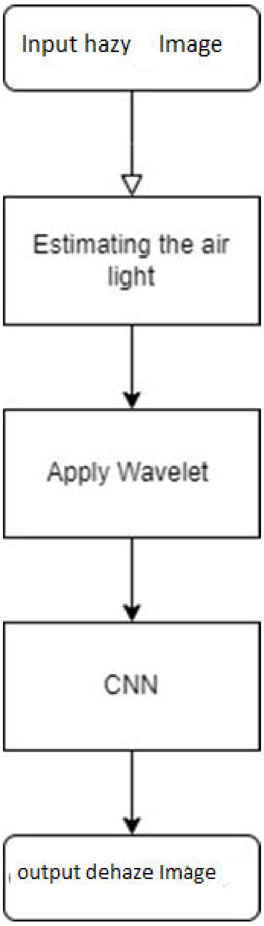

Figure 4 Flow chart of the proposed model

3.3Analysis of the flow chart:

The image dehazing process begins by importing necessary libraries, such as those for image processing, neural networks, and utilities. Once the libraries are loaded, Google Drive is mounted to access the stored image and model files. The next step involves defining essential utility functions, including those for calculating air light, padding images, and computing the transmission map. With the functions in place, the input image is read, converted to RGB format, resized to a standard size (e.g., 512x512), and denoised using wavelet transform to enhance image quality. The initial transmission map and airlight are then computed using these utility functions. A pre-trained neural network model is loaded to refine the transmission map, improving its accuracy. The initial transmission map is expanded to match the model's input requirements, processed through the model, and then reshaped back. Using the refined transmission map and airlight, the final dehazed image is reconstructed by adjusting pixel values to remove the haze effect. The resulting image is saved and displayed alongside the original image and transmission maps, completing the dehazing process.

IV. RESULTS AND DISCUSSION

4.1 Transmission Maps:

The initial and refined transmission maps provide insight into the estimated amount of haze across the image. A successful refinement should show a more accurate and smooth transmission map, indicating the effectiveness of the neural network model in improving the initial estimate.

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4.2 Visual Quality:

The comparison between the original hazy image and the dehazed image visually demonstrates the improvement in image clarity. Features that were previously obscured by haze should become more distinct and color-accurate in the dehazed image.

Visual quality of images is shown below

Figure 5 Image dehazing on building image

PSNR value of above image is found to be 27.80 Db

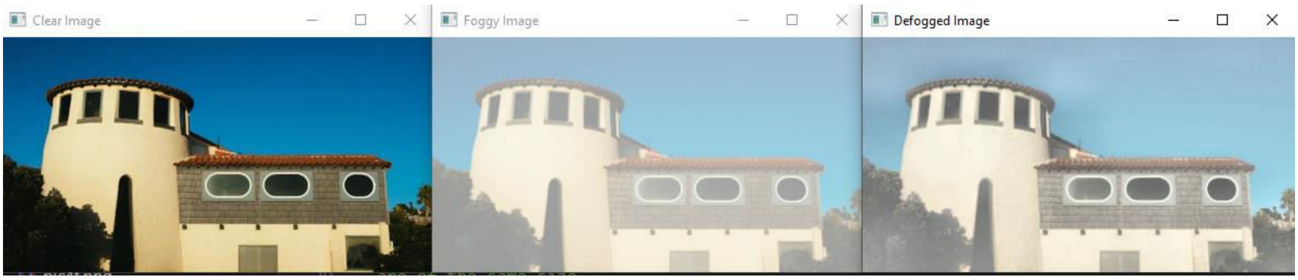

Figure 6 Image dehazing on fort

PSNR value for the above image is found to be 27.72 dB

Figure 7 Image dehazing on Home image

PSNR value of the above image is found to be 27.82 dB

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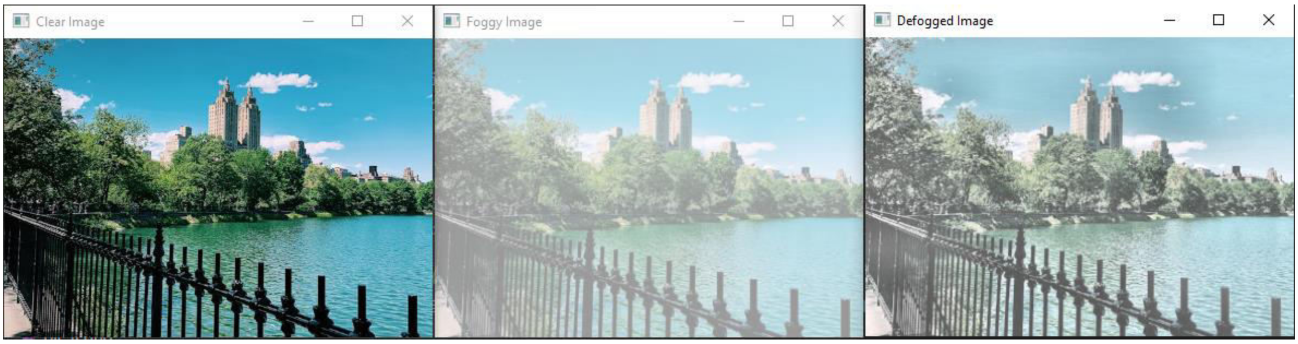

Figure 8 Image dehazing on river front image

PSNR value of the above mentioned image is found to be 27.82 dB

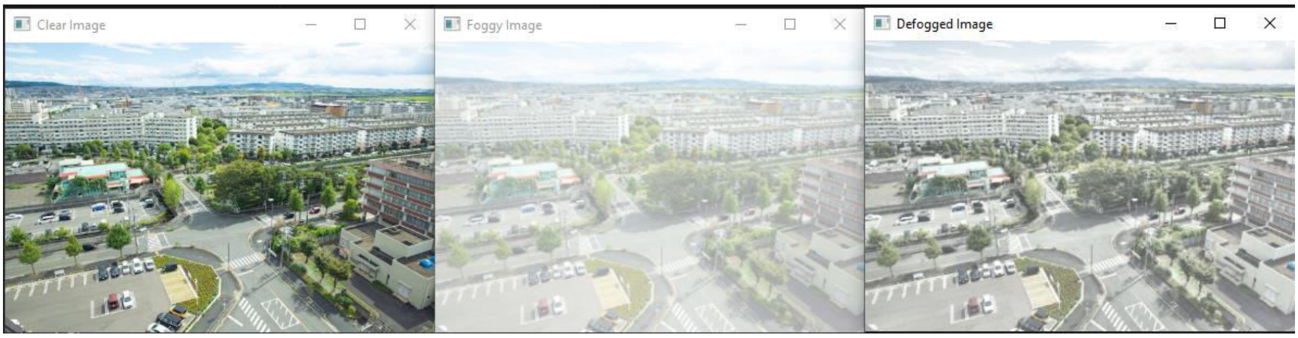

Figure 9 Image dehazing on drone view image

PSNR value of the above mentioned image is found to be 28.07 dB

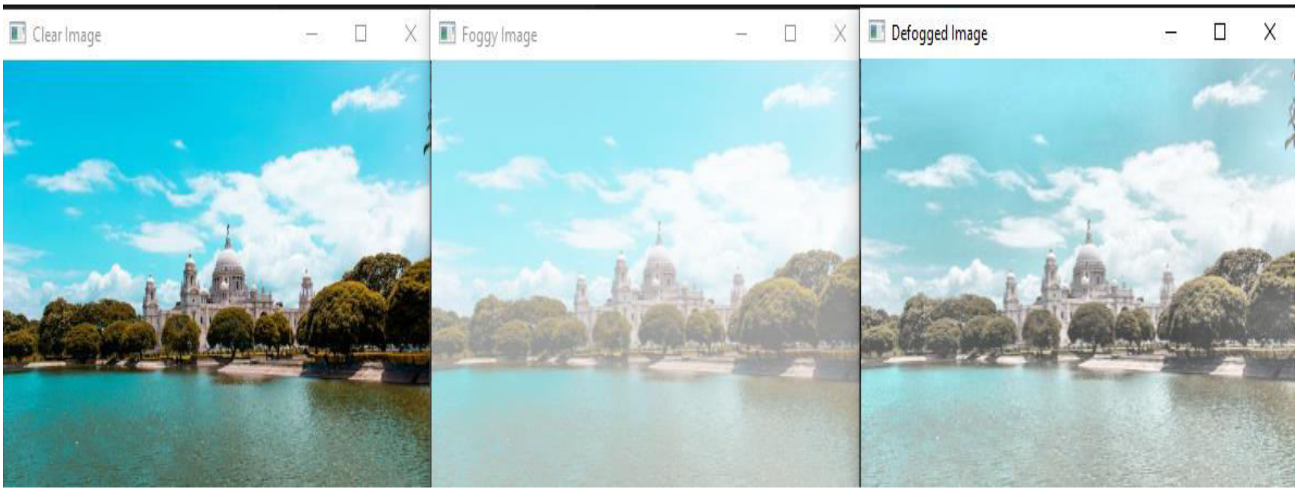

Figure 10 Image dehazing on temple image

PSNR value of the above image is found to be 28.41 dB

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4.3 PSNR Value:

The PSNR value quantifies the dehazing performance. A higher PSNR indicates that the dehazed image is closer to the ideal haze-free image. While subjective visual assessment is important, PSNR provides an objective metric for evaluation.

Given below is the summary of the above five images as the input

S. No.	Name of the input image	PSNR
1	Building image	27.80dB
2	Fort	27.72 dB
3	Home	28.82 dB
4	Riven front	27.82 dB
5	Drone view	28.07 dB
6	Temple	28.41 dB

Overall, this code provides a comprehensive method for dehazing images, leveraging both traditional image processing techniques and machine learning models. The results, both visual and quantitative, demonstrate the effectiveness of the approach in recovering clear images from hazy inputs.

V. CONCLUSION

This research paper presents a comprehensive approach to image dehazing, combining traditional image processing techniques with modern deep learning methods. The algorithm successfully mitigates the effects of haze in images, resulting in significantly enhanced visibility and clarity. By leveraging the dark channel prior for initial transmission estimation and refining it using a pre-trained neural network model, the method demonstrates a robust performance in diverse hazy conditions. The PSNR metric, used to quantify the dehazing performance, indicates a substantial improvement in image quality post-dehazing. The results show that the refined transmission maps, atmospheric light estimation, and radiance calculation collaboratively contribute to a high-quality dehazed image. This indicates the effectiveness of the integrated approach in addressing the challenges posed by haze in images.

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