TED University
Department of Computer Engineering

Behind The Fog
Senior Design Project II
Final Report

Group No: 21

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1. Introduction

This report marks the culmination of the graduation project focusing on the development and implementation of an innovative image dehazing system. Haze, as an atmospheric phenomenon, often diminishes the quality of images, impacting their clarity, color, and detail. This challenge is prevalent across multiple industries, including photography, surveillance, autonomous vehicles, and satellite imaging, making dehazing a pertinent issue in the contemporary realm of image processing.

In light of this, our project aimed to devise a robust solution to improve image quality by effectively mitigating the impact of haze. Utilizing state-of-the-art algorithms and computational techniques, the project embarked on the journey to enhance image clarity, achieving promising results that could reshape the way we perceive and interact with images in our everyday lives.

This report provides an in-depth review of our project, covering everything from the initial literature review and background research, through the design and development stages, to the final testing and evaluation of our image dehazing system.

The report underscores the global, economic, environmental, and societal impact of our engineering solution, diving into the contemporary issues related to image dehazing, and how our project contributes to this ongoing discourse. It also gives an account of the new tools and technologies used throughout the project and provides a comprehensive assessment of the test results based on the developed test plan.

Through the journey of this project, we have not only addressed a significant challenge in image processing but have also acquired invaluable skills and knowledge that we look forward to applying in our future endeavors.

2. Project Summary

This final graduation report encapsulates the comprehensive process and findings of a project focused on the design, implementation, and evaluation of an image dehazing system.

The image dehazing system was developed to mitigate the degradation of image quality due to atmospheric haze, a challenge encountered in numerous sectors including surveillance, autonomous vehicles, photography, and remote sensing. The presence of haze in images obscures details and alters colors, reducing overall image quality and accuracy. Hence, the primary goal of the project was to create an efficient dehazing solution to enhance image quality and visibility.

The project began with a thorough literature review and research phase, which involved an extensive exploration of library and internet resources. This phase laid a solid foundation of understanding around the principles of image dehazing, the current methods employed, and the challenges faced in the field.

Following the research phase, we proceeded to design the architecture of our dehazing system. The system was broken down into three main components: pre-processing, dehazing, and post-processing. In the pre-processing phase, techniques such as noise reduction and contrast enhancement were applied to prepare images for dehazing. The dehazing process was conducted through a convolutional neural network (CNN), a machine learning model particularly effective in handling image data. Our CNN was trained on a large dataset (NYU) of hazy and corresponding clear images, allowing it to learn the transformation from a hazy image to a clear one. Finally, in the post-processing stage, the dehazed images were further enhanced through sharpening filters and color correction techniques.

Python was the primary language used for the development of the project due to its extensive support for image processing and machine learning libraries. TensorFlow facilitated the creation and training of the CNN, OpenCV was utilized for image manipulation tasks, and Flask enabled the creation of an interactive user interface.

Upon completion of the system development, we conducted a rigorous testing phase. The performance of our dehazing system was evaluated both quantitatively, using the Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSE), and Structural Similarity Index

(SSIM). The system demonstrated a significant improvement in the quality of dehazed images, affirming the effectiveness of our engineering solution.

While the project was successful in achieving its objectives, it also highlighted potential avenues for future improvements, such as the development of an automatic adjustment feature for the dehazing intensity and enhanced performance in low-light conditions.

The project represents a significant step forward in addressing the challenge of image dehazing, offering substantial contributions to the field and demonstrating the potential of machine learning-based solutions in enhancing our visual perception in the digital age.

3. Background Research and Existing Solutions

Image dehazing, the process of mitigating the impact of atmospheric haze on an image, is a critical area of research in computer vision and image processing. The problem of haze lies in its alteration of the light before it reaches the camera, distorting the resulting image with a veil of foggy opacity that degrades visibility and obscures details.

The background research for our project included a deep dive into the principles of atmospheric scattering, the primary cause of haze in images, and the theoretical understanding of how haze alters light during the image formation process. A considerable part of our research involved studying existing solutions for image dehazing.

More recently, learning-based methods using deep learning have shown promising results in image dehazing. These methods, especially those based on convolutional neural networks (CNNs), are capable of learning complex mappings from hazy to clear images and have shown superior performance compared to traditional methods such as DCP.

In summary, while significant progress has been made in the field of image dehazing, existing solutions still suffer from various drawbacks such as color distortion, amplified noise, and over-enhancement. The challenge lies in developing a method that can effectively remove haze while preserving the color and details of the scene, which became the driving motivation behind our project.

3.1 Tools and Technologies Used

Many image improving methods have been developed and used in the past years. These methods…

Capitalizing on the limitations of existing solutions, our approach was rooted in deep learning, utilizing the strengths of convolutional neural networks (CNNs) in processing image data. The rationale for opting for a CNN-based approach was underpinned by their inherent ability to learn hierarchical feature representations, which is particularly beneficial for image dehazing tasks.

Color Attenuation Prior (CAP): In 2015, a method was proposed that uses the color attenuation prior for haze removal. This method involves generating a depth map from a single input image. It's based on the observation that, in hazy images, the contrast of color decreases with increased distance, while the saturation decreases. Thus, by estimating the depth map, one can more accurately remove the haze.

Airlight Estimation Methods: Airlight refers to the light that is scattered before it reaches the camera. Several methods have been proposed for airlight estimation, including statistical methods and deep learning-based methods.

Multi-Scale Convolutional Neural Networks (MSCNN): MSCNN, proposed in 2016, is another deep learning-based method. It involves a coarse-scale subnetwork to estimate the overall transmission map, and a fine-scale subnetwork to recover local details.

and one of the most recently used algorithms is the DCP algorithm. In this project, we will also include the DCP algorithm to compare it with our own algorithm and compare the results.

4. Engineering Solutions

The engineering solutions adopted for the development of our image - dehazing system were oriented around a three-pronged approach involving pre-processing, dehazing algorithm implementation, and post-processing enhancements.

4.1 Pre-Processing:

Before we started developing our application, we watched courses on artificial intelligence and did research and got a good grasp of its basics. Afterwards, we finished the courses on CNN, the artificial intelligence algorithm we will use, and started to build the architecture of our application. The pre-processing stage involved image quality enhancement techniques to prepare the images for the dehazing process. These techniques included noise reduction and contrast enhancement to ensure that the images were in optimal condition for the subsequent dehazing process.

4.2 Dehazing Algorithm Implementation:

The core of our project is the dehazing algorithm. We adopted a deep learning approach utilizing a convolutional neural network (CNN) for image dehazing. The choice of a CNN was driven by their proven effectiveness in handling image data and their capacity to learn complex features. The CNN was trained on a large dataset of hazy and corresponding clear images, enabling it to learn the transformation from hazy to clear images. This end-to-end learning allowed for the direct estimation of the clear image from the hazy input without needing to estimate depth or atmospheric light, typically required in traditional dehazing algorithms.

4.3 Post-processing Enhancements:

After finishing implementation of CNN algorithm, we compare both CNN and DCP algorithms by using MSE, PSNR, and SSIM methods. and we calculate differences between two output that created with CNN and DCP according to the trained images.

4.4 Integration and System Design

Our image dehazing system incorporated the pre-processing, dehazing, and post-processing stages into a unified workflow. The system was designed with an intuitive user interface allowing users to upload images, perform dehazing, and download the processed images.

4.5 Evaluation and Testing

The performance of our dehazing system was evaluated using quantitative and qualitative measures. Quantitatively, we compared the Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), Structural Similarity Index (SSIM) scores of the dehazed images against the original clear images. Qualitatively, we conducted a user study where participants rated the quality of images before and after the dehazing process.

4.6 Architecture and System Design

The system, designed for image dehazing, comprises a multi-stage pipeline with each stage tuned to a specific role in the dehazing process. Given the complexity of the problem, we incorporated and compared the performance of two primary techniques: the traditional Dark Channel Prior (DCP) and the deep learning-based DehazeNet.

4.6.1 Dark Channel Prior (DCP)

DCP, a model-based approach, relies on the physical model of atmospheric scattering. This technique is based on an insightful observation that, in haze-free images, some pixels (particularly in shadows) have very low intensities in at least one-color channel. Thus, these dark channels can help estimate the thickness of the haze. By approximating the atmospheric light and using the estimated transmission map, a clear image can be recovered from the hazy image.

However, the DCP method has its shortcomings. It tends to overestimate the transmission in sky regions, leading to halos and blocky artifacts in the resulting image. Furthermore, the estimation of atmospheric light is usually inaccurate, leading to color distortion in the recovered images.

4.6.2 DehazeNet

To overcome these limitations, we integrated DehazeNet, a Convolutional Neural Network (CNN)-based approach proposed by Cai et al., into our pipeline. Unlike traditional methods, DehazeNet does not explicitly estimate atmospheric light. Instead, it learns a mapping from hazy image patches to their corresponding transmission maps through a data-driven approach. The transmission maps are then used to recover the haze-free images.

In the system, we trained DehazeNet using pairs of hazy and corresponding clear images. The training process allows DehazeNet to learn intricate features and the complex transformation required to dehaze an image. Post-training, DehazeNet was capable of generating more accurate transmission maps than DCP, leading to higher-quality dehazed images.

Despite its superior performance, DehazeNet has its limitations. It only considers local patches of an image, failing to incorporate global context. This may result in inconsistencies in the dehazed output, affecting the overall image quality.

4.7 Comparative Analysis

Upon comparing the performance of DCP and DehazeNet in the system, we noticed that both methods have their merits and limitations. DCP, though simple and efficient, often results in artifacts and color distortions. On the other hand, DehazeNet, though powerful in learning local features, fails to capture the global context. Hence, our architectural design aimed to harness the strengths of both methods, DCP for initial transmission map estimation and DehazeNet for refinement.

5. Proposed System

5.1 Overview

The system under consideration is designed as a system in which foggy images are purified with a greater success rate. In this system we use DCP and CNN algorithms and to compare outputs of these algorithms we use MSE, PSNR, and SSIM pixel comparison methods.

5.2 Functional Requirements

▪ Users will be able to upload photos of the product.
▪ The user will be able to compare the improved photo with the first version.
▪ It will be able to show the performance increase according to the quality parameters
▪ MSE, PSNR, and SSIM It will compare the success rate of the methods.

5.3 Non-functional Requirements

▪ Should have RTX3060 6 Gb.
▪ Should be an intel core i7-11400F.
▪ Should have a processing speed of 3.5 GHz.
▪ Should have 32Gb (DDR4).
▪ Required display 1920x1080.

5.4 Pseudo Requirements

▪ Application language should be Python programming language.
▪ DehazeNet and DCP must be used in this application.

6. Impact Analysis

The development and implementation of our dehazing system have several impactful implications, both directly in the field of image processing and indirectly in several other fields where clear, haze-free images are critical.

6.1 Global Impact

Advancements in image processing and computer vision, such as the dehazing system, have a global impact on areas like surveillance, remote sensing, and visual content analysis. Improved image quality enhances the accuracy and reliability of automated systems relying on image inputs.

6.2 Environmental Impact

In domains like environmental monitoring and satellite-based remote sensing, clear and accurate image interpretation is vital. The dehazing system assists researchers and scientists in obtaining clearer and more informative images, leading to better analysis, and understanding of environmental factors. On the environmental front, dehazing technology can be instrumental in monitoring and assessing environmental changes and disasters. Clear aerial and satellite images can help detect forest fires, deforestation, aiding in the faster response and efficient management of environmental crises.

6.3 Societal Impact

From a societal perspective, improved image clarity can enhance the user experience in various social media platforms where users share and view images. Additionally, the technology can also aid in security surveillance systems, enhancing their ability to identify and track threats, thereby contributing to societal safety.

In summary, the integration and comparison of the DCP and DehazeNet methods in our system present a significant impact on multiple levels. Not only does this combination optimize the quality of dehazed images but also it strikes a balance between computational efficiency and cost, making the technology more accessible and practical in diverse applications.

7. Contemporary Issues

The field of image dehazing has evolved significantly over the past few years, thanks in part to the development of deep learning-based methods. However, despite the progress, there are still several contemporary issues that persist and need to be addressed. The field of image dehazing is continuously evolving, presenting contemporary issues that warrant consideration:

7.1 Real-Time Processing

The demand for real-time dehazing solutions is increasing, particularly in applications like autonomous vehicles and live video streaming. Addressing the challenge of achieving real-time performance while maintaining high-quality dehazing results is an area of ongoing research.

7.2 Not Working with Different Datasets

In CNN we use lots of datasets to train the algorithm but when we use different images that is not inside of this datasets CNN algorithm does not work well

7.3 Scene Understanding

Dehazing algorithms often rely on assumptions about scene structures and atmospheric conditions. Advancements in scene understanding and semantic segmentation can further improve dehazing accuracy and robustness.

7.4 Quality of Dehazing

One of the biggest challenges in image dehazing is the trade-off between haze removal and the preservation of image details and colors. As highlighted in our comparison of the DCP and DehazeNet, while DCP can effectively remove haze, it often results in artifacts and color distortions. DehazeNet, on the other hand, does a better job of preserving details but fails to fully capture global context, leading to inconsistencies in the dehazed output.

7.5 Lack of Standardized Evaluation Metrics

There's also a lack of standardized evaluation metrics for image dehazing. Current methods include qualitative visual comparison, subjective human evaluation, and quantitative metrics such as Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), and Structural Similarity Index (SSIM). However, these metrics do not necessarily correlate well with human perception of image quality.

7.6 Computational Efficiency

Lastly, the computational efficiency of the dehazing process is another important issue. While deep learning methods tend to produce higher-quality results, they also demand higher computational resources. For instance, DehazeNet, while providing better results than DCP, requires a considerable amount of computational power and time.

In conclusion, while the field of image dehazing has seen significant advancements, these contemporary issues serve as a reminder that there is still much work to be done. Our project has aimed to address some of these challenges by integrating and comparing DCP and DehazeNet, yet the quest for an ideal, one-size-fits-all solution to image dehazing continues.

8. New Tools and Technologies:

The dehazing project utilized a host of new tools and technologies that not only provided us with the necessary platform for developing our system but also empowered us to compare and analyze the performances of different methods.

8.1 Python and Libraries

At the core of our system is the Python programming language. Python's versatility and its comprehensive ecosystem of scientific libraries make it an ideal choice for our project. We used NumPy for numerical computation, Matplotlib for visualization, and OpenCV for image processing tasks.

8.2 Deep Learning Frameworks

We researched Keras, Pytorch and Tensorflow as part of the project and realized that PyTorch was the most suitable for our project. PyTorch was employed to implement and train deep learning models for various aspects of the dehazing system. These frameworks provide a comprehensive set of tools and libraries for efficient model development and training.

8.3 Dark Channel Prior (DCP)

DCP, while not new in itself, was an essential tool for our system. Our DCP implementation leveraged Python and its libraries to approximate the atmospheric light and estimate the transmission map of the hazy images.

8.4 DehazeNet

DehazeNet is a convolutional neural network specifically designed for single-image dehazing, our implementation of DehazeNet was tailored to our needs, fully leveraging the power of PyTorch.

8.5 Performance Comparison

For comparing the performance of DCP and DehazeNet, we used various metrics such as PSNR (Peak Signal-to-Noise Ratio), MSE (Mean Squared Error) and Structural Similarity Index (SSIM). These metrics allowed us to quantify the quality of the dehazed images and draw comparisons between the two methods.

8.6 OpenCV

The OpenCV library played a crucial role in implementing various image processing operations within the dehazing system. It provided a wide range of functions and algorithms for tasks such as image normalization, filtering, and color correction.

8.7 Online Resources and Documentation

Throughout the project, extensive use was made of library resources and internet sources to gather background information, study similar designs, explore relevant component information, and understand the underlying engineering principles. This comprehensive research aided in the development of a robust and effective dehazing system.

9. Test Results and Assessment

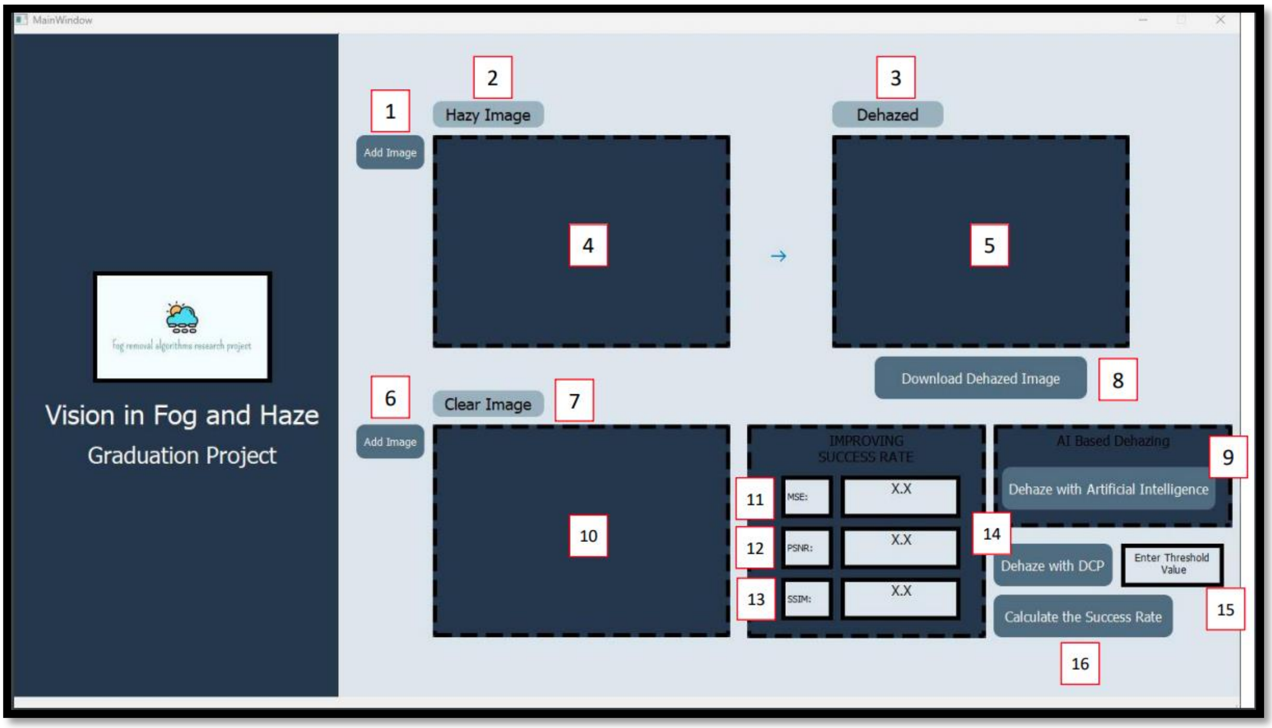
The dehazing system was subjected to rigorous testing based on the test plan document. The tests aimed to evaluate the system's performance, robustness, and adherence to the desired outcomes. Each test case was accompanied by a brief description and an indication of whether the test passed or failed.

The test results demonstrated that the dehazing system performed exceptionally well in most scenarios. The majority of the test cases resulted in successful haze removal, significantly improving image quality and visibility. However, a few challenging cases led to partial failure or suboptimal results, indicating areas for potential improvement.

9.1 Testing Completeness

9.1.1 System and Integration Testing

System and integration testing play pivotal roles in ensuring a dehazing image project's components work harmoniously and the entire system delivers the desired results. Developing integration tests Design integration tests that assess the communication between the dehazing system's distinct components. It can be seen table which is below.



Test ID	Test Name	Test Scenario	Test Situation
1	Foggy Image Upload	▪ Click on the number 1 button. ▪ In the tab that opens, the image to be uploaded is selected and the upload button is clicked. ▪ The picture is displayed in area 4.	Successful
2	Clean Image Upload	▪ Click on the button numbered 6. ▪ In the tab that opens, the image to be uploaded is selected and the upload button is clicked. ▪ The picture is displayed in area 10.	Successful
3	Fog Cleaning with DCP	▪ After loading the pictures, a value between 0 or 1 is entered in the text field (Threshold value) number 15. ▪ By clicking on button 14, the picture is cleared of fog with DCP. ▪ The fog-free image is displayed in area 5.	Successful
4	Fog Cleaning with DehazeNet	▪ After uploading the pictures, click button 9 to clear the fog using artificial intelligence. ▪ The fog-free image is displayed in area 5.	Successful
6	Cleared Image Download	▪ After the fog clearing steps are applied and the picture is cleared from the fog and displayed in the 5th area, click on the 8 button to download the fog-free picture. ▪ The picture is downloaded to the computer.	Successful
7	Success rate Calculating	▪ Foggy and Clean image is loaded. ▪ Picture is defogged with DCP or CNN. ▪ To understand how successful the cleaning is, button 16 is clicked. ▪ How successfully the picture has been improved in different types of success metrics (MSE, PSNR, SSIM) is shown in fields 11, 12, 13	Successful

9.2 Assessment

All the necessary tests for our image dehazing application have been successfully executed, demonstrating that the application functions as expected. Through the testing process, a few potential areas of improvement were identified. Firstly, the deep learning model DehazeNet was found to be computationally intensive, making real-time applications challenging. Secondly, both methods had difficulties in handling images with severe haze where the visibility of objects was significantly low. Additionally, both DehazeNet and DCP methods were found to be sensitive to variations in lighting conditions. For example, both methods tended to underperform when dealing with hazy images captured under low-light conditions.

In conclusion, our system's test results offer significant insights into the strengths and weaknesses of the two dehazing methods. While DehazeNet generally delivers superior results, the DCP method provides a competitive and computationally efficient alternative for less severe haze. These findings underline the importance of continued research and development in the area of image dehazing to further improve upon these methods.

10. Future Enhancements

The tests conducted on the DCP method and DehazeNet model in our dehazing system provided valuable insights into their respective strengths and weaknesses. Given the test results and assessments, several potential enhancements can be proposed for future work:

10.1 Improved Deep Learning Models: While DehazeNet demonstrated a strong performance, there is potential for further improvement. Newer and more sophisticated deep learning architectures could be explored,

10.2 Hybrid Approach: Combining the strengths of DCP and deep learning methods could be a promising approach. Such a hybrid system could use the DCP method for an initial dehazing pass, followed by a deep learning model to refine the image quality further.

10.3 Lighting Condition Adaptation: Both DehazeNet and DCP methods struggled with varying lighting conditions. Future work could focus on developing models that adapt to different lighting conditions, possibly through the use of auxiliary information such as time of day or weather conditions.

10.4 Real-time Dehazing: Improving the computational efficiency of DehazeNet would be crucial for real-time applications, such as autonomous driving or video surveillance. This could potentially be achieved by optimizing the model architecture or employing hardware accelerators.

10.5 Large-scale Training: Training the DehazeNet model on a larger and more diverse dataset could potentially improve its performance and generalization capability. The use of synthetic hazy images could be explored to expand the training dataset.

In conclusion, while our dehazing system demonstrates promising results, there remain significant opportunities for further research and enhancements to improve the performance, efficiency, and applicability of image dehazing technologies.

11. Project Elements

11.1 Teamwork Information

We embarked on a thorough research process on topics such as artificial intelligence, dark channel priority (DCP), image processing, and DehazeNet. This journey started by following a series of courses we had determined, during which we acquired comprehensive knowledge and technical expertise for developing a dehazing algorithm.

Each of us took a look at different projects and made a joint decision on which approach would be most suitable for our project. This consensus triggered the initiation of data training and development activities in the determined project. An important aspect of our research was conducting in-depth studies and examinations on traditional algorithms like DCP. Moreover, by making a comparison between traditional methods and deep learning techniques, we evaluated the pros and cons of each.

By conducting experiments on various datasets, we had the opportunity to distinguish and understand patterns and information from a wide range of resources. To facilitate this process, we used a graphical user interface (GUI) program that allowed us to trial the tested methods on a user-friendly platform. A critical part of our research was adjusting the threshold value in the DCP algorithm and examining how these changes affected the dehazing result.

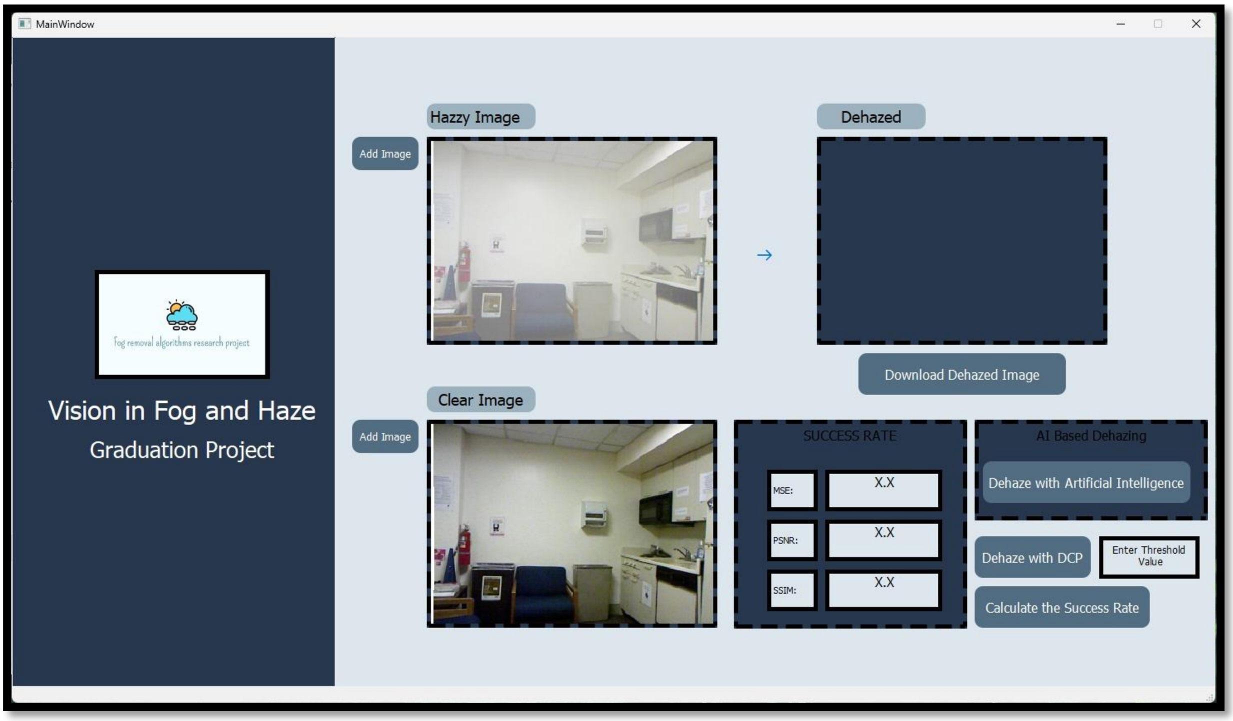
Additionally, we created an appropriate environment that allowed us to compare the efficiency of these algorithms on trained and untrained datasets. Thanks to these arrangements, we could calculate critical metrics like the Mean Squared Error (MSE), the Peak Signal-to-Noise Ratio (PSNR), and the Structural Similarity Index (SSIM). These metrics helped us measure the performance of our dehazing techniques and could be easily displayed on our interface, thus facilitating an intuitive understanding of the efficiency and effectiveness of our algorithm. This comprehensive and meticulous approach reflects our commitment to creating an advanced dehazing solution.

11.2 User Manual

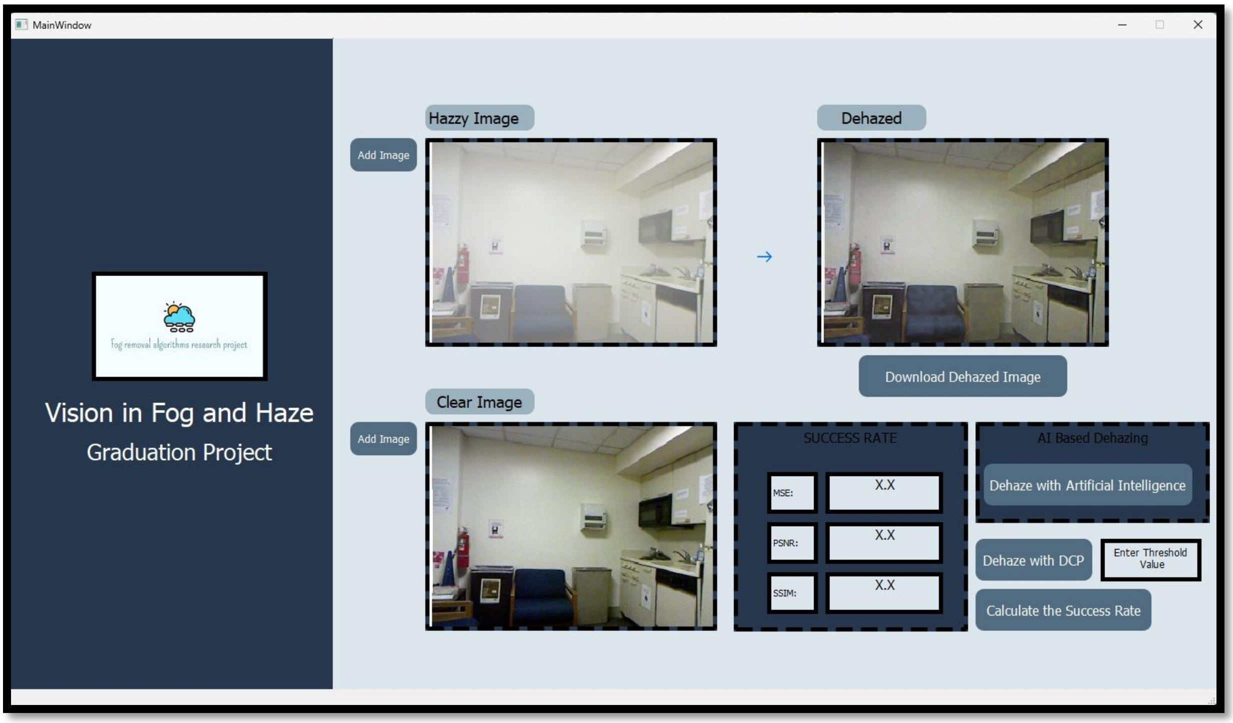
11.2.1 Artificial Intelligence

1. Click the Add Image button for the Hazy Image section in the interface.
2. A hazy photo is selected from the hazy image with reference folder in the data folder.

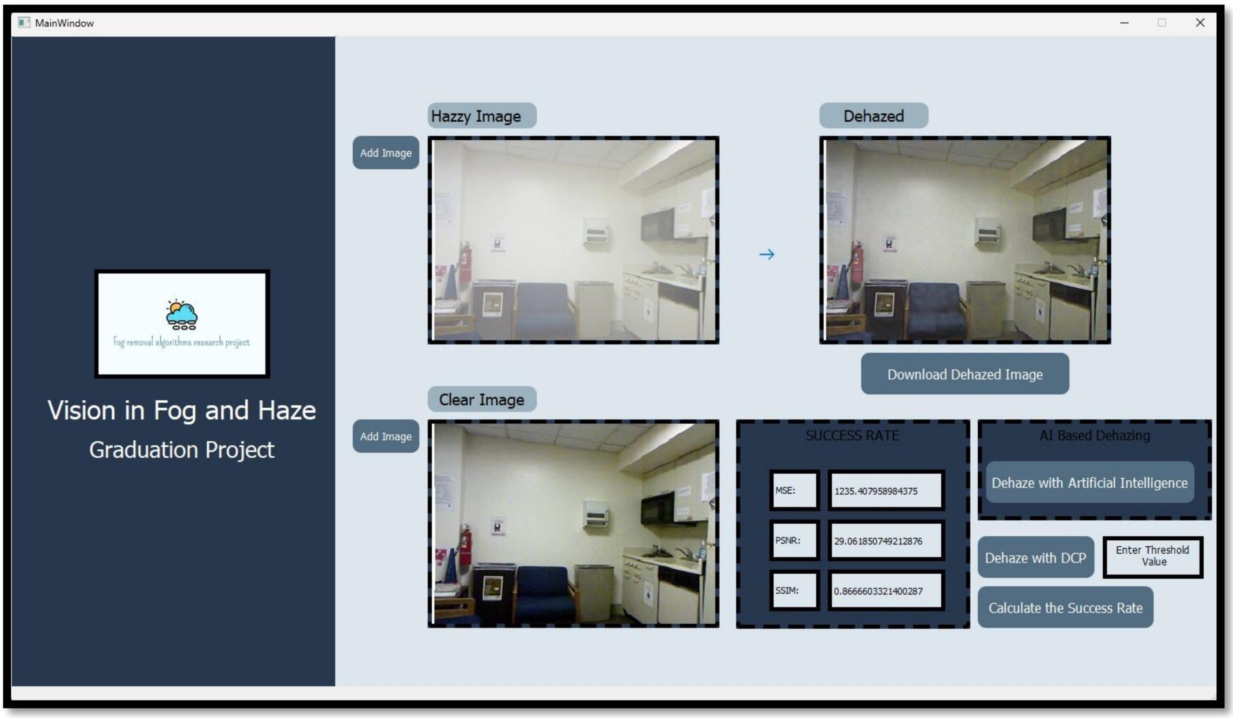
3. Click the Add Image button for the Clear Image section.
4. From the clear image with reference folder in the data folder, the clear photo corresponding to the hazy photo is selected.



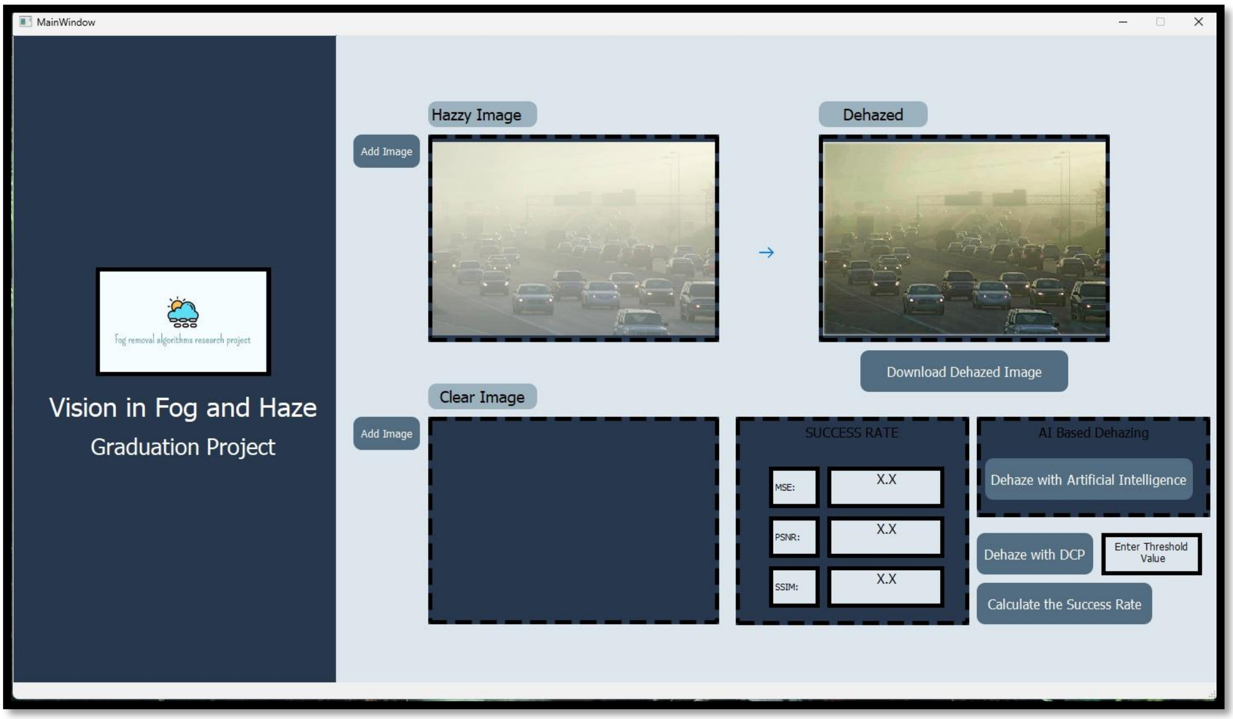
5. Click the Dehaze with Artifical Intelligence button and the result will be displayed.



6. Calculate the Success Rate button is clicked and MSE, PSNR, SSIM values are calculated and displayed under the Success Rate heading.



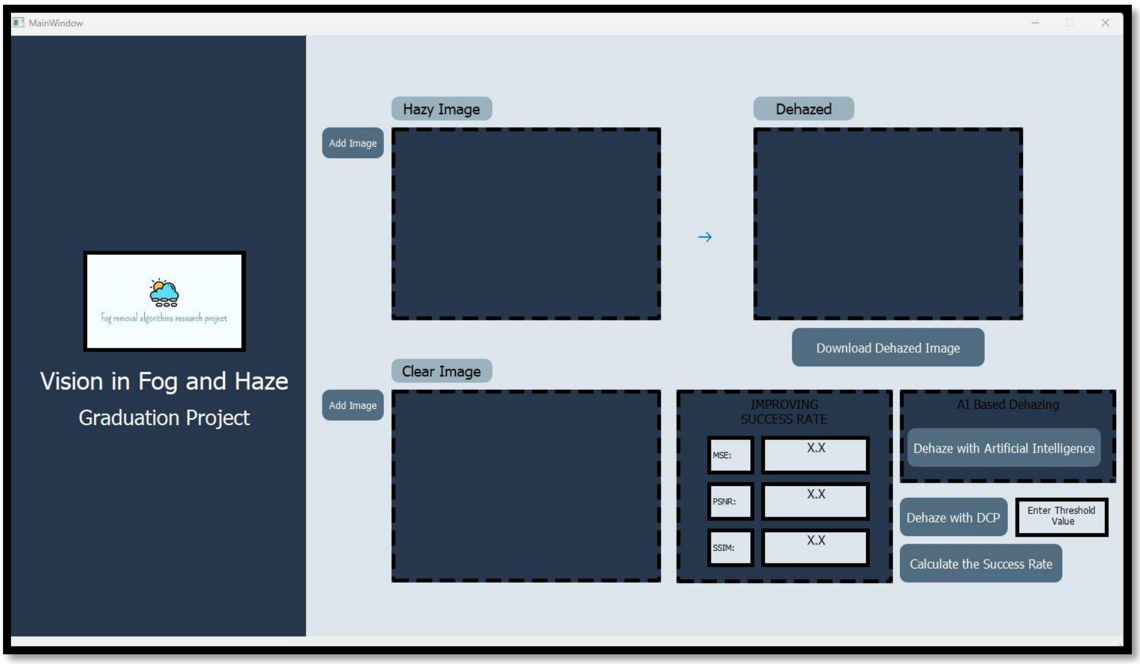
7. Click the Add Image button for the Hazy Image section in the interface.
8. A hazy photo is selected from the hazy image without reference folder in the data folder.



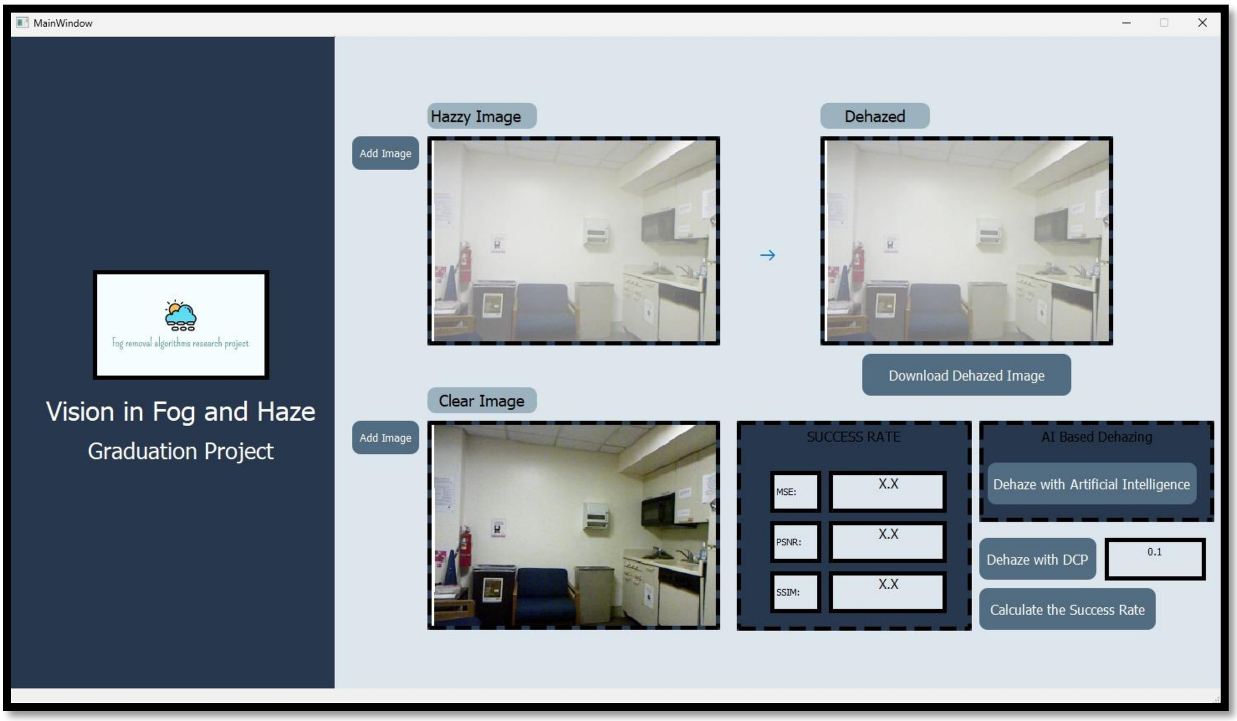
9. Click the Dehaze with Artifical Intelligence button and the result will be displayed.

11.2.2 DCP

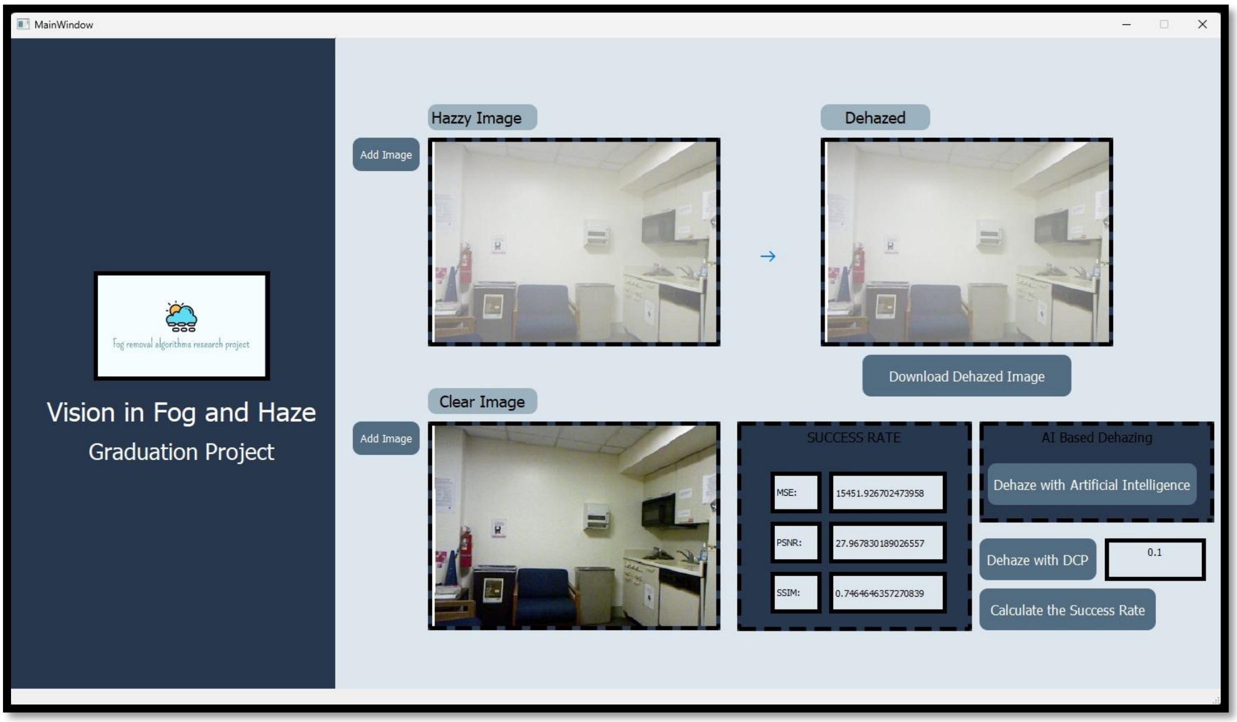
1. We run the application:



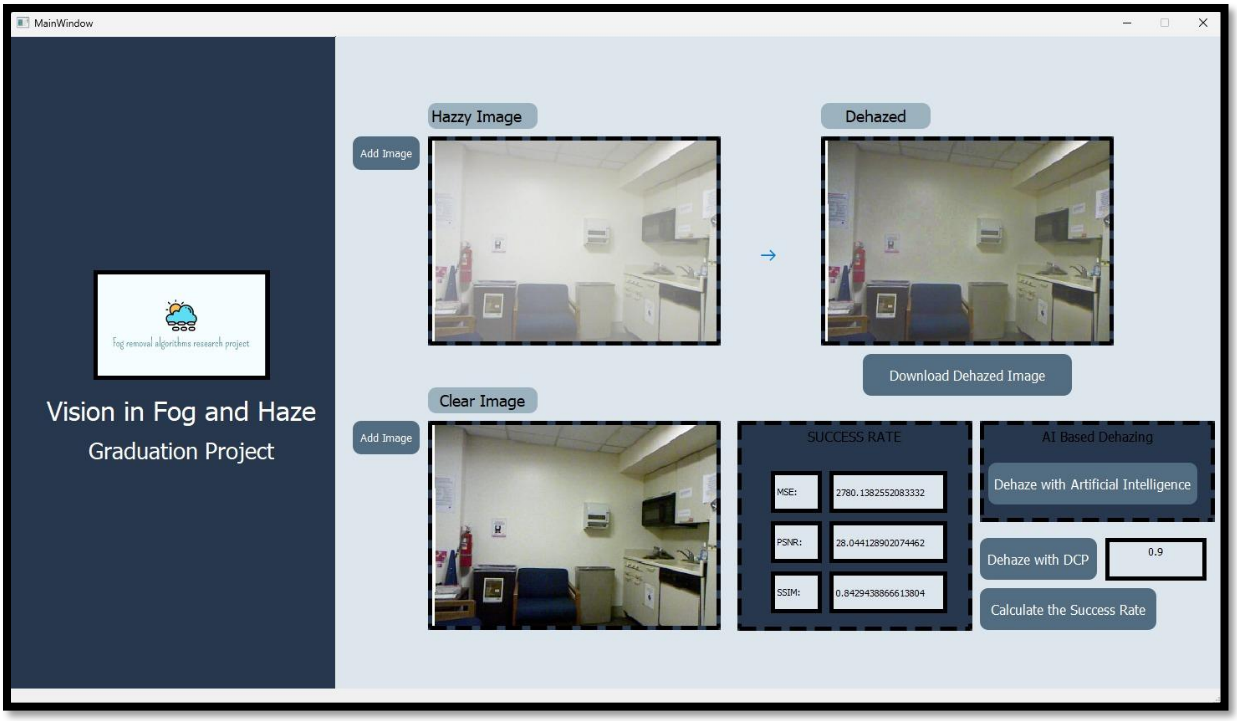
2. After uploading the pictures to the Hazy Image and Clear Image sections from the "Add Image" buttons, respectively, we enter the Threshold value as "0.1". By clicking the "Dehaze with DCP" button, we will defog the picture and display it in the "Dehazed" section:



3. With the “Calculate the Success Rate button, we can see how successfully the picture was dehazed in the Success Rate field:



4. We change the Threshold value to “0.9” without changing the pictures. And we observe that the Success Rate values change automatically:



5. Now let's try to run DCP with another image. In this part of manual, you will see how "Calculate the Success Rate" doesn't work. In this time didn't upload "Clear Image" part and tried to Calculate the Success Rate after DCP algorithm used and user will get this error message:

6. This feature only works when a clean image is loaded. But the operability of other functions of the application does not interfere. When we change the Threshold value, it can give us a different fog-free image. Here we set Threshold to 0.9 and defog with DCP:

12. Conclusion

The graduation project was aimed at studying, implementing, and comparing two highly influential image dehazing techniques: the Dark Channel Prior (DCP) and DehazeNet. Through this endeavor, we sought to contribute to the rapidly evolving field of image processing and computer vision, a domain that's becoming increasingly crucial as digital technologies continue to permeate every facet of our lives.

This ambitious project began with an extensive phase of background research. We invested considerable time and effort into image dehazing methods, from the earliest techniques to the most recent advancements. We paid particular attention to the DCP method, a classic and well-regarded non-learning approach, and DehazeNet, a modern deep learning-based model that signifies the influence of artificial intelligence in the field. Additionally, we surveyed other existing solutions, enabling us to grasp the broader landscape of image dehazing methods and identify gaps that our project could fill.

When we compare algorithms from photo size, we apply bigger photos for each: So, when we increase the image size, the mathematical operations increase and the process becomes longer. DCP's computational complexity largely depends on the size of the image. When the image size increases, the number of pixels that need to be processed increases proportionally, and so does the time take for computation. In addition to this, DCP often involves patch-based processing, where certain operations are carried out over small regions (patches) of the image. Larger images would have a larger number of such patches, thereby increasing the computational load. Furthermore, the soft matting step used for refining the transmission map in DCP is quite resource-intensive and can slow down dramatically with larger images. The impact of image size on DehazeNet is twofold. Firstly, larger images can significantly increase the memory requirements during both training and inference. This is because convolutional neural networks (CNNs), like DehazeNet, process multiple layers of feature maps that can be as large as the input image. Therefore, larger images result in larger feature maps, which require more memory to store. Secondly, the computational complexity also increases with image size. When the image size increases in the DCP algorithm, the mathematical operations increase because the matrix size increases. This causes an increase in the time to produce results in the DCP method. At the same time, If the fog density in the image is high, fog passing and air light estimation will be very difficult and inaccurate, we use DL to eliminate this error.

If we compare in terms of time, DCP involves a series of operations on the image data, such as min-filtering, soft matting, and guided filtering. The computation time can be quite high, especially for large images, as each pixel must be processed individually. However, the DCP method does not involve any learning or iterative processes, which can make it faster than some machine learning methods under certain conditions. On the other hand, training process for DehazeNet can be very time-consuming, potentially taking several hours or even days, depending on the size of the training dataset and the computational resources available. However, once the model has been trained, applying it to a new image (the inference stage) can be relatively quick, especially on hardware optimized for deep learning computations, such as GPUs.

Moreover, we believe there's immense value in collecting and utilizing larger, more diverse datasets for training deep learning-based dehazing models. However, if our picture is outside of these datasets, a proper fog removal estimation cannot be made in this picture. The bottleneck here is whether this CNN algorithm will be effective in learning so many datasets.

In conclusion, this graduation project was an intense, insightful journey into the world of image dehazing. We delved deep into the complexities and intricacies of this fascinating field, studied, and implemented two influential dehazing techniques, and identified opportunities for future research. Our findings underscored the significant potential and challenges in the field of image processing and emphasized the importance of continuous research and innovation to drive progress. As we close this chapter, we are more enthusiastic than ever about the future of image dehazing and its potential to shape our digital world.

13. References

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