Malnad College of Engineering

(An Autonomous Institution under Visvesvaraya Technological University, Belagavi)

Hassan–573202

Dehazing Foggy Images Using Dark Channel Prior Method

A Dissertation submitted to Malnad College of Engineering, Hassan, during the academic year 2023-24 in partial fulfillment for the award of the degree of

Bachelor of Engineering

in

Information Science and Engineering

by

A Nada Fazal (4MC20IS001)   Deepika B V (4MC20IS012)

Namitha D (4MC20IS029)   Tejaswini B S (4MC20IS057)

Under the Guidance of

Dr. NANDITHA B R
(Assistant Professor)

Department of Information Science & Engineering
Malnad College of Engineering
Hassan-573202

Tel.:08172-245093   Fax:08172-245683   URL:www.mcehassan.ac.in

2023-24

Malnad College of Engineering

(An Autonomous Institution under Visvesvaraya Technological University, Belagavi)

Hassan – 573 202

Department of Information Science & Engineering

CERTIFICATE

Certified that the Project Work (20IS802) titled

Dehazing Foggy Images Using Dark Channel Prior Method

is a bonafide work carried out by

A Nada Fazal	(4MC20IS005)	Deepika B V	(4MC20IS012)
Namitha D	(4MC20IS029)	Thejaswini B S	(4MC20IS057)

in partial fulfillment for the award of

Bachelor Degree in Information Science and Engineering

of

Malnad College of Engineering

affiliated to

Visvesvaraya Technological University, Belagavi

during the year 2023-24. It is certified that all corrections/ suggestions indicated for Internal Assessment have been incorporated in the Project report deposited in the Department Library. The Project Report has been approved, as it satisfies the academic requirements in respect of Project Work prescribed for the Bachelor of Engineering Degree.

s

(Dr. Nanditha B R)	(Dr. Chandrika J)	(Dr. A.J Krishnaiah)
Guide	**Head of the Department**	**Principal**

External Viva

Name of the Examiners	Signature with Date
1.	
2.	

ACKNOWLEDGEMENT

We would like to express our gratitude to our respected principal **Dr. A J Krishnaiah** for providing congenital environment and surroundings to work in. We would like to express our sincere gratitude to **Dr.Chandrika J**, Head of the department of information science and engineering, for her continuous support and encouragement.

We are highly indebted to **Dr. Nanditha B R** for her guidance and constant supervision as well asfor providing necessary information regarding the project & also for her support in completing the project.

We would like to express our gratitude to our parents & members of Malnad College of Engineeringfor their kind co-operation and encouragement which helped us in the completion of this project.

Our thanks and appreciations also go to our friends in developing the project and the people who have willingly helped us out with their abilities.

A NADA FAZAL-4MC20IS001

DEEPIKA B V -4MC20IS012

NAMITHA D-4MC20IS029

THEJASWINI B S-4MC20IS057

ABSTRACT

Image dehazing has been an active area of research for more than a decade. Generally, the problem of haze or fog is caused by bad weather condition and it depends on the particle type, size and concentration.Bad weather condition is responsible for shift in color and reduce the contrast of an image or video. It introduces the dark channel prior (DCP) as a novel solution to the ill-posed inverse problem in dehazing. DCP exploits natural outdoor image characteristics, where one color channel within a local window approaches zero intensity. The four-step dehazing process based on DCP includes atmospheric light estimation, transmission map estimation, transmission map refinement, and image reconstruction. This systematic approach offers a stepwise solution to the complex inverse problem. The paper provides a detailed survey and experimental analysis of DCP based methods, highlighting their effectiveness in each dehazing step. The insights gained aim to facilitate the development of advanced dehazing algorithms.

CONTENTS

Chapter 1: Introduction

1.1 Introduction 1

1.2 Potential of the problem 2

1.3 Objectives 2

1.4 Platform and Tools used 3

1.4.1 Platform 3

1.4.2 Tools and Libraries 3

Chapter 2: System Analysis

2.1 Literature Survey 4

2.2 Findings of analysis. 5

2.2.1 Existing System 5

2.2.2 Proposed System 5

2.3 System Requirements Specification 6

2.3.1 Analysis Model 6

2.3.2 Functional Requirements 6

2.3.3 Non-Functional Requirements 6

2.3.4 Software and Hardware requirements 7

Chapter 3: Design

3.1 Design of functions (algorithms/ flowcharts/DFDs) 9

3.2 Dataflow Diagrams 10

3.3 Design of User Interface 13-14

Chapter 4: Implementation

4.1 Dark channel prior calculation 15

4.2 Atmospheric Light Estimation 15

4.3 Transmission Map Estimation 16

4.4 Gaussian filter 17

Chapter 5: Testing 18-20

Chapter 6: User Manual

6.1 Installation Procedure 21

6.2 Snapshots of User Interface 22-23

Chapter 7:Conclusion 24

REFERENCES 25-26

List of Figures

Figures	Page No
Fig 1: Level 0 DFD	10
Fig 2: Level 1 DFD	10
Fig 3: System Workflow	12
Fig 4: The employed dataset and the results generated by the implemented methods	19
Fig 5: Home Page	22
Fig 6: Input Hazy Image	22
Fig 7: Transmission Map for Hazy Images	23
Fig 8: Output Dehazed Image	23

Chapter 1:

Introduction:

1.1 Introduction

Image dehazing has been an active area of research for more than a decade. Generally, the problemof haze or fog is caused by bad weather condition and it depends on the particle type, size and concentration. Bad weather condition is responsible for shift in color and reduce the contrast of an imageor video.

Changes in the color or contrast greatly impact on the object or the surveillance system. Image dehazing is the process of scenically improving the degraded visibility caused by atmospheric conditions.Our main aim is to restore the scene radiance from the hazy image. Fog or Haze decreases the clarity ofunderwater images and satellite images.

Most automatic systems are firmly depending on definition of input images, break to work normally caused by degraded images. There are mainly two different types of dehazing: Daytime and nighttime dehazing. There are various dehazed methods for daytime dehazing. Day time haze model isa linear equation consist of transmission map and the air light.

To produce a stately daytime dehazing image, it has proved to estimate its corresponding transmission map and air light. Aside from daytime dehazing, night dehazing is also a significant topic. In nighttime condition, the dehazing is a challenging task and the atmospheric light is not constant inthe entire image.

Aside from daytime dehazing, its mainly due to the illumination from different sources like street lights, vehicle lights etc. Then the condition of block effect is induced on the image. The light coming from the object is get attenuated and scattered by the atmospheric particles. This is called attenuation. A small amount of light coming from the illumination source get scattered and coming towards the camera is called the air light.

The quality of image may degrade due to bad weather condition and presence of suspended particles like fog, dust, mist and haze etc. in the atmosphere. Therefore, the dehazing of image neededto overcame the impact of this unwanted weather factors. Dehazing is the procedure to extract the haze effect from the degraded image and reconstruct the original colors of the degraded image.

1.2 Potential of the problem

Various algorithms, like dark channel prior and atmospheric scattering models, have been proposed to enhance visibility in such conditions. This issue resonates within the rapidly evolving landscape of computer vision. Tracking this problem effectively has implications for improved visual perception, ranging from surveillance system to autonomous vehicles, making it a key area of a research and development. The exploration of innovative approaches at the intersection of artificial intelligence and trained on diverse datasets, offers promising avenues for enhancing dehazing algorithmsand addressing the complexities of real-world scenarios. This interaction can lead to advancements withbroader applications in fields like remote sensing, autonomous navigation, and environment monitoring.

1.3 Objectives

The problem description is to develop a deep learning-based solution for dehazing foggy images, aiming to enhance visibility and improve overall image quality. By leveraging the power of artificial intelligence, the goal is to create a robust model capable of effectively removing haze from images, addressing challenges in various atmospheric conditions. The focus is on advancing the state-of-the-art in dehazing algorithms, with potential applications in fields like computer vision, photography, and autonomous systems.

Primary Objective: The main goal is to significantly improve the overall quality of image This involves developing a deep learning-based solution that can effectively reduce haze and enhance visibility, contributing to advancements in image processing and computer vision applications. The proposed solution pioneers advancing The focus is on advancing current methodologies to achieve breakthroughs in image quality and visibility enhancement. This proposed solution aims to set new standards at the forefront of dehazing techniques, showcasing advancements at the intersection of artificial intelligence and image processing.

1.4 Platform and Tools used

The platform and tools used for developing a deep learning-based solution to reduce haze in foggyimages and get the better quality of outdoor scene images in adverse weather due to fog an d haze. However, here's a potential setup that incorporates commonly used tools and platforms:

1.4.1 Platform:

- Python: Python is a versatile and widely adopted programming language for machine learning and deep learning tasks. It provides extensive libraries and frameworks for data manipulation, feature extraction, and model development.

1.4.2 Tools and Libraries:

- OpenCV: OpenCV (Opensource Computer Vision Library) is widely used for computer visiontasks, including image processing and manipulation. It provides various functions for image enhancement and restoration, which can be useful for dehazing.
- NumPy: NumPy is a fundamental library for numerical operations in Python. It is often used for handling arrays and matrices, which are common data structures in image processing.
- Scikit-image: Scikit-image is a collection of algorithms for image processing in Python. It provides tools for tasks like filtering, morphology, and color correction, which can be useful in the context of dehazing.
- Pillow (PIL Fork): Pillow is a popular Python library that serves as a fork of the Python Imaging Library (PIL). It provides a wide range of image processing capabilities and makes it easy to manipulate and enhance images using Python.
- Matplotlib: Matplotlib is a plotting library for Python and is often used for visualizing images,plots, and graphs. It can be helpful for visualizing the results of dehazing algorithms.
- Numba: Numba is a powerful just-in-time compiler for Python that is used to optimize the performance of numerical computations. It translates Python code into highly efficient machine code, which can significantly speed up the execution of numerical operations.

This combination of Python as the programming language, OpenCV as the deep learning framework and supporting tools like NumPy, Scikit-image, Pillow(PIL Fork), Matplotlib, and Numba provides a comprehensive and widely adopted ecosystem for developing a deep learning-based solutionfor remove haze in image.

Chapter 2:

System analysis :

2.1 Literature Survey

The analysis of a deep learning-based Dehazing Foggy image solution involves evaluating the performance of the developed model and gaining insights into its effectiveness. Here is a generaloutlineof how the analysis is typically conducted.

The study investigates using the original DCP-based Dehazing algorithm for improving image quality and reducing haze. The follow-up methods are based on the basic structure presented but differ in each step of the dehazing procedure. The DCP-based dehazing algorithms from that are investigated in this paper. Instead of analyzing each method individually, we classify all the methods in accordance with the four steps of image dehazing and then perform a step-by-step analysis. Each of the subsectionsdescribes and compares the various methods used for each step [1].

This paper presents the transmission map refinement schemes were described individually. The parameter sensitivity of each method was also discussed in detail. We then empirically tuned the best parameter for each method and compared the performance of the methods. Some refinement results of the five methods for the same transmission [2].

This research focuses on using efficient computer models to quickly improve image quality. These models need to be small and fast for everyday use. Testing them with real data is crucial to ensurethey work well. By examining smaller computer designs that learn from extensive data, the research identifies a balance between model complexity and their ability to enhance image, highlightingmodels that excel at this task [3].

The article uses supervised learning, deep learning, and different methods like image enhancementand Haze separation to improve Image Dehazing. This is often involves employing multiple techniques,such as image enhancement, contrast adjustment, and dehazing algorithms, to effectively reduce atmospheric haze and improve visibility in the final image [4].

People use image to Travelling, Airlines, and Surveillance, it's a natural way to improve the quality. Researchers have developed a method using a convolutional neural network to remove haze fromimage [5].

They started with a basic image model, improved it using image-to-haze ratio, and tested on the TIMIT dataset. The results showed that this method is effective and faster than some modern techniquesin certain Haze conditions. It makes Haze removal in Image environments simpler [6].

The paper suggests and compares methods for improving Image quality in Haze conditions. Theyuse models and neural networks to estimate clear Image characteristics in the presence of Haze, achievingbetter Haze reduction than traditional methods. These techniques, when combined with cepstral excitation manipulation, significantly boost the quality of the Image quality [7].

This paper aims to improve Image quality in Haze situations, especially when there's Hazzy Images. They propose a two-stage approach: first, they reduce the Haze, and then they restore the Haze cleared Image using special neural networks. This approach enhances Image quality and performs betterthan other methods, even in challenging Haze conditions with interfering Image [8].

The analysis phase is crucial for validating the effectiveness and practical applicability of the developed deep learning model for speech Haze reduction. It combines quantitative assessments with qualitative insights to provide a comprehensive understanding of the model's performance in real-worldscenarios [9].

2.2 Findings of Analysis

The findings of the analysis of the deep learning-based Image Haze reduction solution are crucialfor understanding the model's performance and its implications.

2.2.1 Existing System

Existing dehazing systems like Dehaze Net and MSCNN leverage deep learning for end-to-end training and multi-scale features, respectively. Dense-Haze integrates traditional methods with deep learning for enhanced results in complex scenes. Ongoing improvements to the dark channel prior algorithm refine transmission map estimation. DA-Net and MILD-Net focus on preserving fine details and leveraging multi-input information, respectively, contributing to diverse advancements in dehazing.

2.2.2 Proposed System

The proposed dehazing system employs the Dark Channel Prior (DCP) algorithm to enhance visibility in foggy images. The algorithm calculates the dark channel of the input foggy image, estimates atmospheric light, and computes a transmission map. The approach is computationally efficient and cost-effective, offering improved visibility and detail in foggy conditions. However, the method's efficacy may vary based on input characteristics, and it may not handle extreme scenarios as well as more advanced dehazing techniques.

2.3 System Requirement Specification

After analyzing the requirements of the task to be performed, the next step is to analyze the problemand understand its requirements. The first activity in the phase is studying the existing system and otheris to understand the requirements and domain of the new system. Both the activities are equally important,but the first activity serves as a basis of giving the functional specifications and then successful design of the proposed system. Understanding the properties and requirements of a new system is more difficultand requires creative thinking and understanding of existing running system is also difficult, improper understanding of present system can lead diversion from solution.

2.3.1 Analysis Model

The document doesn't explicitly follow a strict Waterfall approach, but the structured introduction,highlighting objectives, and outlining methodologies, resembles the documentation style often associatedwith these more traditional models.

2.3.2 Functional Requirements

- Haze Model: Accepts the user’s Haze Image. Input module that captures and processes the user-provided image quality.
- Transmission Estimation: This transmission map to recover the true colors and details of the obscured scene by compensating for the atmospheric effects. Techniques like dark channel prior and color attenuation are commonly employed for accurate transmission estimation in dehazing processes.
- Scene Reconstruction: Foggy images involves restoring the true colors and details of a scene that are obscured by atmospheric haze. Once the transmission map is estimated, it is used to enhance the clarity of the image.
- Output: Produces the enhanced and Dehazed Foggy Image.

2.3.3 Non-Functional Requirements

- Performance: Specify the desired speed and accuracy of the dehazing algorithm to ensure efficient processing of foggy images.
- Maintain abillity: Specify guidelines for maintaining and updating the dehazing AI over time, ensuring it remains effective as technology evolves.

- Compatibility: Ensure compatibility with various image formats and resolutions commonly used inreal-world applications.
- Scalability: Define the system's capability to handle a varying number of foggy images, ensuring itremains effective as the workload increases.
- Security: Address any potential security concerns related to the processing and handling of images, especially if the application involves sensitive or private content.

2.3.4 Software and Hardware requirements

For a deep learning-based image processing system focused on hazy image quality suppression,the software and hardware requirements can be outlined as follows.

- **Software Requirements**

  - Operating System: Windows, Linux, or macOS
  - Compatible with the selected deep learning framework and libraries.
  - Reasoning: Choose the operating system based on your team's preferences and software compatibility.
  - Development Environment: PythonVersion: 3.6 or above.
  - Reasoning: Python is a widely-used language for machine learning and deep learning applications.
  - Integrated Development Environment (IDE): Examples: Pillow (PIL Fork), PyCharmReasoning: An IDE provides a convenient and efficient development environment.
  - Git: Latest stable version.
  - Reasoning: For version control and collaboration.

- **Hardware Requirements**

  - CPU and Memory:

    CPU: A modern multi-core processor (e.g., Intel i5, i7, or equivalent).Reasoning: Deep learning tasks can be computationally intensive.

    - Memory (RAM): Minimum 4 GB and more.

      Reasoning: Sufficient RAM is necessary for handling large datasets and deep learning model training.

    - Storage: SSD with at least 20 GB.

      Reasoning: SSDs provide faster read/write speeds, beneficial for handling large datasets.

    - Internet Connection: Stable and High-Speed:

      Reasoning: Required for downloading datasets, libraries, and updates.

Chapter 3:

Design:

Design is the first step in the development phase for any engineered product or system. The designer's goal is to produce a model or representation of an entity that will later be built. Beginning, once system requirement have been specified and analyzed, system design is the first of the three technical activities -design, code and test that is required to build and verify software.

The importance can be stated with a single word "Quality". Design is the place where quality is fostered in software development. Design provides us with representations of software that can assess for quality. Design is the only way that we can accurately translate a customer's view into a finished software product or system. Software design serves as a foundation for all the software engineering stepsthat follow. Without a strong design we risk building an unstable system one that will be difficult to test,one whose quality cannot be assessed until the last stage.

During design, progressive refinement of data structure, program structure, and proceduraldetailsare developed reviewed and documented. System design can be viewed from either technical or project management perspective. From the technical point of view, design is comprised of four activities - architectural design, data structure design, interface design and procedural design.

3.1 Design of Functions

Designing a function, user interface, and reports for the proposed image enhancement methodologyinvolves sevWeral components.

In the designing phase, a sophisticated solution is proposed for the dehazing system employs the Dark Channel Prior (DCP) algorithm to enhance visibility in foggy images. The algorithm calculates the dark channel of the input foggy image, estimates atmospheric light, and computes a transmission map. Leveraging this map, the system then performs image dehazing, attenuating the haze and producing a clearer output. The approach is computationally efficient and cost-effective, offeringimproved visibilityand detail in foggy conditions. However, the method's efficacy may vary based on input characteristics, and it may not handle extreme scenarios as well as more advanced dehazing techniques.

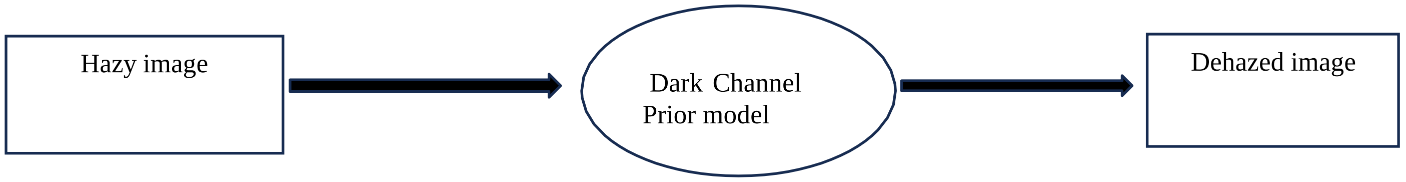

Figure 1: Level 0 DFD

This figure 2 represents the Data Flow Diagram of Level 0 which takes the input as Hazy image. Then this hazy image is processed in the Dark Channel Prior Model, which gives the output as cleared dehazed image.

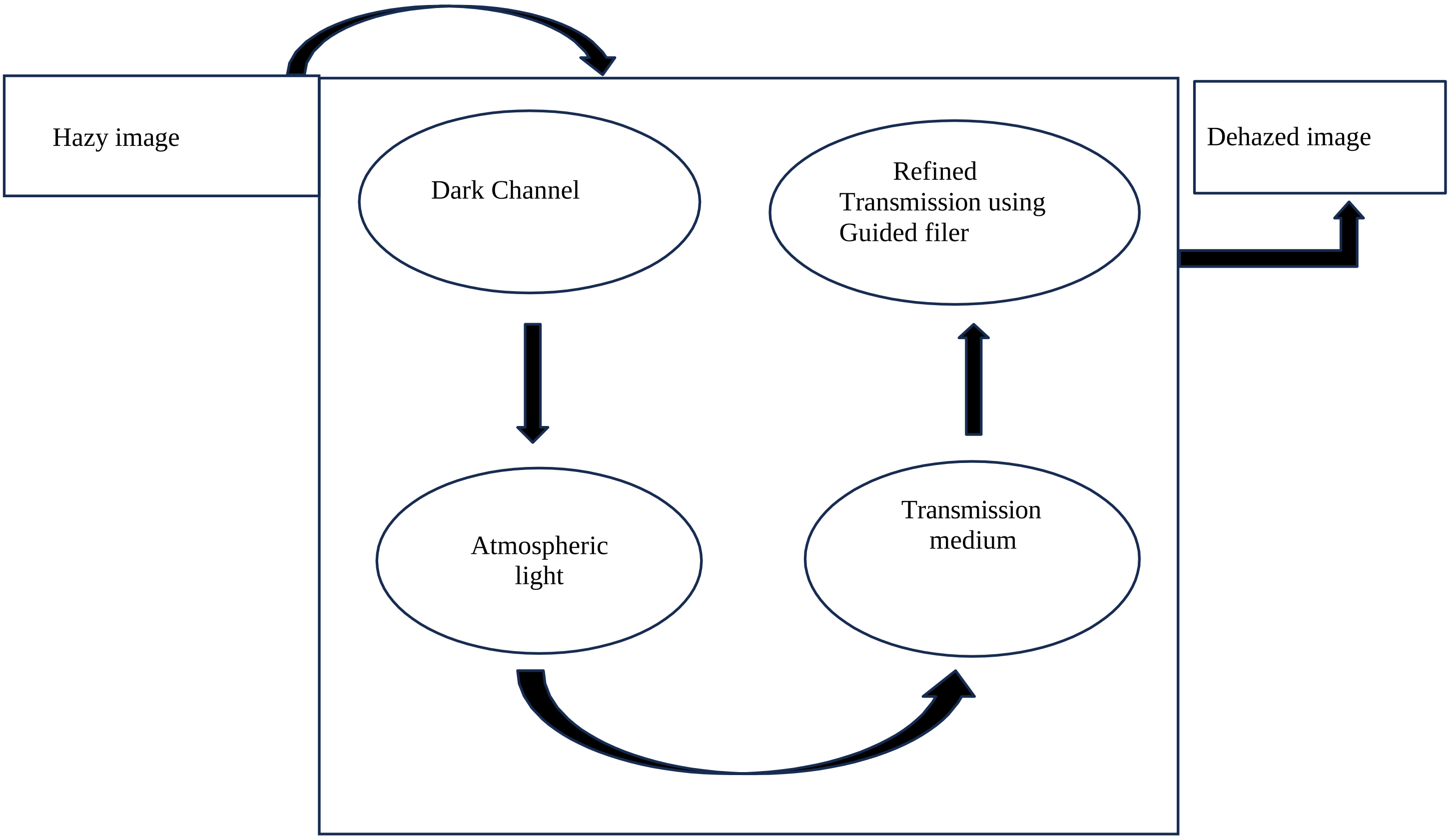

Figure 2: Level 1 DFD

This figure 2 represents the Data Flow Diagram of Level 1 which takes the input as Hazy image. The Dark Channel Prior algorithm calculates the dark channel of the input foggy image, estimates atmospheric light, and computes a transmission map. which gives the output as cleared dehazed image.

Proposed System Consists of:

1.Hazemodel

2.Transmission Estimation

3.Scene Reconstruction

1.Input Foggy Image: The system takes a foggy or hazy image as input, which is characterized by reducedcontrast, color distortion, and limited visibility of distant objects.

2.Dark Channel Prior Algorithm: The core of the proposed system lies in the application of the Dark Channel Prior algorithm. This algorithm exploits the statistical regularity that dark channels in haze-freeimages are often very low in intensity.

3.Dark Channel Computation: The dark channel of the input foggy image is computed by finding the minimum intensity value in a local window for each pixel. This dark channel represents the transmissionof the scene and provides insights into the amount of haze in different regions.

4.Estimation of Atmospheric Light: The next step involves estimating the atmospheric light, which is the light scattered by the haze in the scene. This is typically achieved by analyzing the intensity values of the brightest pixels in the dark channel.

5.Transmission Map Calculation: Using the dark channel and atmospheric light estimation, the system calculates the transmission map. The transmission map describes how much light is transmitted throughthe haze in different parts of the image.

6.Image Dehazing: The transmission map is then used to perform image dehazing. The haze is attenuated based on the calculated transmission values, resulting in an enhanced, haze-free image.

7.Post-Processing (Optional): Additional post processing techniques may be applied to further improvethe quality of the dehazed image. This can include color correction, contrast adjustment, or other enhancement methods.

8.Output Dehazed Image: The final output of the system is a dehazed image that exhibits improved visibility, reduced haze, and enhanced.

3.2 System Architecture

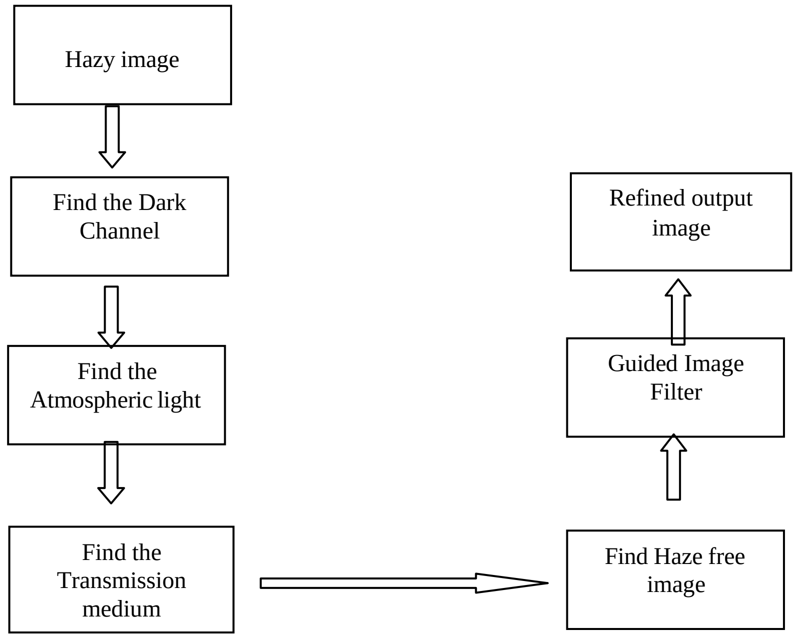

Figure 3: System Workflow

3.3 Design of User Interface

- **Home page:**
    - Application Logo: Incorporate a recognizable logo representing the dehazing application.
    - Navigation Menu: Include clear navigation options such as “Home”, “Upload Image”, “Settings”, and “About”.
- **Image Upload:**
    - Upload Button: A prominent button allowing users to upload foggy images from their devices.
    - Drag-and-Drop Area: Optionally, include an area where users can drag and drop images for upload.
    - Upload Progress: Display a progress bar or indicator during the image upload process.
- **Dehazing Settings:**
    - Algorithm Selection: Provide a dropdown or radio buttons for users to choose the dehazing algorithm (e.g., Dark Channel Prior, Deep Learning).
    - Parameter Adjustment: If applicable, include sliders or input fields for adjusting parametersrelated to the selected algorithm.
    - Apply Button: Allow users to apply the dehazing process after configuring settings.
- **Image Display:**
    - Original and Dehazed Images: Side-by-side or tabbed view showing the original foggy image and the dehazed result.
    - Toggle Switch: Include a toggle switch to easily switch between the original and dehazed views.
- **Result Information:**
    - Metrics Display: If applicable, show quantitative metrics such as PSNR (Peak Signal-to-Noise Ratio) or SSIM (Structural Similarity Index) to indicate the quality improvement.
    - Download Button: Allow users to download the dehazed image.

- **Advanced Features (Optional):**
  - Batch Processing: If the application supports batch processing, provide an option for users to upload multiple images at once.
  - Customization Options: Advanced users might appreciate additional options for fine-tuning the dehazing process.
- **User Feedback:**
  - Notifications: Display informative messages or notifications to guide users through the dehazing process.
  - Error Handling: Clearly communicate any errors or issues that may arise during the image processing.
- **Settings and Preferences:**
  - User Account: If applicable, provide the option for users to create accounts, save preferences, and access their dehazing history.
  - Language and Theme Options: Include settings for users to choose their preferred language and application theme.
- **Footer:**
  - About and Help: Links to pages providing information about the application, its developers, and user guides.
  - Contact Information: Include contact details for user support or feedback.
- **Responsive Design:**
  - Ensure the user interface is responsive, adapting to different screen sizes and devices.
- **Accessibility:**
  - Design with accessibility principles in mind, ensuring that the application is usable by people with various abilities.

Chapter 4:

Implementation :

In computer vision and computer graphic the atmospheric scattering model is widely used to describe the formation of a hazy image. Based on the model, the captured hazy image can be modeled as two components: the direct reflection of light from the object and the reflection from the particles of the medium, it is written as follows: $I(x) = J(x)t(x) + A(1−t(x))$. (1) In (1), I refer to the intensity of the haze image, J is the scene radiance and also the haze-free image, A is the atmospheric light and t is thetransmission map of the medium. The task of haze removal is to retrieve J, A, and t from I. In (1), $J(x)t(x)$ named direct attenuation in the ﬁrst term, indicates the scene radiance. The second term $A(1−t(x))$ called airlight, resulting from previously scattered light, leads to the shift of the image color.The transmission t is defined as $t(x)=e−βd$. (2) In (2), β is the scattering coefﬁcient of the atmosphere and d is the scene depth. This equation shows that the scene radiance J is exponentially attenuated withthe scene depth. He et al. introduced the dark channel prior that is a statistical prior of haze-free outdoor images. They observed most of the local patches in haze-free image contain some pixels that have very low intensities in at least one color channel, which are mainly due to three factors: shadows,colorful objects or surfaces (such as red , blue water and green plants) and dark objects

4.1 Dark channel prior calculation

The dark channel prior is a fundamental concept in haze removal algorithms. It exploits the statistical regularity that in most local patches of an outdoor image, there exists at least one color channel with lowintensity. This low-intensity channel tends to correspond to the presence of haze or fog. The dark channelprior is computed as $Dark(I)=min(min(R,G),B)$ (3) where R, G, and B are the red, green, and blue channels of the image I, respectively

4.2 Atmospheric Light Estimation

The atmospheric light represents the global illumination intensity in the scene. It is estimated by selecting the brightest pixels in the dark channel, which are assumed to correspond to haze-free areas or objects with high reflectance. By averaging these brightest pixels, an estimate of the atmospheric light is found. First, a dark channel is computed to estimate atmospheric light using Eq. (1). A minimum filter of window size ω is applied to compute dark channel where ω is kept as 31 × 31. Hazyimages along with the corresponding dark channel

$$I_{DCP} = \min_{x \in w(k)} (\min_{y \in \{R,G,B\}} I(y))$$

After successfully computed dark channel, atmospheric light Alight is estimated which is a 3 × 1 vector having highest intensity values that are computed from 0.1% brightest pixels of dark channel. Algorithm illustrates the pseudo code to compute atmospheric light where, I is input hazy image, DCPis dark channel prior, N is 0.1% brightest pixel values In the dark channel and m is temporary variable.x, y is the size of dark channel prior. As a first step, DCP is compared with max value of N. If both values are equivalent; then. input image pixels corresponding to N pixel locations are taken as the atmospheric light.

4.3 Transmission map estimation and refinement

Atmospheric light is used to compute transmission map. A transmission map as given in (2) is computed for each RGB color channel by dividing input image with its corresponding color channel atmospheric light.

$$T(x) = 1 - \zeta [\frac{I(x)}{A}]$$

Here, value of ζ depends upon fog density of the hazy input image. Fog density (FD) is computed using FADE where, fFD1 and fFD2 are fixed throughout the algorithm and the values are chosen to avoid over saturation and to completely remove fog from input image. fFD1 and fFD2 are set to 2.5 and 1, respectively. These values are obtained after performing cross validation on RESIDE dataset to estimate the accuracy of the performance of a proposed model. Algorithm 2 illustrates the pseudo code for estimation and refinement of transmission map. After calculation transmission map, refinement of transmission map is required to preserve gradient information. In our proposed methodology, guided image filter (GIF) is used for the refinement process where input image itself is used as guidance image as edge preserving and smoothing filter. GIF is faster than other refinement filters as it reduces the overall computational complexity of the defogging algorithm.

$$T_{\text{refined}}(x) = a_k T_k + b_k \quad \forall k \in W_k$$

Therefore where, T refined is a linear transform of T in a window of size W. a and b are linear coefficients that are constant in Wk. Transmission map and refined transmission maps are shown. After refining the transmission map, defogged image is reconstructed using

$$R(x) = \frac{I(x) - A}{T_{\text{refined}} + \epsilon} + A$$

Where, e is a constant with negligibly small value to avoid division with zero. At the end of defogging algorithm, gamma correction is also used to improve the overall brightness of reconstructed image.

4.4 Gaussian filter

Denoting the transmission map to be refined as ~t , the Gaussian filtered transmission map ^t is given as

$$\hat{t}(x) = \frac{1}{\sum_{y\in\Omega(x)} G_{\sigma_s}(\|x-y\|)} \cdot \sum_{y\in\Omega(x)} G_{\sigma_s}(\|x-y\|)\hat{t}(y),$$

where gos is the 2-D Gaussian function with the standard deviation σs. The Gaussian filter is not very effective in sharpening a blurry transmission map due to its low pass characteristic, but it is often useful in removing color textures remaining in the transmission map. As discussed in Section transmission maps obtained using a small local patch tend to have color textures, and thus, the Gaussian filter can improve the accuracy of the transmission maps. Figure are some examples before and after Gaussian filtering. As can be seen the Gaussian filter is effective in removing false color textures in the transmission ma However, the Gaussian filter can unnecessarily blur the transmission map when there is no annoying false color textures in the transmission map as shown in Figure shows the quantitative quality evaluation results. Here, the transmission maps are obtained with different sizes of the local patch. The Gaussian filter is then applied and the filtered result is compared with the ground-truth transmission map, which can be reconstructed using the FRIDA. As can be seen in Fig, the Gaussian filter is effective when a proper size of the patch size is used, but the RMSE starts increasing when the Gaussian blur becomes excessive. Therefore, the refinement by the Gaussian filterneeds careful treatment with the consideration of the color textures in the hazy image.

Chapter 5:

Testing :

In order to have a reference framework about the performance of the method proposed, a comparison was made against four state-of-the-art methods: the classical DCP method with a soft matting refinement stage the method that use a median filter to refine the transmission, a new approachusing an additional prior known as linear color attenuation prior, and a method that use a deep neural network. Tests were done using 22 images acquired from two datasets used commonly in the literature,in which the affectations were simulated with random values of t a d A. It was perform a quantitative analysis using the peak signal-to-noise ratio (PSNR) and the Structural Similarity Index (SSIM). The PSNR is a quantitative measure of restoration quality between the restored image J and the target image K, and it is defined as:

$$\text{PSNR} = 10.log_{10}\left(\frac{max_I^2}{\frac{1}{n}\sum_{(x,y)}(J(x,y)-K(x,y))^2}\right)$$

where (x, y) is a pixel position, n i s the pixels cardinality of images of J and K, and max2 I is the maximum value possi ble of the images J and K, in this case: 255. The Structural Similarity (SSIM) Index is based on a perception model and is described by three aspects comparison, such as:

Table 1 Comparison in terms of PSNR over 100 synthetic images with different resolutions.

Resolution	Original	320 × 240	600 × 400	800 × 600	1280 × 960
PSNR(Db)	19.21	19.01	19.24	19.05	19.19
Time (s)	9.3	1.2	2.1	4.0	10.2

$$\text{SSIM} = [l, c,s]$$

where l is the luminance comparison, c is the contrast comparison, and s is the structure comparison. The tests were conducted on a computer with a Core i5-2400 processor at 3.10 GHz with 12 GB of RAM using Matlab 2018a.

Figure 4 shows the employed dataset and the results generated by the implemented methods, where it isvisible that the proposed method presents a higher contrast and brightness than the other methods.

Fig 4: The employed dataset and the results generated by the implemented methods

Fig. 4 Haze removal results for synthetic images. a Input images. b Results by He et al, c Results by Gibson etal, d Results by Zhu et al, e Results by Ren et al, f Our method.

Table 2 Comparative analysis using the peak signal-to noise ratio (PSNR) (in Db)

Image	He et al.	Gibson et al.	Zhu et al.	Ren et al.	Proposed
Aloe	12.02	13.40	14.72	13.86	13.19
Baby1	21.79	21.71	19.27	22.56	21.56
Books	20.49	23.08	17.14	20.51	23.46
Bowling1	15.53	16.29	26.13	28.02	21.44
Cones	26.79	19.99	16.67	22.63	21.05
Dolls1	14.03	10.71	9.46	12.22	12.23
Moebius1	22.89	23.64	18.97	21.91	24.20
Monopoly	16.09	18.74	21.25	21.37	19.12
Reindeer	17.38	12.44	10.34	12.49	15.47
Bikes1	20.68	15.47	12.68	14.36	17.97
Church	12.90	14.00	13.77	15.01	13.17
Couch	18.89	17.41	18.90	19.24	18.21
Dolls	19.09	17.85	16.92	18.93	18.59
Flower1	19.92	20.77	18.80	11.30	19.93
Flower2	18.67	18.62	21.45	13.27	18.42
Mansion	20.11	16.98	18.10	17.86	19.60
Moebius	14.76	15.44	18.54	17.16	15.35
Raindeer	18.73	19.12	20.47	17.45	19.22
Roofs2	21.87	17.51	15.40	13.95	19.49
Trees2	19.57	16.60	13.23	14.29	18.33
Average	18.61	17.49	17.11	17.42	18.50

Chapter 6:

User Manual:

6.1. Installation procedure

To facilitate collaboration on the dehazing foggy images using dark channel prior project, we standardized the installation procedure to ensure all team members could easily set up their environments. Our project primarily utilized Python for coding, and to begin, we ensured all members had Python installed on their systems. Using pip, the Python package manager, we collectively installed necessary libraries such as NumPy, OpenCV, and matplotlib. These libraries were essential for image processing tasks. After navigating to the project directory, we made sure to fulfill any additional setup requirements, such as downloading datasets or pretrained models. Running the project was made simple by executing the main Python script and providing input and output paths for the foggy images. For example, a sample command looked like this: 'python main.py --input_path <path_to_input_image> --output_path <path_to_output_image>'. To aid team members encountering issues during installation, we included troubleshooting tips in our documentation and acknowledged any external sources or libraries used in the project.

6.2. Snapshots of User Interface

Fig 5: Home Page

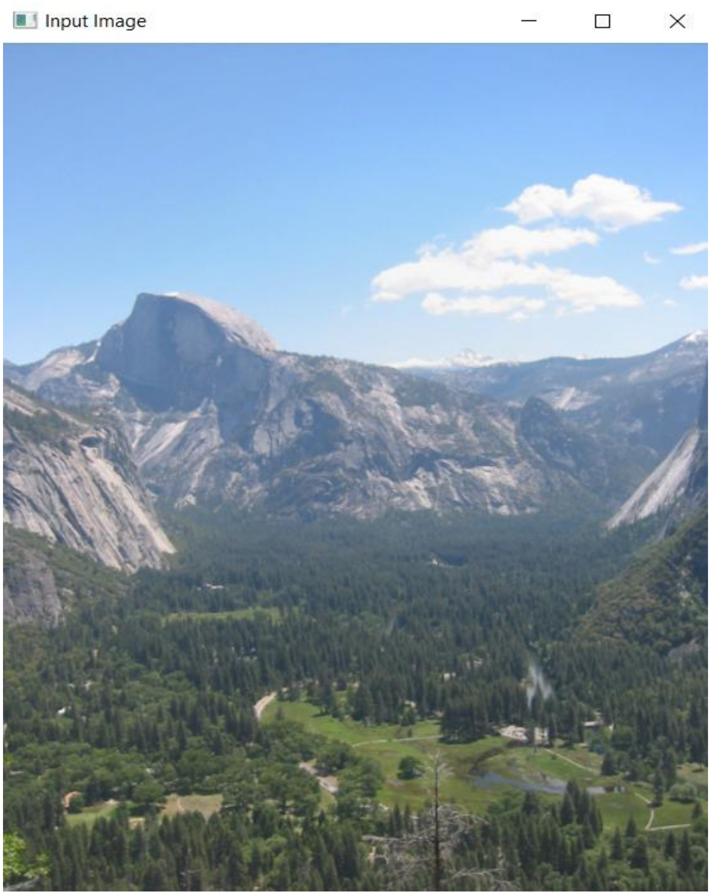

Fig 6: Input Hazy Image

Fig 7: Transmission Map for Hazy Image

Fig 8: Output Dehazed Image

Chapter 7:

Conclusion :

Dark Channel Prior (DCP) algorithm for dehazing foggy images presents a promising approach with both quantitative and qualitative merits. Through systematic model training and evaluation, the performance metrics suchas Mean Squared Error (MSE), Structural Similarity Index (SSI), and Peak Signal-toNoise Ratio (PSNR) indicate themodel's effectiveness in reducing haze and enhancing image quality. The emphasis on perceptual quality assessments, including visual clarity and color fidelity, further underscores the practical utility of the dehazing model. Continuousrefinement and validation against diverse datasets are essential for ensuring the robustness and adaptability of the model across various real-world scenarios.

REFERENCES

1. Codruta Orniana Ancuti, Cosmin Ancuti and Philippe Bekaert, “Effective Single Image Dehazing by Fusion,” IEEE 17th International Conference on Image Processing. (ICIP) Sept 2020, pp. 3541-3544.

2. Metwaly, K., Li, X., Guo, T., & Monga, V. (2020). Nonlocal channel attention for non homogeneous image dehazing. In Proceedings of the IEEE/CVF Conference on Computer Vision and PatternRecognition Workshops (pp. 452- 453)

3. Park, J., Han, D. K., & Ko, H. (2020). Fusion of heterogeneous adversarial networks for single image dehazing. IEEE Transactions on Image Processing, 29, 4721-4732.

4. Ren, W., Pan, J., Zhang, H., Cao, X., & Yang, M. H. (2020). Single image dehazing via multi scale convolutional neural networks with holistic edges. International Journal of Computer Vision, 128(1), 240-259.In European conference on computer vision (pp. 154- 169). Springer, Cham.

5. Liu, X., Ma, Y., Shi, Z., & Chen, J. (2019). Griddehazenet: Attention-based multi-scale network for image dehazing. In Proceedings of the IEEE/CVF International Conference on Computer Vision (pp. 7314-7323).

6. Yang, Y., Hu, Z., Bian, K., & Song, L. (2019, April). Imgsensingnet: Uav vision guided aerial ground air quality sensing system. In IEEE INFOCOM 2019-IEEE Conference on Computer Communications (pp. 1207-1215). IEEE.

7. Yang, X., Li, H., Fan, Y. L., & Chen, R. (2019). Single image haze removal via region detection network. IEEE Transactions on Multimedia, 21(10), 2545-2560.

8. Yibo Tan, Guoyu Wang. "Image haze removal based on superpixels and markov random field." Transactions on IEEE Access, 8(4):60728– 60736, March 2020.

9. Jeong, C.Y., Moon, K. & Kim, M. An end-to-end deep learning approach for real-time single image dehazing. J Real-Time Image Proc 20, 12 (2023)

10. Shaojin Ma ,1 Weiguo Pan , 1 Hongzhe Liu ,1 Songyin Dai, 1 Bingxin Xu,1 ChengXu , Xuewei Li,2 and Huaiguang Guan Image Dehazing Based on Improved Color Channel Transfer

11. A. S. Parihar and G. Gupta, "Prior based Single Image Dehazing using Decision Image", 2020 4th International Conference on Electronics Communication and Aerospace Technology (ICECA), pp. 960-965, 2020.

12. H. Khan, M. Sharif, N. Bibi, M. Usman, S. A. Haider, S. Zainab, J. H. Shah,Y. Bashir, and N. Muhammad, ‘‘Localization of radiance transformation for image dehazing in wavelet domain,’’ Neurocomputing, vol. 381, pp. 141–151, Mar. 2020.

13. B. Li, W. Ren, D. Fu, D. Tao, D. Feng, W. Zeng, Z. Wang, Benchmarking single-image dehazing and beyond. IEEE Trans Image Process. 28(1),492–505 (2019)

14. X. Min, G. Zhai, K. Gu, Y. Zhu, J. Zhou, G. Guo, X. Yang, X. Guan, W. Zhang, Quality evaluation of image dehazing methods using synthetic hazy images. IEEE Trans. Multimed. 21(9), 2319–2333 (2019).

15. Sivaji Satrasupalli, Ebenezer Daniel and Sitaramanjaneya Reddy Guntur, "Single Image Haze Removal Based on transmission map estimation using Encoder-Decoder based deep learning architecture", Optik, vol. 248, December 2021.