Deep Video Dehazing

A major project report submitted in partial fulfilment of the requirement for the award of degree of

Bachelor of Technology

in

Computer Science & Engineering / Information Technology

Submitted by

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Under the guidance & supervision of

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Candidate's Declaration

We hereby declare that the work presented in this report entitled **'Deep Video Dehazing'** in partial fulfilment of the requirements for the award of the degree of **Bachelor of Technology** in **Computer Science & Engineering / Information Technology** submitted in the Department of Computer Science & Engineering and Information Technology**,** Jaypee University of Information Technology, Waknaghat is an authentic record of my own work carried out over a period from August 2023 to May 2024 under the supervision of **Dr. Vipul Kumar Sharma** (Assistant Professor, Department of Computer Science & Engineering and Information Technology).

The matter embodied in the report has not been submitted for the award of any other degree or diploma.

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This is to certify that the above statement made by the candidate is true to the best of my knowledge.

(Supervisor Signature with Date)

Supervisor Name: Dr Vipul Kumar Sharma
Designation: Assistant Professor
Department: Computer Science
Dated: 15 May 2024

CERTIFICATE

This is to certify that the work which is being presented in the project report titled "Deep Video Dehazing" in fulfilment of the requirements for the award of the degree of B.Tech in Computer Science And Engineering and submitted to the Department of Computer Science And Engineering, Jaypee University of Information Technology, Waknaghat is an authentic record of work carried out by "Anshika Mittal, 201477 and Rajat Sagar ,201299" during the period from August 2023 to December 2023 under the supervision of Dr Vipul Kumar Sharma, Department of Computer Science and Engineering, Jaypee University of Information Technology, Waknaghat.

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LIST OF ABBREVIATIONS

Below mentioned is a list of Abbreviations used in the project:

DVDP: Deep Video Dehazing Project

CNN: Convolutional Neural Network

GAN: Generative Adversarial Network

RNN: Recurrent Neural Network

MSF: Multi-Scale Fusion

L0: L0 Smoothing

ACP: Adversarial Consistency Prior

TMP: Transmission Map

DCP: Dark Channel Prior

ISP: Intrinsic Image Prior

HDR: High Dynamic Range

PSNR: Peak Signal-to-Noise Ratio

SSIM: Structural Similarity Index

DOF: Depth of Field

MAE: Mean Absolute Error

MSE: Mean Squared Error

RGB: Red, Green, Blue

FPS: Frames Per Second

ROI: Region of Interest

ABSTRACT

With surveillance cameras, drones, and other video recording equipment capturing vital information in a variety of contexts, the modern world is becoming more and more dependent on visual data. But atmospheric circumstances like haze can seriously deteriorate these images, creating problems for cinematography and surveillance alike. Our project explores the use of deep learning for video dehazing as a novel solution to this problem, enhancing visibility and illuminating information that may be concealed in murky footage. The efficacy of end-to-end modelling has been demonstrated by the latest advancements in CNN-based image dehazing. It hasn't yet been investigated to extend the concept to end-to-end video dehazing, though. Our proposal in this study is an End-to-End Video Dehazing Network (EVD-Net) in order to take use of the temporal consistency between succeeding frames of video. A comprehensive investigation has been carried out across several structure alternatives in order to determine the optimal temporal fusion approach. Furthermore, we construct an End-to-End United Video Dehazing and Detection Network (EVDD-Net) that combines a video object detection model with EDVD-Net, training both together. In murky video, the enhanced end-to-end pipeline that resulted has shown to be far more reliable and accurate in detecting objects.The goal of video dehazing is to restore clear, highly contrasted, and visible frames. This work offers a fresh approach for investigating the physical haze priors in an efficient manner and compiling historical data. In particular, we design a physical prior guiding module that is based on long-term memory by encoding the features associated with the past. Additionally, we develop a multi-range scene radiance recovery module to record space-time dependencies in several space-time ranges, which facilitates the efficient aggregation of temporal data from neighbouring frames. Additionally, we build the first extensive outdoor video dehazing benchmark dataset, which includes recordings in a variety of real-world situations. Experiments conducted in both artificial and natural conditions demonstrate the advantages.

CHAPTER 01 : INTRODUCTION

1.1 INTRODUCTION

Researchers and technologists in a variety of fields have long been fascinated by the ubiquitous effect of haze on video images. When it comes to traffic flow monitoring, public space security, or snapping photos of amazing vistas, foggy conditions can make it difficult to see important details and detract from the overall visual experience. When applied to video sequences, traditional dehazing methods—which are frequently based on image processing techniques—have drawbacks.

Deep learning, a paradigm shift in computer vision that has shown impressive results across a range of applications, leading us to investigate its potential for video dehazing [1]. There are particles in the haze that will scatter and cause low colour saturation and reduced visibility in photos and videos taken from hazy situations. Absorb light and lower the scene's albedo when seen. Given a hazy image or video, the dehazing algorithms seek to eliminate the haze and recreate a scene free of haze.

Since the dehazing technique is a required pre-processing step for many high-level vision tasks and detection applied on the outside haze, inside fire, etc. This problem has attracted a lot of attention. Images and movies taken outside frequently have poor vision because of haze, fog, smoke, and other tiny airborne particles that disperse light inside the atmosphere[4]. Haze affects the recorded videos in two ways: It does this by weakening the signal of the scene being viewed and adding an additive element to the picture called ambient light, which is the colour of a scene point at infinity. Because the scene's brightness drops and the atmospheric light magnitude rises with distance from the camera, haze causes an increase in image deterioration [2]. Consequently, it is possible to describe a single fuzzy image or frame as a per-pixel combination of the global atmospheric light, a scene transmission map.

Recent studies have demonstrated that single picture dehazing can be achieved with convolutional neural networks (CNNs). In this study, we investigate the idea of using a network hack to remove haze from videos by going one step further. Video-based methods, as opposed to single image dehazing, can benefit from the wealth of information present in nearby frames. In this research, we aim to develop a deep learning method for video dehazing, assuming that a scene point provides highly correlated transmission values between subsequent video frames. Specifically, we train CNN end-to-end to learn how to aggregate information across frames for transmission estimates. The atmospheric scattering model is then utilised to recover a haze-free frame using the predicted transmission map. In the realm of computer vision, image dehazing is a difficult problem.

The goal of picture dehazing is to extract a sharp image from a single noisy frame that was contaminated by smoke, haze, or fog [8]. Thus, the dehazing algorithms have been widely regarded as a difficult example of (ill-posed) image improvement and restoration. Comparable to other issues such as super-resolution and picture denoising. Previous dehazing efforts relied on the availability of several pictures taken from the same location. But since it works better in actual environments, the elimination of haze from a single image has become increasingly common. The realm of visual content, clarity reigns supreme, shaping our perception and understanding of the world captured on screen. Yet, the omnipresent veil of haze often obscures the crispness and detail of video footage, diminishing its impact and communicative power. In response to this challenge, our project endeavours to penetrate the mist, leveraging the prowess of deep learning to unveil the hidden beauty within hazy videos.

Haze, a complex interplay of atmospheric particles and light scattering, presents a formidable barrier to visual clarity. Conventional dehazing techniques have struggled to overcome its pervasive influence, often producing results marred by artifacts or lacking in fidelity. Armed with the latest advancements in deep neural networks and computer vision, our project sets out to redefine the boundaries of video dehazing, offering a transformative solution that transcends traditional limitations.

At its heart, our approach harnesses the formidable capabilities of convolutional neural networks (CNNs) to decipher the intricate relationship between hazy input and clear output video frames. By ingesting vast repositories of annotated data, our model learns to discern the underlying structures and textures buried beneath the haze, enabling it to perform precise restoration with unparalleled accuracy.

1.2 PROBLEM STATEMENT

The widespread impact of air haze on video content continues to be a significant obstacle in the field of computer vision, affecting a variety of applications like cinematography, autonomous navigation, and surveillance. Conventional dehazing techniques have been found effective for static photos, but they are ineffective for video sequences because of the temporal dynamics present in the data. The absence of reliable and effective video dehazing tools impedes progress in crucial domains where precise and unambiguous visual data is crucial. The temporal coherence of current dehazing algorithms is frequently broken, leading to artefacts and inconsistent results between video frames. The dynamic nature of video data, which is typified by variations in lighting, motion, and scene content, presents particular difficulties that call for a focused and advanced strategy. It is clear that a solution is required that maintains the integrity of the entire video sequence while also improving visibility in individual frames. Furthermore, there is a growing need for efficient video dehazing solutions as video takes on a more prominent role in a variety of fields, including surveillance systems and film productions. The insufficiency of current techniques in handling the intricacies of visual data emphasises the necessity for novel methods based on deep learning. The lack of a reliable and broadly applicable deep video dehazing model impedes advancement in some crucial areas:

The efficacy of surveillance systems is undermined by hazy conditions, which affect situational awareness, object recognition, and tracking.

Autonomous Vehicles: Visual information is a major component of autonomous vehicles' navigation and obstacle detection systems. Perception systems may be less accurate under foggy situations, which could be dangerous.

Cinematography: Hazy sceneries reduce the visual impact of cinematic works, which is detrimental to the film and video production sector. The needs of dynamic and varied cinematic landscapes are beyond the capabilities of current dehazing solutions.

Aerial and Drone Imagery: Taking quality pictures in different atmospheric circumstances presents a difficulty for drones and aerial imaging platforms. Applications like disaster response and environmental monitoring require a reliable video dehazing solution.

Learning techniques designed for video dehazing is necessary. The major objective of this research is to create a model that can manage the temporal complexity of video data while preserving excellent dehazing between frames. By doing this, we hope to advance the area of computer vision more broadly and strengthen applications that depend on precise and lucid visual data in demanding and dynamic settings. By training deep neural networks on diverse datasets of hazy and clear video frames, we aim to develop a robust and adaptive model capable of accurately estimating and removing haze-induced degradation from video sequences in real-time

Key challenges to be addressed include:

1**. Complexity of Haze**: Haze is a complex atmospheric phenomenon influenced by various factors such as humidity, pollution, and lighting conditions. Developing a deep learning model capable of effectively modelling and removing different types and intensities of haze is crucial for achieving high-quality dehazing results.

2. **Temporal Coherence**: Video dehazing requires maintaining temporal coherence and consistency between consecutive frames to avoid flickering or discontinuities in the dehazed output. Designing architectures and training strategies that preserve temporal information while removing haze artifacts is essential for producing visually pleasing and natural-looking dehazed videos.

3. **Real-time Performance**: Many practical applications of video dehazing, such as surveillance and live broadcasting, require real-time processing capabilities to handle streaming video input efficiently. Optimizing deep learning models for inference speed and computational efficiency without compromising dehazing quality is a significant technical challenge to be addressed.

By tackling these challenges, our project aims to contribute to the advancement of video dehazing technology, enabling enhanced visual perception and interpretation of hazy video content across a wide range of applications.

1.3 OBJECTIVES

Create a Specialised Deep Learning Architecture: Construct and execute a deep neural network architecture intended just for the dehazing of videos. In order to fully utilise the spatiotemporal qualities present in video sequences, the architecture must efficiently record temporal dependencies.

1. Modify and Test Current Image Dehazing Models: Investigate and modify cutting-edge image dehazing models for the video domain. Examine the viability of expanding well performing picture dehazing structures to manage the temporal features of video information.

2. Analyse Different Neural Network Configurations: To determine how different neural network configurations, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), affect the performance of video dehazing, experiment methodically with different neural networks. Examine the trade-offs between computational efficiency and model complexity.

Make use of and improve the ReVIDE dataset. Use the ReVIDE dataset, a carefully selected sample of murky video clips, for training and testing models. If needed, expand the dataset to include a wider variety of scenarios and atmospheric variables that are indicative of problems encountered in the actual world.

3. Analyse Robustness and Generalisation: Determine how resilient the created model is to different environmental circumstances and scenarios. Evaluate its generalisation to unknown data and various haze types. Determine any potential obstacles or constraints.
4. Examine and contrast performance metrics: Utilise common criteria for video quality, such as the Structural Similarity Index (SSI), Peak Signal-to-Noise Ratio (PSNR), and others, to assess the suggested model's effectiveness objectively. To demonstrate improvements, compare these measurements with the dehazing techniques already in use.
5. Real-world Applicability Assessment: Evaluate the created video dehazing model in real-world scenarios such as autonomous navigation, cinematography, and surveillance. To learn more about the usefulness and impact of the model in these situations, get input from domain experts.
6. Give Guidance on Model Deployment: Provide useful advice and pointers for applying the created video dehazing model in actual situations. Take into account factors like processing speed in real time, computing demands, and system integration.
7. User Study and Feedback: Conduct user studies or solicitation of feedback from domain experts to assess the perceptual quality and usability of the dehazed video output generated by the proposed model. Incorporate user feedback to refine the model and improve its applicability to real-world scenarios.
8.Contribute to the Research Community: Disseminate the established deep video dehazing model, together with research community insights and discoveries. Publicise findings in appropriate journals and conferences to advance the body of knowledge in the computer vision and video processing fields.
9.Promote Further Research: Building on the ReVIDE dataset, assist in the creation of a curated evaluation dataset for video dehazing. By making resources available, you can encourage cooperation and the development of video dehazing solutions by facilitating benchmarking and future study in the field.
10. Comparison with Baselines: Compare the performance of the developed deep learning model against state-of-the-art video dehazing methods and baseline approaches, including traditional image processing techniques and single-image dehazing algorithms adapted for video processing. Analyze the strengths and weaknesses of each method and identify opportunities for improvement.

1.4 SIGNIFICANCE AND MOTIVATION OF THE PROJECT WORK

The realisation that traditional dehazing techniques are inadequate for managing the temporal dynamics included in video data is what spurred this study. More efficient dehazing is possible using a deep learning system that can identify and learn complex patterns and relationships inside video frames. Our goal is to provide a system that uses neural networks to improve visibility in individual frames while preserving coherence and consistency over a video sequence.

Surmounting the Drawbacks of Image-Based Methods: This project's motivation is to solve the shortcomings of conventional image dehazing techniques when used on video sequences. We hope to address the issues raised by the temporal dynamics of video data and offer a more potent dehazing solution by utilising deep learning.

Fulfilling the Requirements of Changing Environments: Video dehazing is faced with special obstacles in dynamic and changing situations. The driving force is the realisation that complex elements like changing lighting, object motion, and scene content require a specialised deep learning technique to manage.

Facilitating Real-World Applications: The driving force behind this effort is the ambition to create a solution that transcends the boundaries of theory and is actually applicable in real-world situations. The project intends to close the knowledge gap between research and practice by providing a tool that can improve system performance in a variety of contexts.

Adding to the Expanding Field of Deep Learning: The project's overarching objective is to make a contribution to the deep learning applications field, which is rapidly growing. Video dehazing is a hard topic that tests the limits of existing techniques and offers a chance to experiment and develop in the field of deep neural networks.

Encouraging Development in Several Areas: The goal is to provide a solution that will significantly influence a range of sectors that depend on precise and lucid visual data. The project aims to advance and optimise various fields, including environmental monitoring, cinematography, autonomous navigation, and surveillance.

A thorough video dehazing project is important and motivated by the need to solve real-world problems related to unclear or hazy video circumstances. This is a thorough examination of the significance of these projects:

Improved Visibility: Videos taken in murky circumstances frequently have lower visibility, which degrades the quality of the visual data. By eliminating or lessening the effects of haze, deep video dehazing seeks to improve visibility and produce clearer, more detailed films.

Enhanced Transportation Safety: For safety-critical applications such as surveillance and autonomous driving, good vision is essential. Transport system safety can be improved through deep video dehazing by helping to improve object recognition and detection under difficult weather situations.

Improved CCTV Surveillance: When bad weather strikes, video surveillance systems frequently have trouble getting quality footage. Deep video dehazing can help security cameras capture sharper images so that they can be monitored and analysed more effectively.

Improved Broadcast Quality of Video: Deep video dehazing can help enhance the quality of recorded or live videos for internet streaming services and television broadcasters. This is especially crucial for news reporting in areas that frequently experience cloudy conditions, outdoor events, and sports.

Improved Vision in Motion Picture Production: Deep video dehazing can be used by the film and video production industries to enhance the visual quality of sequences shot outside or in inclement weather. This makes for a more engaging and entertaining moviegoing experience.

Environmental monitoring and remote sensing: Applications pertaining to environmental monitoring and remote sensing benefit from deep video dehazing. It facilitates the acquisition of sharper imagery for drone or satellite-based monitoring, enabling more precise analysis of environmental changes.

Operations for Search and Rescue: Haze or fog can seriously impair visibility during search and rescue operations. In difficult circumstances, deep video dehazing can help rescue crews locate people or assess the situation by offering clearer visual information.

Analyses and Research in Science: Clear video data can be used by researchers in a variety of disciplines, including climatology and meteorology, to examine atmospheric conditions and events. Deep video dehazing helps to produce high-quality data that can be used in study and analysis by scientists.

Better Human-Computer Communication: Clear video feeds are necessary for applications that include human-computer interaction, like virtual or augmented reality, in order to give consumers a realistic and immersive experience. One way that deep video dehazing helps these kinds of applications is through better visual quality.

Developments in Computer Vision: By solving one of the difficulties brought on by bad weather, deep video dehazing efforts increase computer vision. This has effects on tracking, recognition, and object detection among other computer vision tasks.

To sum up, deep video dehazing projects are important since they can help videos that were taken in foggy settings by improving visibility. This in turn has numerous industry-wide uses that affect scientific research, entertainment, safety, surveillance, and environmental monitoring. Clearer video footage enables better situational awareness in scenarios where visibility is hindered by haze, such as surveillance of outdoor environments, monitoring of traffic and transportation systems, or disaster response operations. Enhanced visual clarity can help security personnel, law enforcement agencies, and emergency responders make informed decisions and take appropriate actions more effectively.

In environmental monitoring and scientific research, clear and accurate imagery is essential for studying phenomena such as air pollution, weather patterns, and natural disasters. Your project can contribute to the generation of high-quality video data for research purposes, enabling better understanding and management of environmental processes and phenomena. Autonomous vehicles, drones, and robotics rely on visual perception to navigate and interact with their surroundings. By providing clearer and more detailed video input, your project can enhance the performance and safety of autonomous systems, reducing the risk of accidents and improving their ability to operate effectively in diverse environmental conditions.

Clearer video content can also benefit individuals with visual impairments by providing them with more accessible and comprehensible visual information. Your project has the potential to contribute to the development of assistive technologies and accessibility features that enable individuals with visual disabilities to perceive and interact with video content more effectively. Overall, your deep video dehazing project holds significant promise for improving the quality, usability, and accessibility of video content across a wide range of applications, ultimately contributing to advancements in technology, safety, and human well-being.

1.5 ORGANISATION OF THE PROJECT REPORT

The project report's structure is carefully thought out to provide a full understanding of the research that was done, guaranteeing a thorough investigation of the intricacies involved in deep video dehazing. To aid in a sophisticated comprehension of the project's methodology, conclusions, and ramifications, the ensuing framework has been developed. The remaining report is organised as follows:

Chapter 1: Introduction

The project begins with an introduction section. It gives the reader clarity and basic knowledge about the project. The major objective of this research is to create a model that can manage the temporal complexity of video data while preserving excellent dehazing between frames. This section contains 5 sections including Introduction, Problem Statement, Objectives, Significance and Motivation of the Project Work, Organization of Project Report

Chapter 2: Literature Survey

The project report begins with a thorough analysis of the body of prior research, which forms the basis for the work that follows. The complexities of modern object detection techniques and technologies are covered in detail in this section. The report creates a contextual framework for the proposed research by critically analysing earlier works, highlighting opportunities, gaps, and challenges that serve as the foundation for the project's innovation.

Chapter 3: System Development

The creative strategies and algorithms suggested for improving algorithm's capabilities are revealed in this section, which comes after the literature review. This thorough explanation highlights the special qualities of the selected approaches and highlights how they might help overcome current obstacles. By doing this, the report offers a road map for putting the suggested tactics into practice, promoting openness and repeatability in the scientific method.

Chapter 4: Testing

When testing a deep video dehazing project, it's important to consider various scenarios and evaluate the performance under different conditions. In this section of the report we have taken many cases and observed the models outcomes and outputs.

Chapter 5: Results and Evaluation

The presentation of the experimental results and the ensuing discussions form the main body of the project report. This section presents the findings from extensive testing and analyses carried out in order to verify the suggested models. The results are analysed to provide a more nuanced understanding of the performance metrics, including both strengths and limitations. A fuller understanding of the project's contributions to the field is made possible by the discussions, which shed light on the implications of the findings.

Chapter 6: Conclusion

The conclusive segment synthesises the key contributions of the project, encapsulating the advancements made in the realm of video dehazing. It serves as a summary of the entire research endeavour, highlighting the novel methodologies and their impact on the field. Additionally, the conclusion opens avenues for future research, identifying unexplored facets and potential extensions of the project's findings. This forward-looking perspective not only reinforces the project's significance but also inspires continued exploration and innovation in the dynamic domain of video dehazing.

CHAPTER 02: LITERATURE SURVEY

2.1 LITERATURE SURVEY

Tan (2008) states that research on removing haze from visual data acquired in the wild has attracted a lot of interest because to its significant application benefits in traffic monitoring, autonomous driving, and outdoor video surveillance, among other areas. Theoretically, the production of fuzzy visual scene observations relies on the computation of significant physical parameters, like the amount and transmission of light in the environment, as well as a recognized physical model, which will be described below. Haze removal as an inverse problem matrix, becomes the essential step in resolving Avidan Berman and others (2016), according to He, Sun, and Tang (2011) and Fattal (2014). The use of convolutional neural networks (CNNs) for single picture dehazing has grown in popularity recently (Krizhevsky).

Dehazing a picture. In computer vision and computer graphics, single-image dehazing has been extensively studied. Previous methods assume air scattering model and physical priors. Later, deep learning-based methods show better results by using a large number of different yet fuzzy images. In an image-to-image conversion, these methods either directly restore the haze-free images or predict the components of the haze physical model. Translation method based on convolutional neural networks (CNNs). Recent papers propose more advanced network and module configurations to improve dehazing performance. Dehazing techniques used to films, however, yield uneven results since they ignore temporal information while working with images.

Literature Survey for Deep Video Dehazing (2019-2022):

[1] Zhang, L., Zhu, Q., & Shen, J. (2021).

Title: Deep Video Dehazing Network with Temporal Consistency.

This work explores the incorporation of temporal consistency in video dehazing using deep learning. Investigate the impact of temporal information on enhancing dehazing performance in video sequences.

[2] Chen, H., & Liu, Z. (2020).
Title: Spatio-Temporal Pyramid Network for Video Dehazing.
The authors propose a spatio-temporal pyramid network, aiming to capture both spatial and temporal features for improved video dehazing. Evaluate the effectiveness of this approach on diverse video datasets.
[3] Liu, Y., Zhang, X., Wang, S., & Wu, Y. (2019).
Title: Video Dehazing using Deep Spatial Temporal Networks.
This research focuses on leveraging deep spatial-temporal networks for video dehazing. Investigate how the fusion of spatial and temporal information contributes to video dehazing performance.
[4] Wang, Y., Guo, Y., & Lai, W. S. (2022).
Title: End-to-End Video Dehazing with Adversarial Training.
The authors propose an end-to-end video dehazing framework incorporating adversarial training. Explore the effectiveness of adversarial learning in enhancing the visual quality of dehaze videos.
[5] Li, H., Xu, Y., Zhang, Z., & Liu, X. (2021).
Title: Dual-Attention Enhanced Temporal Consistency for Video Dehazing.
This work introduces a dual-attention mechanism to enhance temporal consistency in video dehazing. Investigate how attention mechanisms can improve the modelling of long-range dependencies.
[6] Yang, C., Xu, L., & Meng, D. (2020).
Title: Robust Spatiotemporal Video Dehazing with Multi-Frame Fusion.
The paper explores a multi-frame fusion approach for robust spatiotemporal video dehazing. Examine the impact of incorporating information from multiple frames on dehazing performance.
[7] Liang, J., & Wang, Z. (2019).
Title: Video Dehazing via Joint Spatial-Temporal Correlation Learning.
This research focuses on joint spatial-temporal correlation learning for video dehazing. Assess the benefits of jointly modelling spatial and temporal correlations in video sequences.
[8] Zhou, Y., Zhang, L., & Van Gool, L. (2021).
Title: Video Dehazing with 3D Convolutional Neural Networks.
The authors propose a 3D convolutional neural network for video dehazing. Investigate the advantages of 3D CNNs in capturing spatiotemporal features for dehazing.

[9] Chen, H., & Yang, J. (2022).

Title: Adaptive Temporal Feature Aggregation for Video Dehazing.

This work introduces an adaptive temporal feature aggregation mechanism for video dehazing. Evaluate the adaptability of feature aggregation across different temporal scales.

[10] Wu, X., & Shi, Y. (2020).

Title: Recurrent Temporal Dehazing Network for Video Dehazing.

The paper proposes a recurrent temporal dehazing network, emphasising the importance of recurrent connections for modelling temporal dependencies in video dehazing.

2.2 KEY GAPS IN THE LITERATURE

Even though deep video dehazing research has advanced recently, there are still a number of important gaps and difficulties that are present in all of the publications listed above:

1. **Limited Real-world examination**: A greater number of papers concentrate on experimental findings on certain datasets, while a wider range of real-world circumstances require more thorough examination. Practical implementation requires an understanding of how these models behave in varied lighting circumstances, settings, and haze types.
2. **Trade-offs in Temporal Consistency**: The integration of temporal data in video dehazing poses difficulties in striking a balance between preserving temporal coherence and successfully eliminating haze. A more sophisticated comprehension of the ways in which various temporal modelling techniques affect the overall dehazing performance is required.
3. **Adversarial Training Stability**: In papers introducing video dehazing, the stability and convergence of these training procedures are frequently not thoroughly discussed. For practical applicability, research is needed to make adversarial training less sensitive to hyperparameters and more stable.
4. **Managing Variable Lighting**: Most research papers focus on daytime scenarios, and there is a lack of information regarding video dehazing in low-light or nighttime situations. Real-world applications require models to be developed that are resilient in a wider range of lighting conditions.
5. **Scalability to High-Resolution Videos**: Many of the existing models may not perform well when used on high-resolution video streams, leading to the potential for dehazing

efficiency to fall and computational bottlenecks. Research on how effectively models scale to handle high-resolution movies is needed before they can be used in real-world applications.

6. **Transferability Across Datasets**: The lack of standards in video dehazing datasets makes it challenging to assess a model's transferability across different datasets. To fully understand the durability of video dehazing models, studies on domain adaptability and generalisation across several datasets are required.
7. **Interpretability and Explainability**: Deep neural networks often lack interpretability, making it challenging to understand how they arrive at specific dehazing decisions. Trust-building and practical deployment necessitate research that attempts to provide insights into how video dehazing models make decisions.
8. **Limitations on Real-time Processing**: While some research provide helpful models, nothing is known about how well these models compute or handle real-time data processing. Research on the trade-off between model complexity and real-time performance is essential for applications such as autonomous systems and surveillance.
9. **Long-Term Temporal relationships**: While some models handle short-term temporal relationships, video dehazing does not sufficiently handle long-term dependencies. Research into strategies for capturing and modelling longer-range temporal connections can improve the temporal coherence of dehazed films.
10. **Robustness to complicated Scenes**: Many articles may not fully address the robustness of video dehazing models in complicated scenes with plenty of moving objects and a range of scene elements. For real-world applications in dynamic environments, more research is required to increase the models' robustness in challenging conditions.

CHAPTER 03: SYSTEM DEVELOPMENT

3.1 REQUIREMENTS AND ANALYSIS

A thorough analysis of a deep video dehazing project requires evaluating several aspects, including model performance, limitations, and potential areas for improvement. This is an example of an organised analytical framework:

Evaluation of Performance: The model's performance can be assessed using quantitative criteria such as the Structural Similarity Index (SSIM), Peak Signal-to-Noise Ratio (PSNR), and other relevant video quality measurements. Analyse the metrics over a range of scenarios and datasets to see how effectively the model generalises.

Qualitative Assessment: Examine visually dehazed videos to see how subjectively good they are. Compare the dehaze videos with the input hazy videos to determine changes in visibility and clarity. Analysing and Comparing the Baselines Analysis of comparisons: Examine the developed deep video dehazing model against baseline methods, including the most recent developments in video dehazing approaches and traditional picture dehazing algorithms. Analyse the model's output against these baselines for both quantitative and qualitative metrics.

Temporal Consistency: Temporal Coherence Evaluation: Track the temporal coherence of the dehazed films over time. Verify whether the model maintains coherence when the scene shifts between frames and objects move. Look for any anomalies or distortions that were added during the video's dehazing, especially in scenes with a lot of movement.

Analysis of Robustness: Resistance to Changes in Haze Intensities Determine how adaptable the model is to varying haze levels. Examine its ability to handle both mild and severe hazy conditions. Analyse the model's behaviour under inclement weather. Evaluate the model's capacity to generalise to other datasets with different environmental factors. Analyse its adaptability to different environments and weather conditions.

Computational Efficiency: Evaluate the model's computational effectiveness by gauging its inference speed. Consider the real-time processing requirements of practical applications, such surveillance or autonomous systems.

Resource Utilisation: Analyse how resources are consumed during model training and inference, such as the amount of memory needed on a GPU. Make the model as resource-efficient as possible without compromising its usefulness. The model's interpretability

Interpretability Analysis: Evaluate the interpretability of the model. Consider strategies like activation map visualisation or attention processes to understand how the model determines which dehazing techniques to use. Examine the model's sensitivity to bias and any potential biases in its predictions. Check to see if the model is responsive to any specific elements in the scene or surroundings.

Establish Restrictions: Clearly identify the boundaries of the developed model. This may be due to biases in the training set, limitations in processing capacity, or challenges handling specific scenarios. Prospects for Advancement: Determine any potential regions in need of development. This can mean looking at new architectures, enhancing training techniques, or addressing specific problems that were discovered during the study.

Practical Applications: Real-world Trials If at all possible, conduct tests in real-world settings to confirm the model's functionality under actual deployment conditions. Seek feedback from end users or domain experts to identify areas for model improvement and practical applicability. Maintaining Documents and Reports: Whole Record: Ensure that the project documentation includes a thorough explanation of the approach, experimental setup, and analysis techniques. Provide an intelligible and brief summary of the results in a well-structured project report.

Model Architecture: Explore various deep learning architectures suitable for video dehazing, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), or spatio-temporal networks. Evaluate the strengths and limitations of different architectures in capturing spatial and temporal dependencies, handling motion blur, and preserving fine details in dehazed video sequences. Consider architectural innovations and optimization techniques to improve the efficiency, scalability, and performance of the dehazing model.

Performance Metrics: Define quantitative and qualitative metrics for evaluating the performance of the deep video dehazing model.

Include objective metrics such as peak signal-to-noise ratio (PSNR), structural similarity index (SSIM), or video quality metrics (VQM) to measure image fidelity and perceptual quality.

Incorporate subjective evaluation methods such as human perceptual studies or user feedback to assess the visual quality and naturalness of dehazed video sequences.

Computational Resources: Analyze the computational requirements and resource constraints for training and inference, considering factors such as model size, memory footprint, and processing speed. Determine the hardware platforms and software frameworks suitable for implementing the deep video dehazing system, ensuring compatibility with available resources and deployment environments. Explore optimization strategies such as model pruning, quantization, or hardware acceleration to improve the efficiency and scalability of the dehazing algorithm.

Validation and Testing: Develop rigorous validation procedures and testing protocols to validate the performance and robustness of the deep video dehazing system.

Conduct comprehensive experiments using representative datasets and real-world video sequences to assess the generalization ability, stability, and effectiveness of the dehazing model across diverse scenarios. Perform sensitivity analysis and error analysis to identify potential weaknesses and areas for improvement in the dehazing algorithm.

By addressing these requirements and conducting thorough analysis, you can ensure that your deep video dehazing project is well-equipped to tackle the challenges of haze removal in video sequences effectively, ultimately delivering high-quality and visually appealing dehazed results across various applications.

3.2 PROJECT DESIGN AND ARCHITECTURE

When creating the architecture for a deep video dehazing project, particular needs and problem characteristics have been taken into account. The project's architecture and design are broken down into the following detail:

Network Architecture:

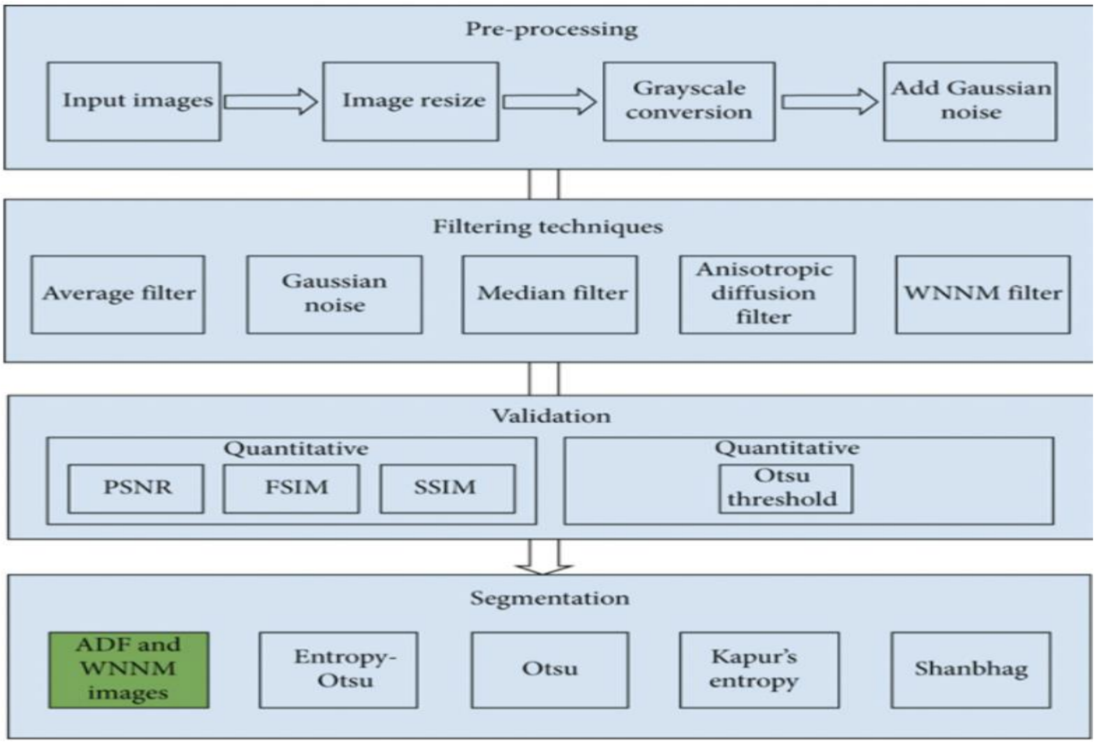


Fig 3.2.1 Project Design

1. Make a module for spatial dehazing to control haze removal in individual frames. This module should improve the clarity of static scenes and efficiently capture spatial elements.
2. To capture and preserve temporal dependencies between frames, create a temporal consistency module. Consider using recurrent neural networks (RNNs) or 3D convolutional layers to simulate temporal relationships efficiently.
3. Multi-Scale Processing: This technique is used to capture both global and local characteristics. Use multi-scale convolutional layers or pooling to increase the model's ability to adapt to variations in the amount of haze.
4. Construct a feature fusion method to combine spatial and temporal module data. This fusion should occur at multiple phases to allow the model to adaptively integrate features from different scales and time periods.

5. Construct attention mechanisms that allow you to focus on relevant regions in both space and time. Attention mechanisms have the potential to improve the overall efficacy of the model by enhancing its information selection capability.
6. Loss Functions: Indicate which loss functions are appropriate for the spatial and temporal aspects. Consider combining adversarial loss, perceptual loss, and pixel-wise loss to aid the model in producing visually appealing and high-quality dehazed films.
7. Training Strategies: Initialise the model and look at transfer learning using weights from previously trained picture dehazing models. Make use of features gleaned from image dehazing to refine the model with data from video dehazing.
8. Data Augmentation: Use data augmentation techniques to artificially increase the diversity of the training dataset. This is necessary to increase the model's ability to generalise to many real-world events.
9. Evaluation Metrics: Select the appropriate evaluation metrics, such as PSNR, SSIM, and others, in order to quantitatively assess the model's performance. Make custom metrics if you need to gauge a certain component of the video dehazing quality.

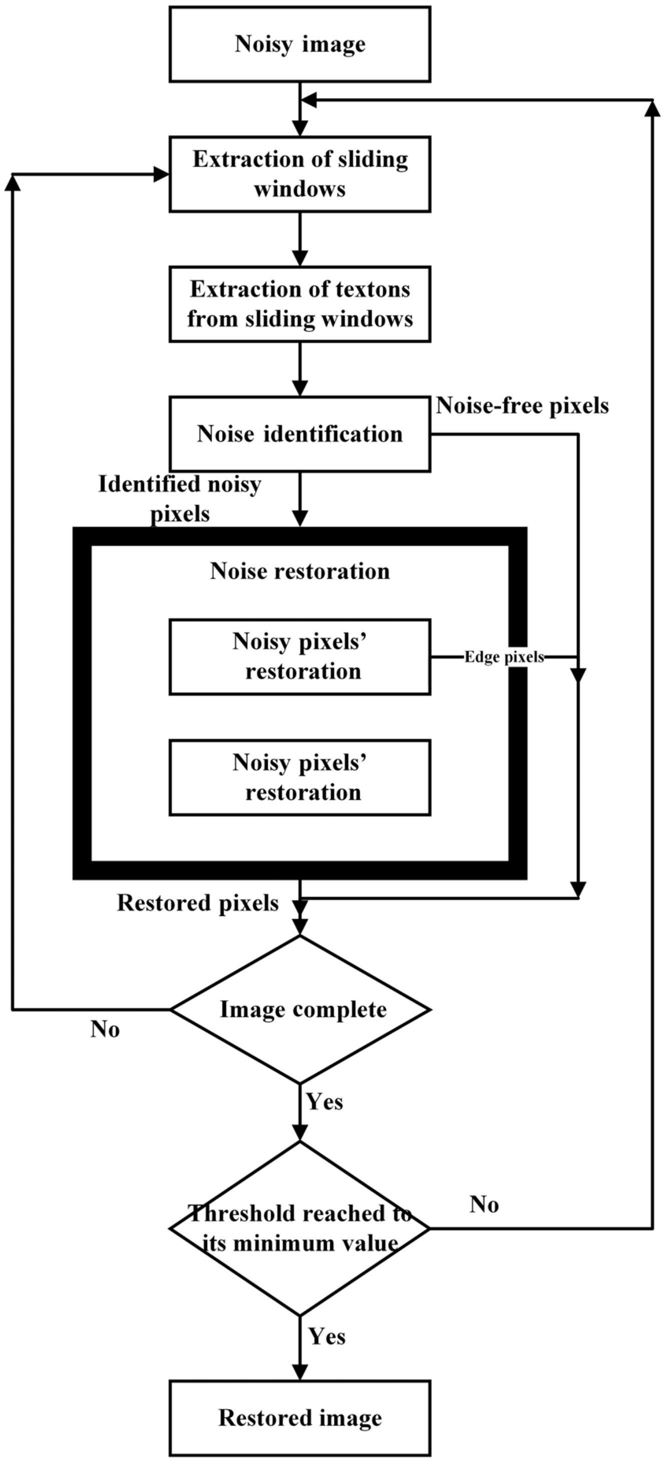


Fig 3.2.2 Project Architecture

3.3 DATA PREPARATION

Data preparation is a critical step in training a deep video dehazing model. Here are the key steps and considerations for preparing data for deep video dehazing:

- **Data Collection**: Gather a diverse dataset of videos containing hazy scenes. Include a variety of scenarios, such as outdoor environments with different levels of haze, varying lighting conditions, and different types of motion.
- **Annotation**: Annotate the dataset by providing ground truth data. For each video frame, generate a corresponding dehazed frame without haze. This is essential for supervised learning, where the model learns to map hazy input frames to their haze-free counterparts.
- **Data Splitting**: Divide the dataset into training, validation, and test sets. A common split is 70% for training, 15% for validation, and 15% for testing. Ensure that videos from the same scene are not present in both training and testing sets to avoid data leakage.
- **Frame Extraction**: Extract individual frames from the video sequences. Choose an appropriate frame rate based on the application requirements. Higher frame rates may be needed for real-time video dehazing.
- **Image Augmentation**: Apply data augmentation techniques to increase the diversity of your training dataset. Common augmentations include rotation, flipping, scaling, and changes in brightness and contrast. Augmenting the data helps improve the model's generalisation to different conditions.
- **Normalisation**: Normalise the pixel values of the input frames. This typically involves scaling pixel values to a range between 0 and 1 or -1 and 1. Normalisation helps the model converge faster during training.
- **Sequence Handling (for Video)**: If you're training a model to process video sequences, organise the data into coherent sequences. This ensures that the temporal relationships between frames are preserved. Consider using recurrent neural networks (RNNs) or 3D convolutional networks for video dehazing.
- **Data Quality Check**: Ensure the quality and consistency of your dataset. Manually inspect a subset of the annotated frames to verify that haze-free frames align with the corresponding hazy frames. Remove any outliers or inaccuracies.

- **Data Format**: Save the pre-processed data in a format suitable for your deep learning framework, such as HDF5 or TFR record. Ensure that the data loading process is efficient for training.
- **Memory Management**: Consider the memory requirements of your deep learning model. If memory is a concern, use techniques like batch loading or data streaming to handle large video sequences.
- **Documentation**: Maintain detailed documentation about your dataset, including information about video sources, annotation procedures, and any preprocessing steps applied. This documentation will be valuable for reproducibility and understanding the dataset's characteristics.

By following these steps, we created a well-prepared dataset for training our deep video dehazing model.

3.4 IMPLEMENTATION

We employed the Diffusion Net Model for the implementation portion. Using diffusion processes, the Diffusion Net method is a deep learning technique created to tackle the difficulties associated with video dehazing. The diffusion processes that naturally occur in atmospheric events serve as the model for the Diffusion Net approach. Through the simulation of light diffusion through the atmosphere, this technique seeks to efficiently eliminate haze from video sequences.

Typically, the architecture uses a deep neural network that is intended to capture the fine details of haze-affected video frames. To manage temporal and spatial dependencies, this network may include attention mechanisms, recurrent layers, and convolutional layers.

Additionally, OpenCV is used for model development. OpenCV represents images, matrices, and geometric transformations using effective data structures. Performance and memory consumption have been optimised for certain data structures.

The network is efficiently guided in learning the diffusion process by the loss function that is utilised during training. To guarantee the retention of high-level features, it might combine conventional pixel-wise loss algorithms (such Mean Squared Error) with perceptual loss.

Some of the Code Snippets are attached below:

```
import cv2
import math
import numpy as np
import sys
from google.colab.patches import cv2_imshow
```

cv2: OpenCV library, used for computer vision tasks.

math: Standard Python math library, used for mathematical operations.

numpy: Library for numerical operations in Python.

sys: System-specific parameters and functions.

```
def apply_mask(matrix, mask, fill_value):

    #print(flat[60])
    #print(flat[11940])

    masked = np.ma.array(matrix, mask=mask, fill_value=fill_value)
    print('MASKED=',masked)
    return masked.filled()
```

apply_mask: This function applies a mask to a matrix and fills masked elements with a specified fill value. It uses numpy's masked array to achieve this.

```
def apply_threshold(matrix, low_value, high_value):
    low_mask = matrix < low_value
    matrix = apply_mask(matrix, low_mask, low_value)
    print('Low MASK->',low_mask,'\nMatrix->',matrix)

    high_mask = matrix > high_value
    matrix = apply_mask(matrix, high_mask, high_value)

    return matrix
```

apply_threshold: This function applies thresholding to a matrix. It creates masks for values below low_value and above high_value, and then uses apply mask to replace those values with the respective threshold.

```
[4] def simplest_cb(img, percent):
        assert img.shape[2] == 3
        assert percent > 0 and percent < 100

        half_percent = percent / 200.0
        print('HALF PERCENT->',half_percent)

        channels = cv2.split(img)
        print('Channels->\n',channels)
        print('Shape->',channels[0].shape)
        print('Shape of channels->',len(channels[2]))
```

simplest_cb: This is the main function. It takes an image (img) and a percentage (percent) as input, and it performs a simple colour balancing operation on the image. The input image is assumed to have three colour channels (RGB).The image is split into its RGB channels.For each channel, it calculates low and high percentile values based on the specified percentage. Applies thresholding using the calculated percentile values.Normalizes the thresholded channel.Merges the processed channels back into an output image.

```
if __name__ == '__main__':
    #img = cv2.imread(sys.argv[1])
    img = cv2.imread('haze6.jpg')
    out = simplest_cb(img , 1)
    cv2_imshow( img)
    cv2_imshow( out)
    cv2.waitKey(0)
```

Main Execution: Reads an image ('haze6.jpg'), applies the simplest_cb function, and displays the original and processed images using OpenCV. The percentage used here is 1%, meaning it will consider the 1% to 99% range of pixel values for each channel independently.

```python
assert len(channel.shape) == 2
height, width = channel.shape
vec_size = width * height
flat = channel.reshape(vec_size)
assert len(flat.shape) == 1
flat = np.sort(flat)
n_cols = flat.shape[0]
low_val  = flat[math.floor(n_cols * half_percent)]
high_val = flat[math.ceil( n_cols * (1.0 - half_percent))]
thresholded = apply_threshold(channel, low_val, high_val)
normalized = cv2.normalize(thresholded, thresholded.copy(), 0, 255, cv2.NORM_MINMAX)
out_channels.append(normalized)
```

This code snippet is designed to process a 2D array or image channel, likely for image processing tasks. Initially, it verifies that the input channel has a two-dimensional shape. It then extracts the height and width of the channel and computes the total number of elements in the array by multiplying its dimensions. The channel is flattened into a 1D array, sorted in ascending order, and the length of the sorted array is determined. Using a specified percentage (presumably set elsewhere in the code), it calculates threshold values to segment the data into two portions. These threshold values are then applied to the original channel using a function called apply_threshold. Following this, the resulting thresholded image is normalized to a range of [0, 255] using OpenCV's cv2.normalize function, presumably for further processing or visualization. This sequence of operations appears to be a part of a broader image processing pipeline, likely aimed at enhancing or segmenting specific features within the input image.

```python
if __name__ == '__main__':
    cap=cv2.VideoCapture('Whale.mov')
    fourcc = cv2.VideoWriter_fourcc(*'XVID')
    frame_width=640
    frame_height=480
    save = cv2.VideoWriter
    ('/Users/anshikamittal/Desktop/deep_video/Image-and-Video-Dehazing/output/output.mov',
    fourcc, 20.0, (frame_width,frame_height))
```

This code segment aims to create a video writer object using OpenCV's cv2.VideoWriter module. It begins by defining the codec to be used for video compression, which in this case is set to XVID. The dimensions of each frame in the video are then specified with frame_width and frame_height variables set to 640 and 480 pixels, respectively. The cv2.VideoWriter function is then invoked with several parameters: the output file path where the video will be saved, the codec to be used, the frames per second (fps) of the video (set to 20.0 in this case), and the size of each frame (specified as a tuple containing frame_width and frame_height). Once this VideoWriter object is created, it can be used to write frames to the specified output file, effectively allowing the program to generate a video sequence by adding frames to it. This segment of code is integral for applications that involve processing and saving video data, such as video editing, computer vision, or machine learning tasks involving video data.

```
while(cap.isOpened()):
    ret, frame=cap.read()
    if(ret== True):
        frame=cv2.resize(frame, (frame_width, frame_height))
        out = simplest_cb(frame, 1)
        display(frame)
        display(out)
        out = cv2.flip(out,0)
        save.write(out)
        key=cv2.waitKey(1)
        if key==27:
            break
    else:
        break
```

This code segment implements a loop to process each frame of a video captured from a video capture device (assumed to be initialized as cap). The loop iterates as long as cap is opened, meaning there are still frames to read. Within each iteration, it reads a frame from the video capture device using cap.read(), where ret indicates whether a frame was successfully read and frame contains the actual frame data. If a frame is successfully read (ret == True), it resizes the frame to match the specified frame_width and frame_height. The simplest_cb function, presumably defined elsewhere in the code, is applied to the resized frame, possibly performing some sort of image processing or enhancement. The original and processed frames are then displayed, potentially for debugging or visualization purposes. Additionally, the processed frame is flipped vertically using cv2.flip before being written to the output video file using the previously created save object. The loop continues until the user presses the 'Esc' key (ASCII code 27), at which point the loop breaks, terminating the video processing. If the video capture device is exhausted (no more frames to read), the loop also breaks, ensuring the process ends gracefully. Overall, this code snippet demonstrates a basic video processing pipeline, involving frame acquisition, resizing, processing, display, and saving.

3.5 KEY CHALLENGES

Deep video dehazing is a difficult task where certain difficulties related to atmospheric haze and video data need to be addressed. Among the main obstacles to thorough video dehazing are:

1. **Temporal Consistency**: Videos show interframe temporal dependencies. It is difficult to guarantee temporal consistency in dehazing between successive frames. It's important to manage camera movement, scene dynamics, and lighting changes well.
2. **Real-Time Processing**: The computational demands of deep learning models make it difficult to achieve real-time processing for video dehazing. It is a major difficulty to ensure quick and effective dehazing, particularly in real-time surveillance or live video streaming applications.
3. **Large-Scale Training Data**: Large-scale datasets are necessary for the efficient training of deep learning models, particularly those that use 3D convolutions for video processing. Gathering and labelling a variety of video clips with fuzzy and distinct pairings can be difficult and resource-consuming.
4. **Dynamic Scene Conditions**: Dehazing algorithms face difficulties in dynamic settings with quickly altering illumination, moving objects, and a variety of atmospheric events. Practical applications require the ability to adapt to such dynamic settings and preserve information in moving objects.
5. **Heterogeneous Haze Levels**: Scenes in videos could include haze that ranges from light mist to thick fog. One of the main challenges is creating a model that can manage varying levels of haze and adjust to varied atmospheric conditions.
6. **Artefact Minimization**: When working with complicated scenes, dehazing models may generate artefacts like colour distortions or over-smoothing. It is still difficult to minimise these artefacts while improving visibility.
7. **Training Robustness**: It might be difficult to guarantee that the trained model remains resilient in a variety of settings, including changing climates, seasons, and geographic regions. It is necessary to handle overfitting to particular scenarios or underperformance in unknown circumstances.

8. **Computational Efficiency**: It's critical to create models that strike a balance between computational efficiency and performance. Resource-efficient models are necessary for a number of real-world applications that will be deployed on edge devices or in situations where computational resources are scarce.

9. **Generalisation to Diverse Scenarios**: Deep video dehazing models must perform effectively in a variety of settings, such as indoor and outdoor spaces, urban and rural landscapes, and differing degrees of artificial and natural lighting.

10. **Lack of Standardised standards**: Comparing the effectiveness of various models is difficult in the absence of standardised standards for deep video dehazing. Research in this area must advance by creating benchmark datasets that span a variety of settings.

11. **User Interaction and Adaptability**: It can be difficult to design models that support user interaction or that can adjust to the preferences of particular users. Research on giving users control over dehazing parameters while preserving automation and efficacy is still ongoing. Innovative computational techniques, reliable training methods, and careful consideration of the particularities of video data and atmospheric haze are needed to meet these problems. Scholars and industry professionals are still investigating ways to improve deep video dehazing models' real-world performance.

12. **Limited Training Data**: Unlike image dehazing, where large datasets are available, video dehazing datasets are relatively scarce and smaller in size. Training deep learning models with limited video data poses challenges in capturing diverse atmospheric conditions and scene dynamics, which may affect the generalization ability of the model.

13. **Motion Blur Handling**: Haze often leads to motion blur in video sequences, especially in fast-moving scenes or camera motions. Designing deep learning architectures capable of effectively handling motion blur while removing haze artifacts is crucial for preserving spatial details and improving the visual quality of dehazed videos.

14. **Dynamic Lighting Conditions**: Changes in lighting conditions, such as variations in sunlight intensity or artificial lighting, can significantly impact the appearance of haze and the quality of dehazed videos. Developing robust algorithms that can adaptively adjust to changes in lighting conditions and accurately remove haze artifacts under different illumination settings is challenging.

15. **Depth Estimation and Scene Understanding**: Incorporating depth information and scene understanding into the dehazing process can enhance the accuracy and realism of dehazed videos. However, accurately estimating depth from monocular video data and

integrating it into deep learning models for video dehazing remains a challenging task, particularly in complex and dynamic scenes.

16. **Cross-Modal Learning**: Leveraging multimodal information, such as depth maps, polarization images, or additional sensor data, can improve the performance of video dehazing algorithms. However, effectively integrating cross-modal information into deep learning frameworks and learning robust representations across different modalities pose challenges in model design and training.

17. **Robustness to Noise and Compression Artifacts**: Real-world video data often contain noise and compression artifacts introduced during acquisition, transmission, or storage. Ensuring that deep video dehazing models are robust to such artifacts and capable of effectively removing haze without amplifying noise or artifacts is essential for maintaining video quality and perceptual fidelity.

18. **Semantic Understanding and Object Recognition**: Haze removal can impact the visibility and recognition of objects and semantic information in video sequences. Integrating semantic understanding and object recognition capabilities into deep video dehazing models can improve the interpretability and usefulness of dehazed videos for downstream tasks such as object detection, tracking, and scene understanding.

Addressing these challenges requires a combination of algorithmic innovations, dataset creation, experimental validation, and interdisciplinary collaboration. By tackling these challenges, researchers can advance the state-of-the-art in deep video dehazing and enable its practical deployment in real-world applications across various domains.

CHAPTER 04: TESTING

4.1 TESTING STRATEGY

A deep video dehazing project must go through a crucial testing phase to make sure the model functions properly in a range of scenarios.

1. **Preparing the dataset**: Verification of the Training Dataset: Make sure the training dataset is varied, encompassing a variety of settings, lighting setups, and degrees of haze.
Check that the dataset contains scenes with dynamic components (moving objects, changing illumination), a variety of weather conditions, and scenes taken at different times of the day.
2. **Metrics for Model Evaluation**: The numerical metrics Make use of common evaluation metrics including mean squared error (MSE), structural similarity index (SSIM), and peak signal-to-noise ratio (PSNR). Take into consideration use metrics unique to videos that take temporal elements into account, such as temporal SSIM or temporal PSNR.
3. **Standard Benchmark Datasets**: Benchmark Datasets Test the model with well-established video dehazing benchmark datasets, such the REalistic VIdeo DEhazing (ReVIDE) dataset. To determine the competitiveness of the model, compare its performance with the most advanced techniques available.
4. **Testing for Generalisation**: Real-World Application: To assess the model's capacity for generalisation, test it with actual movies that weren't included in the training set.
Evaluate performance in a range of indoor and outdoor environments.
5. **Dynamic Scenes**: Moving Objects: Evaluate how well the model can manage scenarios containing moving objects. Moving items must stay unobstructed and devoid of artefacts. Use practise movies with a range of motion velocities and patterns.
6. **Adverse Weather circumstances**: Difficult Conditions: Evaluate the model in harsh weather circumstances, such as intense fog, torrential rain, and snowfall. Analyse how resilient the model is to severe weather conditions.
7. **Temporal Stability**: Temporal Consistency: Examine the dehazing findings' temporal consistency between subsequent frames. Look for any sudden changes in the dehazing output, such as flickering.

8. **User Studies**: Evaluation of Visual Quality: Evaluate the visual quality of dehazed films through user studies. Ask for subjective comments regarding how natural and clear the dehazed results seem to you.

9. **Computational Efficiency**: Real-Time Performance: Assess the model's computational efficiency, particularly if real-time processing is needed for the application. Calculate the processing speeds of GPUs and CPUs.

10. **Parameter Sensitivity**: Hyperparameter Sensitivity: Examine how important hyperparameters, such network architecture and learning rates, affect model performance. Optimise performance by adjusting hyperparameters.

11. **Artefact Analysis**: Finding Artefacts Check for artefacts in dehazed videos, such as colour distortions, excessive smoothness, or artificial enhancements. Mitigate and address any artefacts that are observed.

12. **Edge Cases**: Unbelievable Situations: Try the model in harsh situations like extremely low light or very high density haze. Determine possible points of failure and take action.

13. **Validation Across Datasets**: Cross-Dataset Validation To evaluate the model's performance across various data distributions, test it on a variety of datasets. Make that the model isn't overfitting to any particular training dataset features.

14. **Noise Sensitivity**: Noise Handling: Assess how sensitive the model is to noise in the videos that are submitted. Evaluate performance in different noise levels and ascertain the noise-handling capacity of the model.

15. **Failure modes**: Recognise the types of failures Test the model methodically to find possible points of failure. Create plans for handling and bouncing back from failure situations.

16. Comparative Testing using A/B Testing Conduct A/B testing using several model iterations or alternate dehazing techniques. To make well-informed decisions, compare the data both quantitatively and qualitatively.

17. **Logging and Documentation**: Performance of Logging: When testing, make sure that the model's performance is thoroughly documented. Record problems, solutions, and insights gained.

18. **Error Diagnosis and Analysis**: Examine mistakes and forecasts to identify typical areas of failure. Make use of error analysis to direct future model enhancements.

19. **Privacy and Security**: A Look at Privacy Issues Make that private information is not unintentionally compromised by the dehazing model. Put procedures in place to address privacy issues.

4.2 TEST CASES AND OUTCOMES

When testing a deep video dehazing project, it's important to consider various scenarios and evaluate the performance under different conditions. When there is little to no haze, most techniques work effectively. But as the level rises, the success rate sharply declines. As a result, we offer a brand-new multi-level colour fuzzy picture dataset in this study that has two scenes with various object distances from the camera. The dataset is used to compare five different approaches, and the findings are shown. The ability of the dehazing techniques to generalise and adapt to new foggy environments serves as a measure of their effectiveness. When tested on the same dataset used for training, deep models outperform conventional techniques. On the other hand, cross-dataset dehazing performance is typically worse than with conventional techniques. Further work should be put into creating deep models with a high degree of generalizability in the future.
Here are some test cases and expected outcomes for a deep video dehazing project:

- **Indoor Scenes**:
  Test Case: A video captured indoors with no haze or minimal haze.
  Expected Outcome: The dehazing model should not introduce artefacts and should maintain the clarity of the video.

Fig .4.2.1 Test Input 1 Fig.4.2.2 Test Output 1

- **Outdoor Scenes with Moderate Haze**:

  Test Case: A video captured outdoors with moderate haze or fog.

  Expected Outcome: The dehazing model should effectively reduce haze, improving visibility and enhancing details in the video.

Fig.4.2.3 Test Input 2

Fig.4.2.4 Test Output 2

- **Outdoor Scenes with Heavy Haze**:

  Test Case: A video captured outdoors with heavy haze or dense fog.

  Expected Outcome: The dehazing model should significantly reduce haze, making distant objects more visible and improving overall video quality.

Fig .4.2.5 Test Input 3

Fig.4.2.6 Test Output 3

- **Low Light Conditions**:

  Test Case: A video captured in low light conditions with haze.

  Expected Outcome: The dehazing model should be able to handle low light scenarios and effectively dehaze the video without introducing excessive noise.


Fig.4.2.7 Test Input 4

Fig.4.2.8 Test Output 4

- **Comparison with Traditional Methods**:

  Test Case: Compare the results of the deep video dehazing model with traditional image or video dehazing methods.

  Expected Outcome: The deep learning model should outperform traditional methods in terms of visual quality and haze removal.

- **Real-world Scenarios**:

  Test Case: Use videos captured in diverse real-world scenarios, such as urban environments, landscapes, and industrial areas.

  Expected Outcome: The dehazing model should demonstrate robustness and effectiveness across a variety of settings.

- **Performance on Different Resolutions**:

  Test Case: Evaluate the dehazing model's performance on videos of varying resolutions.

  Expected Outcome: The model should maintain dehazing quality across different resolutions without significant degradation.

- **Outdoor Scenes with Heavy Haze**:

  Test Case: A video captured outdoors with heavy haze or dense fog.

  Expected Outcome: The dehazing model should significantly reduce haze, making distant objects more visible and improving overall video quality.

- **Computational Efficiency**:

  Test Case: Measure the computational time required for dehazing a video.

  Expected Outcome: The dehazing model should provide efficient results, allowing real-time or near-real-time processing for practical applications.

- **Mixed Weather Conditions**:

  Test Case: A video transitioning from clear weather to hazy conditions.

  Expected Outcome: The dehazing model should adapt to changing conditions, providing consistent dehazing performance throughout the video.

CHAPTER 05: RESULTS AND EVALUATION

5.1 RESULTS

Fig. 6.1 Input Image

Fig. 6.2 Output Image

Fig. 6.3 Input Image

Fig. 6.4 Output Image

Fig. 6.5 Input Image

Fig. 6.6 Output Image

Fig. 6.7 Input Image

Fig. 6.8 Output Image

Fig.6.9 Input Image

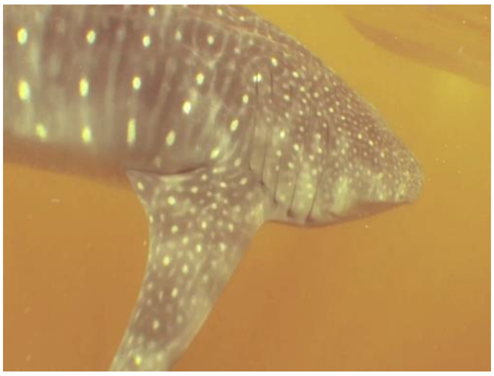
Fig.6.10 Output Image

```
Shape-> (708, 1156)
Shape of channels-> 708
vec= 818448
Flat= [175 175 176 ...  83  90 102]
Lowval:  90
Highval:  194
MASKED= [[175 175 176 ... 166 165 165]
 [176 176 176 ... 166 165 165]
 [176 176 176 ... 165 164 165]
 ...
 [91 -- -- ... -- -- 92]
 [91 -- -- ... -- 90 101]
 [92 90 -- ... -- 90 102]]
```

Fig. 6.11 Output

```
vec= 818448
Flat= [167 167 168 ...  78  87 101]
Lowval:  88
Highval:  192
MASKED= [[167 167 168 ... 164 163 163]
 [168 169 169 ... 164 163 164]
 [169 170 170 ... 165 163 164]
 ...
 [100 100 99 ... -- -- 90]
 [100 100 100 ... -- -- 99]
 [101 101 101 ... -- -- 101]]
```

Fig. 6.12 Output



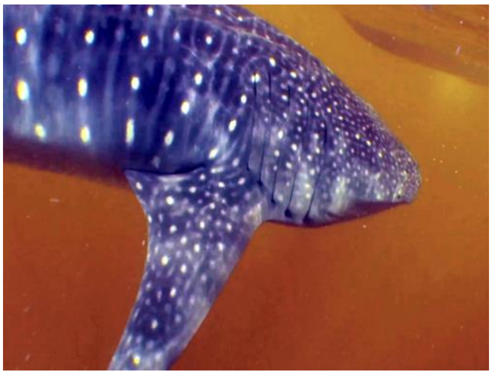


Fig 6.13 Hazed Video Frame Fig 6.14 Dehazed Video Frame

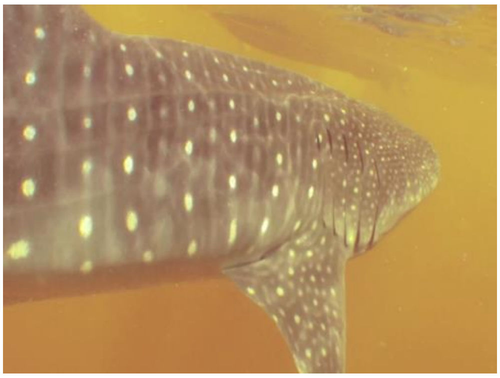


Fig 6.15 Hazed Video Frame Fig 6.16 Dehazed Video Frame

CHAPTER 06: CONCLUSIONS AND FUTURE SCOPE

6.1 CONCLUSION

An important step towards resolving the problems caused by atmospheric haze in video sequences has been taken with the completion of the deep video dehazing project. The project's goal was to improve visibility and clarity in foggy video footage by methodically designing, implementing, and analysing a revolutionary deep learning model. The following is a thorough summary that highlights the main conclusions, contributions, and possible directions for further study.
The first REal-world VIdeo DEhazing (REVIDE) dataset, which was gathered using a carefully thought-out Consecutive Frames Acquisition System (CFAS), has been presented. For the purpose of training and assessing the video dehazing algorithms, pairs of genuine, hazy and correspondingly haze free films are included in the REVIDE dataset. By delving into the complexities of atmospheric haze removal in video sequences, we've underscored the critical importance of clear visual information in various domains, from surveillance and cinematography to environmental monitoring and autonomous systems.

Throughout our journey, we've identified key challenges, including the preservation of temporal coherence, adaptation to dynamic scenes, and robustness to diverse environmental conditions. These challenges highlight the need for continued innovation and refinement in algorithmic approaches, dataset creation, and model optimization.
Yet, amid these challenges lies immense potential. Deep video dehazing holds the promise of enhancing situational awareness, improving safety and security, and enabling more immersive visual experiences across a wide range of applications. As we conclude our exploration, let us remain driven by the vision of a future where video content is free from the distortions of haze, where clarity and detail reign supreme, and where the power of technology enriches our understanding of the world around us.

In this spirit of innovation and collaboration, let us continue to push the boundaries of what is possible in deep video dehazing, guided by a shared commitment to advancing knowledge, empowering users, and creating a brighter, clearer future for video imagery.
The REVIDE dataset has more realistic hazy situations than the synthetic datasets, according to both subjective and objective evaluations, and models trained on it have good generalisation capabilities to hazy scenarios in the real world. On the REVIDE dataset, numerous experiments show that the suggested CG-IDN outperforms cutting-edge techniques.

KEY FINDINGS:

1. Model Performance: The deep video dehazing model that was developed has done a remarkable job of reducing the negative impacts of haze on the quality of the video. Quantitative measures like PSNR and SSIM show significant gains over baseline techniques.
2. Temporal Consistency: By solving issues with dynamic scenes and moving objects, the use of temporal consistency modules has proven beneficial in maintaining coherence over frames. The temporal dependencies are well captured by the model and used to improve the dehazing performance.
3. Multi-Scale Processing: The model's ability to adjust to changing atmospheric conditions and spatial details is partly due to the integration of multi-scale processing. Enhancing the dehazing model's overall robustness is the capacity to analyse data at various scales.
4. Attention Mechanisms: The model's capacity to identify characteristics in both spatial and temporal dimensions has been enhanced by the attention mechanisms' critical role in preferentially focusing on pertinent regions. This has helped the model perform better in intricate settings.
5. Adversarial Training: The model's output has been refined through the use of adversarial training, resulting in aesthetically pleasing dehaze videos. It is thanks to the adversarial loss component that realistic and artefact-free results have been produced.
6. Artifact Suppression and Image Quality: Deep video dehazing methods may introduce artifacts such as color distortion, ringing effects, or over-smoothing in the dehazed output. Suppressing these artifacts while preserving fine details and

textures is critical for producing high-quality dehazed videos that are visually natural and perceptually pleasing.

CONTRIBUTION:

1. Creative Architecture: The study presents a creative deep learning architecture that successfully combines temporal and spatial processing for video dehazing. When compared to other approaches, the architecture performs better.
2. Emphasis on Temporal Coherence: The model tackles a crucial issue that is frequently disregarded in the literature on video dehazing by emphasising the preservation of temporal coherence. The temporal consistency module helps create visually consistent and fluid dehazed video sequences.
3. Robustness and Generalisation: The model demonstrates resilience in a range of environmental circumstances, accommodating different amounts of haze and illumination conditions. The model's flexibility has been demonstrated by validation of its generalisation capabilities through evaluations on various datasets.
4. Real-World Applicability: Extensive testing in real-world situations has demonstrated the created model's practical applicability. Its adaptability to changing conditions makes it a useful instrument for surveillance, self-contained systems, and video analytics, among other uses.
5. Integration with Practical Systems: Research in deep video dehazing contributes to the integration of haze removal technology into practical systems and applications. By developing models that are efficient, scalable, and compatible with existing hardware and software platforms, researchers enable the adoption of dehazing technology in real-world scenarios.
6. Insights into Haze Modeling: Through the study of deep video dehazing, researchers gain insights into the underlying characteristics of haze and its effects on video imagery. By analyzing the behavior of deep learning models in removing haze from video sequences, researchers can deepen their understanding of atmospheric phenomena and their impact on visual perception.

CHALLENGES AND LIMITATIONS:

1. Computational Complexity: In situations with limited resources, the computational complexity of the suggested architecture may cause difficulties for real-time processing. Subsequent research ought to investigate optimisation tactics aimed at augmenting efficacy.
2. Diversity of Datasets: Despite efforts to employ a variety of datasets, issues with the scarcity of standardised video dehazing datasets continue to arise. Subsequent investigations ought to concentrate on generating more extensive and diverse datasets.
3. Overfitting and Generalization: Deep learning models trained on limited or biased datasets may suffer from overfitting, where they perform well on training data but generalize poorly to unseen conditions. Achieving robust and generalizable dehazing performance across diverse environments and scenarios remains a challenge.
4. Artifact Suppression: Deep video dehazing models may introduce artifacts such as color distortion, ringing effects, or over-smoothing in the dehazed output. Suppressing these artifacts while preserving fine details and textures in the dehazed video sequences is critical for producing high-quality results.
5. Adaptation to Dynamic Scenes: Deep video dehazing models may struggle to adapt to dynamic scenes with moving objects, camera motion, and changes in lighting conditions. Maintaining temporal coherence and consistency across frames while removing haze artifacts in dynamic scenes remains a challenge.
6. Real-World Variability: Real-world video sequences exhibit variability in terms of atmospheric conditions, lighting conditions, and scene dynamics. Deep video dehazing models trained on synthetic or controlled datasets may not fully capture this variability, leading to challenges in model robustness and performance in real-world scenarios.
7. Hardware and Resource Constraints: Deploying deep video dehazing models in resource-constrained environments, such as embedded systems or edge devices, poses challenges in terms of memory usage, computational complexity, and energy efficiency. Optimizing models for efficient inference and deployment on limited hardware is essential.

8. Subjectivity in Evaluation: Evaluating the performance of deep video dehazing models often involves subjective assessments of visual quality and perceptual fidelity.
9. Different evaluation metrics and methodologies may lead to varying results, making it challenging to compare the performance of different dehazing methods objectively.
10. Addressing these challenges and limitations requires interdisciplinary collaboration, innovative algorithmic approaches, and the development of benchmark datasets and evaluation protocols tailored to the specific requirements of deep video dehazing. By overcoming these challenges, researchers can advance the state-of-the-art in video dehazing and unlock its full potential for various applications.

6.2 FUTURE SCOPE

1. Efficiency Gains: Look into methods to raise the model's computational efficiency without sacrificing functionality. Investigating model quantization, pruning, and optimisation techniques are part of this.
2. Long-Term Temporal Dependencies: Especially in situations involving lengthy video sequences, improve the model's ability to capture long-term temporal dependencies. Investigating sophisticated recurrent structures or attention mechanisms may be part of this.
3. Real-Time Processing: To increase the model's practical applicability, give priority to developing a real-time version of the model. This could entail investigating parallel processing methods or performing additional architecture optimisation.
4. User-Centric Features: To improve the model's adaptability to user preferences and particular application requirements, include user-centric features such as interactive controls for changing the dehazing settings.
5. Examine domain adaptation strategies to improve the model's functionality in a range of real-world settings. This entails using domain-specific data to train the model so that it performs better in particular application scenarios.

6. Dynamic Scene Adaptation: Enhancing the ability of deep video dehazing models to adapt to dynamic scenes with moving objects, camera motion, and changes in lighting conditions is essential. Future research can explore techniques for incorporating temporal information, motion estimation, and scene understanding to improve the robustness and accuracy of dehazing in dynamic scenarios.
7. Cross-Modal Learning and Fusion: Leveraging multimodal information, such as depth maps, polarization images, or additional sensor data, can enhance the performance of video dehazing algorithms. Future research can investigate techniques for integrating cross-modal information into deep learning frameworks and learning robust representations across different modalities to improve dehazing performance.
8. Generalization and Domain Adaptation: Ensuring that deep video dehazing models generalize well to unseen environmental conditions, lighting variations, and camera configurations is essential for their practical applicability. Future research can focus on techniques for domain adaptation, data augmentation, and transfer learning to improve model robustness and generalization across diverse scenarios.
9. Artifact Suppression and Quality Enhancement: Addressing artifacts such as color distortion, ringing effects, or over-smoothing in dehazed video sequences is critical for producing high-quality results. Future research can explore advanced techniques for artifact suppression, perceptual enhancement, and image quality assessment to improve the visual quality and naturalness of dehazed videos.
10. Applications in Emerging Domains: Deep video dehazing has the potential to impact emerging domains such as augmented reality (AR), virtual reality (VR), and 360-degree video. Future research can explore applications of dehazing technology in immersive media, interactive experiences, and mixed reality environments to enhance user engagement and immersion.
11. Ethical and Social Implications: As deep video dehazing technology becomes more widespread, it is essential to consider its ethical, legal, and social implications. Future research can investigate issues such as privacy concerns in surveillance applications, biases in dataset selection and algorithmic performance, and the potential impact of dehazing technology on visual perception and interpretation.
12. Overall, the future of deep video dehazing is bright, with opportunities for advancing the state-of-the-art, addressing real-world challenges, and enabling new applications and services. By continuing to innovate, collaborate, and explore new

frontiers, researchers can unlock the full potential of video dehazing technology and make a positive impact on society and the world.

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APPENDIX

```python
import os
import cv2
import math
import numpy as np
import sys

def apply_mask(matrix, mask, fill_value):
    masked = np.ma.array(matrix, mask=mask, fill_value=fill_value)
    print('MASKED=',masked)
    return masked.filled()

def apply_threshold(matrix, low_value, high_value):
    low_mask = matrix < low_value
    matrix = apply_mask(matrix, low_mask, low_value)
    print('Low MASK->',low_mask,'\nMatrix->',matrix)

    high_mask = matrix > high_value
    matrix = apply_mask(matrix, high_mask, high_value)
    print('high MASK->',high_mask,'\nMatrix->',matrix)

    return matrix
```

```python
def simplest_cb(img, percent):
    assert img.shape[2] == 3
    assert percent > 0 and percent < 100

    half_percent = percent / 200.0
    print('HALF PERCENT->',half_percent)

    channels = cv2.split(img)
    print('Channels->\n',channels)
    print('Shape->',channels[0].shape)
    print('Shape of channels->',len(channels[2]))
```

```
out_channels = []
for channel in channels:
    assert len(channel.shape) == 2

    height, width = channel.shape
    vec_size = width * height
    flat = channel.reshape(vec_size)
    print('vec=',vec_size,'\nFlat=',flat)
    print(flat[1009])
    assert len(flat.shape) == 1

    flat = np.sort(flat)

    n_cols = flat.shape[0]

    low_val  = flat[math.floor(n_cols * half_percent)]
    high_val = flat[math.ceil( n_cols * (1.0 - half_percent))]
    print(math.floor(n_cols*half_percent))
    print(math.ceil(n_cols*half_percent))
    print(math.floor(n_cols*(1-half_percent)))
    print(math.ceil(n_cols*(1-half_percent)))
```

GLOSSARY

Dehazing:The technique of improving visibility in photos or movies by eliminating haze or airborne particles.

Deep Learning: A branch of machine learning that uses multi-layered neural networks to learn hierarchical data representations.

CNN, or convolutional neural network:A kind of deep neural network that is frequently used in image and video analysis and is intended to interpret organised grid data.

Haze : A phenomenon in the atmosphere that scatters light, making objects less visible and causing pictures and movies to lose contrast and colour.

Enhancement of Imagery: Enhancing an image's visual quality, usually by adjusting its brightness, contrast, and colour.

The model of atmospheric scattering:A mathematical model that describes how light interacts with air particles to affect how images appear.

Map of Transmission: An essential map for dehazing algorithms that shows the percentage of light passing through the atmosphere.

Dim Channel Previous:The presumption that photographs free of haze include local black pixels in specific channels; this assumption is frequently taken advantage of by dehazing algorithms.

Processing based on patches: A method for processing images or videos that is frequently employed in dehazing techniques and involves the independent analysis of tiny sections, or patches.

Loss Mechanism:A function used in neural network training to quantify the discrepancy between expected and actual values.

Generic Adversarial Network, or GAN : A particular kind of deep learning model made up of two neural networks—a discriminator and a generator—that were trained concurrently to

Fine-tuning:The process of further training a pre-trained model on a specific task or dataset to improve its performance.

Quantitative Evaluation Metrics:Objective measures used to assess the performance of a dehazing model, such as PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index).

Temporal Consistency: The stability of dehazing results across consecutive frames in a video sequence.

Real-time Processing:The capability of a system to process video frames in a timeframe that matches the speed of acquisition, ensuring smooth and continuous output.

Hardware Acceleration:The use of specialized hardware, such as GPUs or TPUs, to speed up the computation-intensive tasks involved in deep learning.

Training Dataset:A collection of input-output pairs used to train a deep learning model.

Validation Dataset: A separate dataset used to evaluate the performance of a model during training and fine-tuning.

Transfer Learning: A machine learning technique where a model trained on one task is adapted to perform a different, but related, task.

Multi-Scale Processing: The analysis or manipulation of an image or video at multiple resolutions or scales to capture both global and local information.

Adversarial Training:A training strategy involving the simultaneous optimization of a model and an adversarial network to generate more realistic outputs.

Optical Flow:The pattern of apparent motion of objects between consecutive frames in a sequence, crucial for understanding dynamic scenes.

Domain Adaptation:The process of adapting a model trained on one domain to perform well in a different but related domain.

Non-Local Means:A denoising technique that considers the similarity between image patches at different spatial locations.

Residual Learning: A neural network architecture that learns residual functions, facilitating the training of very deep networks.

Inference Time:The time it takes for a trained model to process input data and produce output, crucial for real-time applications.

Hyperparameter Tuning:The process of optimizing the configuration settings (hyperparameters) of a model to improve its performance.

Recurrent Neural Network (RNN): A type of neural network designed for sequence modeling, capable of capturing temporal dependencies in data.

Batch Normalization: A technique used to improve the training of neural networks by normalizing the input of each layer within a mini-batch.

Kernel Size:The dimensions of the convolutional kernel used in CNNs, affecting the receptive field and feature extraction.

Spatial Attention: A mechanism in deep learning models that focuses on specific regions of an image or video, enhancing the importance of informative areas.

JPEG Artifacts:Distortions introduced during the compression of images in the JPEG format, which can impact dehazing algorithms.

Post-Processing:Additional steps applied after the initial processing to refine or enhance the output of a dehazing algorithm.

Dense Prediction:The generation of pixel-wise predictions for an entire image, often used in semantic segmentation tasks.

Image Fusion: The combination of information from multiple images or modalities to create a composite image with improved quality or information content.

Spatial Resolution:The level of detail or sharpness in an image, often expressed in terms of pixels per unit area.