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INTELLIGENT SMOKE AND HAZE REMOVAL USING MACHINE LEARNING

Vaduganathan D[1], Navaneethan S[2], Sridhar V V[3], Guru Shalinaa T[4]

[1]Assistant Professor, Dept of CSE, Erode Sengunthar Engineering College, Perundurai.
[2,3,4] Student, Dept of CSE, Erode Sengunthar Engineering College, Perundurai.

ABSTRACT :

This project focuses on the development of an intelligent system for real-time smoke and haze removal from video streams using machine learning techniques. The core of the system is powered by a Convolutional Neural Network (CNN) trained to detect and reduce atmospheric distortions caused by smoke, fog, or haze. By leveraging a diverse dataset of videos affected by various levels of haze and smoke, the system is designed to generalize across different environmental conditions, ensuring clarity and visibility in challenging visual scenarios. The model enhances critical visual details, making it ideal for applications such as surveillance, autonomous navigation, and environmental monitoring. The intelligent de-hazing system significantly improves video clarity, facilitating better decision-making and operational efficiency across industries reliant on visual accuracy in obscured environments.

Keywords—Intelligent De-hazing, Smoke Removal, Atmospheric Distortion, Image Enhancement, Haze Reduction, Fog and Haze Detection.

Introduction:

In many real-world environments, visibility is frequently compromised due to atmospheric conditions such as haze, fog, or smoke. These elements, rich in airborne particles, scatter and absorb light, resulting in diminished visual clarity. Whether in urban areas impacted by pollution or natural landscapes affected by wildfires, these conditions significantly impair our ability to see clearly, particularly over long distances. The reduction in visibility caused by such conditions can have far-reaching effects across a variety of industries.

For critical activities such as surveillance, the ability to capture clear, high-resolution images and videos is essential. Law enforcement agencies, security personnel, and traffic management systems rely heavily on visual data to monitor public safety and control traffic flow. However, the presence of haze or smoke can blur visual feeds, making it difficult to detect important details like license plates, facial features, or movement patterns. Consequently, this compromises the ability to respond effectively to potential threats or incidents. By improving visibility, the Intelligent De-hazing system can have a transformative impact on a wide range of industries.

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Haze and atmospheric distortions also present challenges in environmental monitoring and research. Scientists and conservationists use visual data to track wildlife, monitor deforestation, and observe environmental changes. When these visuals are blurred by fog or smoke, it reduces the accuracy of their observations and limits their ability to make informed decisions regarding conservation efforts. Clear images are vital for documenting changes in ecosystems and responding to environmental crises.

Fortunately, recent advancements in machine learning (ML) have opened up new possibilities for overcoming these challenges. In particular, Convolutional Neural Networks (CNNs), a type of deep learning algorithm specialized for image processing tasks, have shown tremendous promise in enhancing images and videos. CNNs can be trained to detect patterns of distortion caused by atmospheric conditions and apply intelligent corrections, thereby restoring clarity to affected visuals.

Ultimately, this project aims to provide a robust solution to the problem of haze-induced visual impairment. By utilizing the power of ML and CNNs, the system offers an advanced method for enhancing video clarity, contributing to improved safety, operational efficiency, and decision-making in haze-affected environments. This innovation holds great potential to address the visibility challenges posed by atmospheric conditions across multiple industries and applications.

LITERATURE SURVEY:

1. "A Framework for Objective Evaluation of Single Image De-Hazing Techniques" [1]

Image de-hazing has gained significant attention in recent years due to the increasing need for enhanced visibility in hazy environments. Haze, fog, and smoke cause scattering and absorption of light, resulting in reduced visual clarity, which poses significant challenges across various fields such as surveillance, navigation, and environmental monitoring. Early image de-hazing methods were based on traditional image processing techniques like histogram equalization and contrast adjustment, but they often produced poor results when handling complex haze conditions. These methods relied on physical models, such as Koschmieder's law, which explains the relationship between scene radiance and observed intensity in hazy conditions. The **Dark Channel Prior (DCP)**, proposed by He et al. in 2009, emerged as one of the most widely used techniques based on physical models. It assumes that in a haze-free image, one color channel will have low intensity at most pixels. While DCP and other filtering techniques like bilateral filtering and guided filtering offered some improvement, they suffered from common drawbacks such as halo artifacts and over-saturation.

2. "Underwater Images Enhancement by Revised Underwater Images Formation Model" [2]

Underwater image enhancement has become a crucial area of research due to the increasing importance of underwater exploration for applications such as marine biology, underwater archaeology, and autonomous underwater vehicles. The primary challenge with underwater images is the significant loss of visibility and color fidelity caused by the absorption and scattering of light as it travels through water. Unlike in-air images, underwater images suffer from color distortions, reduced contrast, and blurring due to the medium's varying optical properties, such as depth, turbidity, and light wavelength absorption. These challenges necessitate the development of specialized enhancement techniques.Traditionally, underwater image enhancement techniques have been divided into two main categories: **image restoration** and **image enhancement**. Image restoration methods, based on the **Underwater Image Formation Model (UIFM)**, aim to reverse the physical degradation by modeling the interaction between light and water. Early models, like those based on **Koschmieder's law**, attempted to decompose an underwater scene into its different components of attenuation and scattering. However, these methods often performed poorly in highly turbid environments or when depth information was unavailable. In recent years, **deep learning** has emerged as a powerful tool for underwater image enhancement. Models based on **Convolutional Neural Networks (CNNs)**, such as **Water- Net** and **UWGAN**, have demonstrated the ability to learn complex patterns of light propagation in underwater environments. These data-driven approaches have significantly outperformed traditional models by utilizing large datasets of underwater images to generalize across a variety of conditions. However, deep learning models rely heavily on the quality and diversity of training data, which can limit their performance in previously unseen or rare underwater conditions.

3. "A Practical Calibration Method for RGB Micro-Grid Polarimetric Cameras" [3]

Polarimetric imaging has become an increasingly valuable tool in various fields such as remote sensing, biomedical imaging, and computer vision, due to its ability to capture polarization information that provides additional insights into the texture, material composition, and surface orientation of objects. **Micro-grid polarimetric cameras** have emerged as a compact and practical solution for acquiring polarization data, with each pixel of the image sensor equipped with a polarizer oriented at different angles. One prominent type is the **RGB micro-grid polarimetric camera**, which captures both color and polarization information, allowing for richer scene interpretation. Calibration is a critical step in the deployment of these cameras, as it corrects for errors and inaccuracies introduced during the image acquisition process, such as misalignment between the micro- polarizers and the image sensor, variations in pixel response, and color polarization dependencies. Early approaches to calibrating polarimetric cameras often involved complex laboratory setups and time-consuming procedures. For instance, traditional calibration methods relied on mechanical rotation of external polarizers or specialized calibration targets, making the process cumbersome and impractical for field applications.

4. "Multi-Scale Boosted Dehazing Network with Dense Feature Fusion Supplementary Material" [4]

Image dehazing has become a critical area of research in computer vision due to its practical significance in enhancing visual clarity for applications like autonomous driving, video surveillance, and environmental monitoring. Haze, caused by the scattering of light through particles such as dust, fog, and smoke, severely degrades image quality by reducing contrast and color fidelity. Early methods of image dehazing were primarily based on **physical models**, such as the **atmospheric scattering model**, which sought to estimate the transmission map and airlight to recover the haze-free image. These methods, while theoretically sound, often struggled with real-world complexities like varying haze densities and scene depth. To address these challenges, researchers have turned to deep learning techniques, particularly **Convolutional Neural Networks (CNNs)**, for end-to-end learning of dehazing. Initial CNN-based dehazing models, such as **DehazeNet** and **AOD-Net**, successfully demonstrated the advantages of learning haze-related features directly from data. However, these early models were typically designed with a single-scale feature extraction approach, which limited their ability to capture the hierarchical and multi- scale characteristics of haze.

5. "A Trainable Monogenic ConvNet Layer Robust in Front of Large Contrast Changes in Image Classification" [5]

The development of image classification models has seen remarkable improvements with the advent of deep learning techniques, particularly **Convolutional Neural Networks (CNNs)**. However, one persistent challenge in image classification is maintaining robustness in the face of large contrast changes. Variations in lighting and contrast often cause CNNs to struggle in extracting consistent features, leading to degraded classification performance. Traditional CNN layers are sensitive to such changes, as they rely heavily on pixel intensity distributions, which are directly influenced by contrast and illumination variations. The **monogenic signal representation**, based on the principles of phase congruency, provides a way to describe an image using amplitude, phase, and orientation information. Unlike traditional pixel-based methods, the monogenic signal separates the local phase and amplitude of an image, making it less sensitive to contrast variations. This representation has proven effective in areas like texture analysis and feature detection, but its integration into deep learning frameworks has been limited. Recent research has proposed a **trainable monogenic ConvNet layer** that incorporates the monogenic signal into the architecture of CNNs to enhance robustness to contrast changes. This approach builds upon the idea that the monogenic representation can extract intrinsic image features that remain stable under varying contrast conditions. By making the monogenic signal trainable, the network can adapt and fine-tune these features during the learning process, leading to more robust performance across different contrast levels. In conclusion, the introduction of a **trainable monogenic ConvNet layer** represents a promising advancement in the field of image classification. By embedding the monogenic signal into CNN architectures, this approach addresses one of the key limitations of traditional models: sensitivity to contrast changes. The adaptability of this layer, combined with its robustness to illumination variations, offers significant potential for improving classification performance in challenging visual environments.

6. "An End-to-End Network for Image De-Hazing and Beyond" [6]

The problem of image de-hazing has been extensively studied in recent years, especially as the demand for clear images in various applications like autonomous driving, aerial imaging, and outdoor surveillance has grown. Haze, caused by the scattering of light by atmospheric particles such as dust, smoke, and water droplets, significantly reduces visibility and affects image quality. Traditional de-hazing techniques include prior-based methods like **dark channel prior (DCP)** and **atmospheric light estimation**, which rely on assumptions about the scene but often fail in complex environments or when such assumptions do not hold. While these methods perform adequately in specific scenarios, they typically suffer in real-time applications and fail in more dynamic or diverse scenes. With advancements in deep learning, **end- to-end de-hazing networks** have emerged as powerful solutions, removing the need for hand-crafted features or priors. These networks, based on **Convolutional Neural Networks (CNNs)**, directly learn the haze removal process from large datasets. An end-to-end network processes the input hazy image and outputs a clear image, learning the necessary features automatically during training. This approach significantly improves the adaptability of de- hazing techniques across varying conditions and environments. In recent research, **multi-scale architectures** and **attention mechanisms** have been incorporated into these networks to enhance performance further. Multi-scale networks allow the model to focus on both global scene understanding and local details, while attention mechanisms enable the network to concentrate on regions most affected by haze. These innovations have led to impressive results in terms of clarity and detail preservation in de-hazed images.

7. "Deep Learning Strategies for Analysis of Weather- Degraded Optical Sea Ice Imagesg" [7]

The analysis of sea ice images is critical for climate monitoring, maritime navigation, and environmental research. However, optical sea ice images are often affected by weather conditions such as fog, haze, snow, and clouds, which obscure visual details and make image interpretation challenging. Traditional image enhancement and restoration techniques have been used to address these issues, but they often fall short when dealing with complex and highly dynamic weather patterns. In recent years, deep learning has emerged as a powerful tool for processing and analyzing weather-degraded sea ice images. Convolutional Neural Networks (CNNs), in particular, have demonstrated strong performance in various image restoration tasks, including haze removal, contrast enhancement, and denoising. These networks automatically learn features from large datasets, allowing them to adapt to different degradation patterns caused by weather conditions. Some of the earliest applications of deep learning in this domain focused on using CNNs to enhance the visibility of sea ice in satellite images, improving the accuracy of ice classification and segmentation.

8. "Underwater Image Restoration via Constrained Color Compensation and Background Light Color Space-based Haze-Line Model" [8]

Underwater image restoration has garnered significant attention due to the challenges posed by the aquatic environment, such as color distortion, scattering, and poor visibility. The absorption and scattering of light in water cause images to appear hazy, with colors often appearing overly green or blue due to the differential absorption of wavelengths. Traditional methods like histogram equalization and contrast stretching have been employed to address these issues, but they often struggle with severe color distortion and the complex interactions of light with particles in water. Recent advances in image processing have led to more sophisticated models for underwater image restoration. One such approach is based

on **haze-line models**, originally developed for terrestrial de-hazing but adapted for underwater environments. These models leverage the relationship between the depth of underwater scenes and the intensity of scattered light to estimate the scene's background light and transmission map. This method has proven effective in estimating the haze caused by scattering, but the presence of varying color distortion still presents a significant challenge

9. "Light-DehazeNet: A Novel Lightweight CNN Architecture for Single Image Dehazing" [9]

Light-DehazeNet: A Novel Lightweight CNN Architecture for Single Image Dehazing has emerged as a solution to address the growing demand for real-time image dehazing in environments with limited computational resources, such as mobile devices and embedded systems. Image dehazing techniques have traditionally relied on complex deep learning models, often requiring significant computational power and memory. Early methods, such as dark channel prior (DCP) and atmospheric scattering models, laid the groundwork for haze removal by estimating transmission maps and background illumination. However, these approaches were limited by their inability to generalize across diverse haze conditions and scene complexities. As deep learning gained prominence, more advanced methods, particularly using **Convolutional Neural Networks (CNNs)**, significantly improved the quality of haze removal. Models like AOD- Net and DehazeNet utilized deeper architectures with multiple layers to extract features and predict clear images from hazy inputs. While these architectures produced high- quality results, they often required extensive computational resources, making them impractical for real-time applications in constrained environments. This is where **Light-DehazeNet** offers a significant improvement by proposing a lightweight yet effective architecture.

10. "Automatic Early Detection of Wildfire Smoke With Visible Light Cameras Using Deep Learning and Visual Explanation" [10]

The topic of **Automatic Early Detection of Wildfire Smoke with Visible Light Cameras Using Deep Learning and Visual Explanation** has gained increasing attention due to the growing threat of wildfires, which have devastating environmental and economic impacts. Traditional methods of wildfire detection, such as satellite- based monitoring, human surveillance, and sensor networks, often suffer from delayed response times and limited accuracy, especially when early signs of wildfire are subtle and not easily distinguishable. These methods are also hindered by environmental factors, such as clouds, fog, or haze, which can obstruct visibility. As a result, researchers have turned to **deep learning** and **computer vision** techniques, particularly using visible light cameras, to automate the early detection of wildfire smoke. The application of deep learning in wildfire detection has been explored extensively in recent years. Early approaches employed **Convolutional Neural Networks (CNNs)** for image classification tasks, leveraging large datasets of smoke and non-smoke images to train models capable of distinguishing between normal environmental conditions and the presence of wildfire smoke. These models, including architectures like **VGGNet** and **ResNet**, have demonstrated high accuracy in identifying smoke patterns in static images. However, early detection remains challenging due to the often indistinct and dispersed nature of smoke in its initial stages, which may not be immediately obvious to human observers or traditional algorithms.

11. "De-smokeGCN: Generative Cooperative Networks for Joint Surgical Smoke Detection and Removal" [11]

De-smokeGCN: Generative Cooperative Networks for Joint Surgical Smoke Detection and Removal addresses a critical issue in **minimally invasive surgeries (MIS)** where visibility is often compromised due to surgical smoke. This smoke, produced by electrocautery devices during procedures, obstructs the surgeon's view, increasing the risk of errors and prolonging operation time. Traditional smoke evacuation systems help to some extent, but they are not always effective in fully removing the smoke, especially in real-time scenarios. The challenge of surgical smoke detection and removal has led to a growing interest in applying **deep learning** and **computer vision** techniques for automated solutions. Conventional approaches have used **image enhancement** and **denoising algorithms**, such as histogram equalization and wavelet- based techniques, to improve the clarity of images affected by smoke. However, these methods often struggle with real-time performance and fail to generalize well to varying levels of smoke density and illumination conditions in surgical environments. Recent advancements in **Generative Adversarial Networks (GANs)** have shown potential in generating clear, smoke-free images from hazy or smoke-filled inputs. Building on this, **De-smokeGCN** introduces a **Generative Cooperative Network (GCN)**, which leverages both detection and removal tasks simultaneously. This joint approach allows the system to not only identify areas affected by smoke but also to generate a cleaner version of the image, facilitating clearer visualization during surgery. The generative model learns to reconstruct images by removing smoke, while the detection model ensures accurate identification of smoke- affected regions in real-time.

12. "Progressive Negative Enhancing Contrastive Learning for Image Dehazing and Beyond" [12]

The topic Progressive Negative Enhancing Contrastive Learning for Image Dehazing and Beyond explores a novel approach for addressing the challenging task of image dehazing by leveraging contrastive learning, a technique increasingly applied in self- supervised learning and unsupervised representation learning. In traditional image dehazing methods, various models have been developed that rely on atmospheric scattering models, prior-based methods (such as dark channel prior), and more recently, deep learning-based methods that utilize convolutional neural networks (CNNs) to enhance image quality by removing haze. These methods, though effective in some cases, often suffer from limitations when generalizing across varying environmental conditions or handling diverse haze levels. Contrastive learning has shown significant promise in various computer vision tasks by enabling models to learn better feature representations. In contrastive learning, models are trained to pull similar images closer in the feature space while pushing dissimilar ones apart. This paradigm, when combined with dehazing tasks, offers the potential to improve the robustness and generalization of dehazing models. The method introduced in **Progressive Negative Enhancing Contrastive Learning (PNECL)** builds on this concept by progressively learning from negative examples (hazy images) and enhancing the model's ability to distinguish between hazy and clear images in a more structured manner.

13. "Vision Transformers for Single Image Dehazing" [13]

The use of **Vision Transformers (ViTs)** for **single image dehazing** is an emerging research direction, leveraging the powerful capabilities of transformers, initially designed for **natural language processing**, in the field of computer vision. Traditionally, image dehazing techniques have relied on **convolutional neural networks (CNNs)**, which excel at capturing local spatial features but often struggle with capturing long-range dependencies in complex scenes, especially when haze is distributed unevenly. Vision Transformers, on the other hand, inherently model global contextual relationships, making them well-suited for handling the complexity of hazy environments. Recent studies in image dehazing have explored deep learning-based approaches such as **Generative Adversarial Networks (GANs)** and **autoencoders**, which aim to reconstruct clear images from hazy inputs. While effective, these methods can suffer from limitations like loss of fine details or inaccurate color reproduction, particularly in images with dense or irregular haze. ViTs address these challenges by offering a different architecture that divides images into patches and processes them using self-attention mechanisms. This allows the model to focus on relationships between different image regions, capturing both local and global features more effectively.

14. "Contrastive Learning for Compact Single Image Dehazing" [14]

Contrastive learning has emerged as a powerful approach in the field of computer vision, particularly for tasks like image dehazing. Traditional methods for single image dehazing often rely on handcrafted features or explicit models of atmospheric scattering. However, recent advancements have demonstrated that leveraging contrastive learning can significantly enhance the performance of dehazing models by effectively learning robust representations from data. The core idea behind contrastive learning is to train models to differentiate between similar and dissimilar image pairs, allowing them to capture the inherent features that define hazy versus clear images. In the context of single image dehazing, several studies have explored the use of deep convolutional neural networks (CNNs) in conjunction with contrastive loss functions, enabling the model to learn a latent space where clear images are closer together while hazy images are positioned further away. This approach has led to improved generalization capabilities across different haze levels and environmental conditions. Notably, researchers have integrated contrastive learning with generative adversarial networks (GANs) to further enhance visual quality, as these networks can generate high-fidelity images that retain essential details lost in traditional dehazing methods. Moreover, the incorporation of self-supervised learning techniques within contrastive frameworks has shown promise in reducing the reliance on large annotated datasets, making the training process more efficient. Overall, the integration of contrastive learning in single image dehazing represents a significant shift towards data- driven methodologies, enabling more compact and effective models that perform well under varied conditions.

15. "Practical Blind Image Denoising via Swin-Conv-UNet and Data Synthesis" [15]

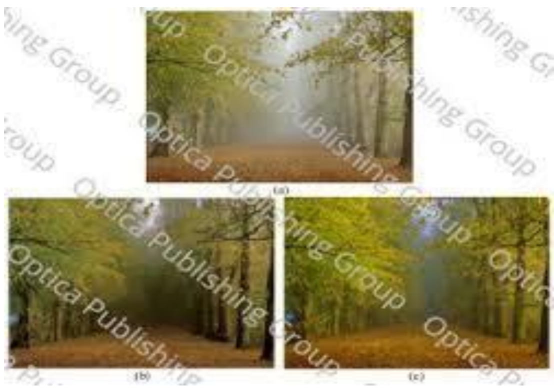
Blind image denoising, a critical challenge in image processing, aims to remove noise from images without prior knowledge of the noise characteristics. Recent advancements in this field have highlighted the effectiveness of deep learning architectures, particularly the Swin-Conv-UNet, which combines the strengths of Swin Transformer and convolutional neural networks (CNNs). The Swin Transformer's hierarchical representation and efficient self-attention mechanisms allow it to capture long- range dependencies and fine-grained details, making it particularly suitable for handling various noise levels and types.

The UNet architecture enhances the model's ability to retain spatial information while downsampling and upsampling features, leading to improved denoising performance. Additionally, data synthesis has emerged as a powerful technique to augment training datasets, particularly when real noisy images are scarce. By generating synthetic noisy images using various noise models and incorporating them into the training process, researchers can create more robust denoising models that generalize better to unseen data. Literature indicates that combining Swin-Conv-UNet with data synthesis significantly improves denoising outcomes across diverse scenarios, including real-world images. Furthermore, studies have shown that this approach not only enhances visual quality but also preserves essential features and textures in the denoised images. As a result, the integration of advanced architectures like Swin-Conv-UNet with effective data synthesis strategies represents a promising direction for practical blind image denoising, paving the way for applications in photography, surveillance, and medical imaging, where noise reduction is critical for accurate analysis.

DISCUSSION :

The development of intelligent smoke and haze removal systems using machine learning (ML) has garnered significant attention due to its potential in improving visibility in various environments affected by atmospheric conditions. Haze, fog, and smoke reduce the clarity of visual data, posing challenges for applications like video surveillance, autonomous vehicles, and environmental monitoring. Traditional image enhancement techniques often fail to effectively mitigate these issues, especially in real-time applications, where speed and accuracy are crucial. In this context, machine learning, particularly deep learning approaches like Convolutional Neural Networks (CNNs), offers a promising solution by enabling automatic and adaptive de-hazing in real-time.

One key challenge in Lack of Ground Truth Data, highlighted in papers such as " A Framework for Objective Evaluation of Single Image De-Hazing Techniques" [1], The provided image seems to present a framework for the objective evaluation of single-image de-hazing techniques. In this context, the framework is likely designed to assess how effectively different algorithms or methods remove haze from images in a quantifiable manner. This is crucial because de-hazing algorithms vary in their performance, and an objective evaluation helps in identifying the best techniques for practical applications.

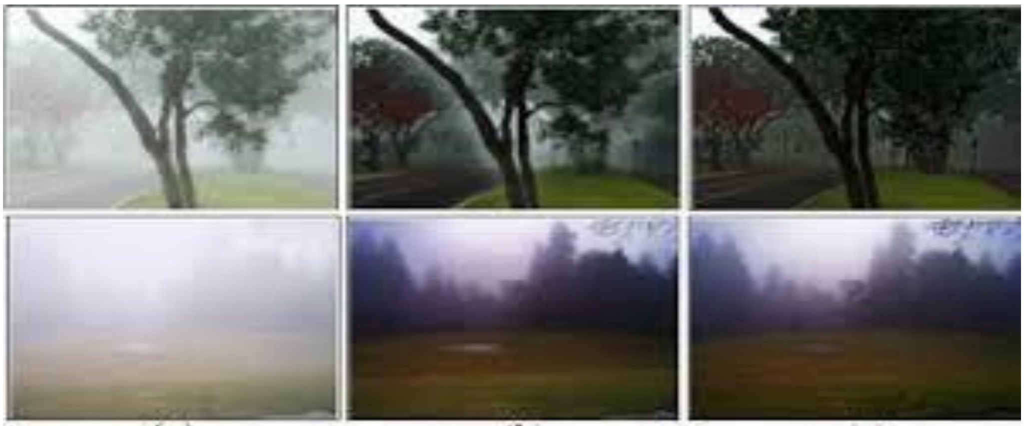


Moreover, the emphasis on Light Absorption and Scattering" Underwater Images Enhancement by Revised Underwater Images Formation Model"[2] In underwater environments, light is absorbed and scattered more significantly than in air, especially at different depths. This affects color and image clarity. Different wavelengths of light (such as red, green, and blue) are absorbed at different rates, which can result in a heavy green or blue tint in underwater images. Addressing the complex interaction of light with water and particles is a major challenge in image enhancement.

Complex Polarimetric Calibration "A Practical Calibration Method for RGB Micro-Grid Polarimetric Cameras"[3]. Polarimetric cameras capture intensity, color, and polarization information. Calibrating these cameras to ensure that the polarization data is accurate across all pixelsin the image is technically complex due to the micro-grid structure, where each pixel measures a specific polarization angle. Misalignment or imprecision in calibration can lead to significant errors in polarization measurements.

The "Multi-Scale Boosted Dehazing Network with Dense Feature Fusion Supplementary Material" [4] Develop a Multi-Scale Boosted Dehazing Network (MSBDN) that employs dense feature fusion to enhance dehazing performance. Extract multi-scale features from hazy images using convolutional layers, fuse these features to retain spatial information, and employ a boosting mechanism to iteratively refine the output, resulting in clear and natural- looking dehazed images.

Another challenge addressed in our project is End- to-End Architecture Design, as discussed in "An End-to- End Network for Image De-Hazing and Beyond" [5]. Designing an end-to-end dehazing network requires a carefully structured architecture that can process hazy images directly without relying on additional intermediate steps. The challenge lies in ensuring that the network can accurately capture and address various haze-related distortions while remaining simple enough to train efficiently.



(a) (b) (c)

The paper "Deep Learning Strategies for Analysis of Weather-Degraded Optical Sea Ice Images" [6] One key approach in using DL for weather-degraded images is image preprocessing. Techniques such as image enhancement, denoising, and deblurring can be applied before feeding the images into the DL model. Preprocessing helps improve the visibility of key sea ice features by compensating for the weather-induced distortions. DL-based models like autoencoders or Generative Adversarial Networks (GANs) can be used to restore degraded images to a more usable form, enhancing the effectiveness of subsequent analysis.

In terms of Maintaining Real-Time Processing, papers such as "Light-DehazeNet: A Novel Lightweight CNN Architecture for Single Image Dehazing" [7] For practical applications, especially in video processing, surveillance, or autonomous systems, **Light-DehazeNet** must be capable of real-time processing. Achieving this while maintaining a lightweight architecture is a challenge,as reducing the network complexity to increase processing speed may reduce the overall dehazing effectiveness, creating a trade-off between speed and quality.

Lastly, Real-Time Processing Requirements"De- smokeGCN: Generative Cooperative Networks for Joint Surgical Smoke Detection and Removal" [8] In surgical environments, the removal of smoke must occur in real time to avoid obstructing the surgeon’s view. One of the main challenges for **De-smokeGCN** is ensuring that the network can process video streams rapidly enough to detect and remove smoke without introducing delays. This is particularly difficult when balancing the need for both accuracy and speed in the detection and dehazing processes.

Convolutional Neural Networks (CNNs) have been widely used in image processing tasks, including haze and smoke removal. By integrating attention mechanisms into CNNs, the model can focus more on the critical areas of the image that are heavily impacted by smoke or haze. Attention mechanisms help guide the network to prioritize regions with significant degradation, improving the accuracy and efficiency of the dehazing process. This combination enhances visual clarity by ensuring that the model processes relevant image features more effectively.

Conclusion :

In conclusion, the Entropy-Optimized Facial Landmark Cryptosystem combines advanced facial recognition and cryptographic techniques to address security challenges in digital transactions. By leveraging innovations from various IEEE papers, it ensures robust recognition under occlusions, low resolution, and uncontrolled environments while maintaining high accuracy and efficiency. This system sets a new standard for secure, biometric-enhanced data transmissions, offering a scalable solution for future applications in IoT, mobile devices, and financial transactions, safeguarding user data in the digital age.

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