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A Survey of Image Enhancement and Dehazing Algorithms to Improving Autonomous Navigation in Fog and Dust.

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Abstract

Video captured during sand-dust weather conditions indicates significant degradation, diminished contrast, and pronounced color distortion. The reason behind this phenomenon is the impact of sand-dust particles, which result in the dispersion and assimilating of light. Consequently, the resultant image seems blurred and lacks contrast. Additionally, the alteration in color is attributed to the swift reduction of blue light. Adverse weather circumstances, such as fog, sand, and dust storms, cause problems with vision for deploying self-driving automobiles. Video enhancement plays a vital role in facilitating vehicular mobility and navigation in both road and air transportation to guarantee secure and seamless operations during frequent adverse weather conditions. To improve the safety and efficiency of operation, it is imperative to employ video dehazing techniques, particularly in adverse weather conditions. The purpose of our overview is to offer interested researchers a thorough and methodical examination of image enhancement approaches, serving as an important point of reference for their work. The text explored different image enhancement methods, along with the challenges, constraints, advantages, and drawbacks associated with using these techniques throughout the past five years. Specifically, it focused on three aspects: supervised algorithms, unsupervised algorithms, and quality evaluation.

Keywords: video enhancement, Low-Light Image and Video Enhancement, Deep Learning, Surveillance Video Visibility, convolutional neural networks.

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1. Introduction

Iraq and the Middle East regions are regularly impacted by severe dust storms during the months of April and May every year. The country's international airports have had to stop flights. Last year, thousands were hospitalized for health complications caused by the extreme weather. Officials believe increased dust storms and extreme weather conditions will continue[1]. Iraq Baghdad International Airport was closing its airspace and halting all flights until further notice because of low visibility [1]. Poor vision and reduced brightness in dusty and foggy weather provide a significant hazard to motorist safety. These circumstances raise the risk of traffic collisions and are a significant contributor to injuries and deaths on roads that are enveloped in dust or fog.

The presence of extremely small droplets in the dust or fog results in the obstruction of light shown in Fig. 1. This results in a decrease in the amount of light that reaches the driver's eye, resulting in poorer contrast and, therefore, less visibility. Enhancing visibility in adverse conditions is a subject that greatly interests' researchers. Multiple research has been conducted to observe and simulate the impacts of different weather conditions on visual systems [2].

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Fig. 1 (a) image in normal weather (b) image in dusty weather (c) image in foggy weather conditions

Image enhancement is a primary objective of image processing. It involves adjusting images to align with the visual response characteristics and emphasizing specific areas of interest by introducing more information or manipulating the existing image data using specific techniques. The primary objectives of image enhancement are to improve the contrast among various elements in images, suppress irrelevant features, enhance image quality, increase the amount of information, enhance image interpretation and recognition, and fulfill the requirements of specific analysis. Automated Driving Systems (ADS) offer new possibilities for future transportation However, perception and sensing for autonomous driving under adverse weather conditions have been the problem that keeps autonomous vehicles (AVs) from going to higher autonomy for a long time [3].

The low visibility increases the risk of accidents and cannot see the obstacles in the road or bad road conditions. Also, dust and fog can cause a sudden reduction in roadway visibility and dramatic changes in driving conditions. This unpredictability of dust and fog formation makes it one of the major causes of motor vehicle crashes [1]. Sandstorms in Iraq have also had a terrible impact on the country's economy, where three of the Iraqi airports closed for several days due to the lack of visibility of the sandstorm [4]. For military ground troops, it affects daily operations of searching for terrorists and also protecting themselves and others from terrorists [5]. Severely hamper visibility, meaning that the transport of gas and oil over land or sea reduces the country's export capacities [6].

We give the latest comprehensive evaluation on video and image improvement in low light using two primary groups: classical and deep learning techniques also numerous studies have been offered for detecting adverse weather.

The remaining parts of the survey are divided into the following categories: A brief background on dust and fog components in section 2. A public dataset for weather details is explained in Section 3. Section 4 provides a literature review that includes adverse weather conditions detection, unsupervised learning visibility enhancement, supervised deep learning visibility enhancement, and image quality evaluation in low-light conditions, and finally conclusion in Section 6 concludes all-weather detection and enhancement techniques.

2. Background

Fog and dust have a substantial effect on sensors and imaging systems, particularly in video-based visibility detection and LiDAR (Light Detection and Ranging). In the case of LiDAR, the presence of fog particles causes the laser beam to scatter, resulting in decreased intensity and accuracy of the measurements. The presence of dense fog can cause point cloud data to become distorted, leading to a decrease in the accuracy of object detection and ranging. Advanced LiDAR systems utilize algorithms to eliminate noise resulting from fog particles [7].

Fog diminishes the contrast and dulls the colors in images captured by cameras that detect visible light. Foggy conditions significantly impair object recognition, lane detection, and scene interpretation by reducing visibility. Image enhancement Algorithms such as dark channel prior and fast-guided filtering improve the visibility of foggy images[1]. Additionally, they can be used with other sensors for further enhancement. Integrating camera data with LiDAR or radar aids in mitigating the reduction in visibility [8].

Essentially, it is essential to comprehend the influence of fog and dust on various sensors to create resilient visibility detection systems. The combination of sensor fusion, sophisticated algorithms, and adaptive sensor selection enhances the dependability of performance in challenging weather conditions.

Fog Detection: Fog greatly reduces visibility, particularly during the periods of sunrise and sunset. It presents hazards to the safety of traffic, aircraft, and public health. Fog is created by the presence of tiny water droplets that are suspended in the air. The appearance of weak solar radiation between sunrise and sunset contributes to it. Precise identification of fog enables effective traffic management, secure transportation, and prompt emergency intervention [8].

Dust Detection: The presence of dust particles in the atmosphere has an impact on the quality of air, climate conditions, and human well-being. Dust originates from both natural sources, such as arid regions and volcanic eruptions, as well as human activity, including construction and cultivation. Traditional de-noise filters improve the quality of LiDAR point clouds in challenging weather conditions, such as the presence of dust. The use of [3] in Dust detection contributes to pollution monitoring, weather forecasting, and early warning systems [7].

3. Public database

There are several adverse weather image datasets available that we can take dusty and foggy images from as we need in our study, but there is no specific dusty and foggy weather image dataset available also, there are currently no notable databases that contain videos about dusty or foggy weather.

3.1 SHRP2 NDS Dataset

It is an image dataset that was divided into two distinct datasets: the training dataset and the testing dataset. The training dataset comprised 8000 images of good weather, 6800 images of far fog, and 1200 images of close fog, totaling 16,000 images and approximately 1,333 minutes of video data. Furthermore, the testing dataset comprised 2000 images depicting clear weather conditions, 1700 images depicting fog at a distance, and 300 images depicting fog in proximity. This dataset included an overall of 4000 images, which is approximately comparable to 333 minutes of video data. The images are in RGB format. The dataset was gathered by [3]. The VTTI exclusively designed the Data Acquisition System (DAS) specifically for the SHRP2 program. The DAS comprises a front radar, four cameras for video, color wide-angle cameras facing ahead, accelerometers, vehicular network data, and a Geographic Positioning System (GPS). The dataset can be accessed via the Virginia Tech Transportation Institute (VTTI) [9].

3.2 FRIDA (fog road image database)

It comprises 18 road scenes and 90 synthetic images of PNG. The Hazy dataset has 35 images with hazy and 35 images without haze, each depicting distinct scenes. The training images are scaled to a resolution of 256 × 256 resolution RGB (color images) and used a 0.001 learning rate. Also, the FRIDA2 dataset comprises 330 synthetic images of 66 varied road scenes. FRIDA and FRIDA2 include distinct types of haze applied to each of the four corresponding images: uniformity fog, heterogeneity fog, cloud haze, and cloud heterogeneity fog. The dataset has been collected by [4]. The dataset is available through the website [10]. A sample of the dataset is shown in Fig. 2 below.

3.3 Detection in Adverse Weather Nature (DAWN)

This dataset has been collected by [11]. The dataset comprises 1,000 RGB (colored images) depicting traffic scenarios, categorized into four primary groups: Fog, rainfall, Snow, and Sands. The database comprises 6,344 items that have been modeled to represent six different types of cars and six distinct groups of pedestrians [5]. The composition of the total includes cars (82.21%), buses (2.05%), trucks (8.22%), motorbikes and bicycles (1.36%), and people (6.07%), it is available through the website [12]. A sample of the dataset is shown in Fig. 3 below

3.4 NH-HAZE dataset

It comprises 55 outdoor scenes, this dataset is the first for a non-homogeneous image dehazing one. This dataset has JPG and ARW (RAW) 5456×3632 resolution of RGB (color images), with 24-bit depth. The dataset was collected by [13]. They used hardware consisting of a tripod and a Sony A5000 camera that can be handled remotely using the Sony RM-VPR1. Every scene capture started via the manual adjustment of the camera's settings. The dataset is available through the website [13]. A sample of the dataset is shown in Fig. 4 below.

3.5 Open-source dataset

This dataset consists of road images illustrating eight distinct categories of climate and roadway circumstances, namely sunny, cloudy, foggy, rainy, wet, clear, snowy, and icy. These images were taken from publicly accessible YouTube videos recorded and shared by 'Alan Z1000sx' we downloaded 25 videos submitted by 'Alan Z1000sx', each with an average period of 8 minutes. We created a Python script that retrieves images from videos at regular intervals of 10 seconds. A grand total of 2,498 images have been extracted for the purpose of annotating images. The dataset has been collected by [14]. They used a surveillance camera installed on the dashboard of a large transport vehicle to record its journeys throughout the United Kingdom. The dataset can be accessed via the website [15]. A sample of the dataset is shown in Fig. 5 below:

3.6 The O-HAZE dataset

It comprises 45 distinct outdoor images that capture identical visual information in both haze-free and foggy circumstances while maintaining consistent illumination characteristics. The dataset has been collected by [8]. The fog had been produced using an expert fog generator that precisely imitates realistic foggy circumstances with high fidelity; the setup comprises items including a tripod for support and a Sony A5000 camera that was operated remotely using the (Sony RM-VPR1 controller). obtained JPG and ARW (RAW) images with a resolution of 5456 × 3632 pixels and a color depth of 24 bits. The dataset is available through the website [16] A sample of the dataset is shown in Fig. 6 below. However, the summary of the dataset is illustrated in Table 1.

(a) (b) (c)

Fig. 2 (a, b, c) sample of the FRIDA dataset

(a) (b) (c)

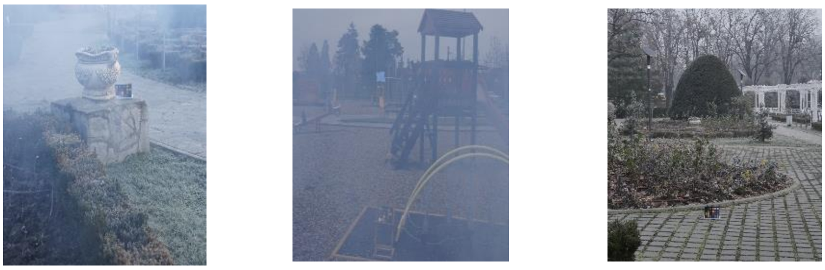
Fig. 3 (a, b, c) sample of the DAWN dataset

(a) (b) (c)

Fig. 4 (a, b, c) sample of the NH-HAZE dataset

(a) (b) (c)

Fig. 5 (a, b, c) sample of the Open-source dataset



(a) (b) (c)

Fig. 6 (a, b, c) sample of the O-HAZE dataset.

Table: 1 The summary of the datasets

No.	Reference	Dataset	Type	Available or not
1	Khan and Ahmed [1]	SHRP2 Naturalistic Driving Study (NDS) video data	Video	N/A
2	G. Zahra et al., [9]	FRIDA dataset	Image	Available
3	M. Zaman, et al., [3]	DAWN	Image	Available
4	Y. Si, F. Yang, and Z. Liu [10]	NH-HAZE dataset	Image	Available
5	C. Peláez-Rodríguez et al. [11]	open-source dataset	Image	Available
6	Z. Shuker [12]	O-HAZE dataset	Image	Available

4 Literature review

This section provides a concise overview of Deep Learning (DL) and its application in detecting adverse weather conditions and improving the quality of images and videos, specifically in the context of evaluating scenes captured by cameras in adverse weather conditions. Accurately assessing visibility levels is essential for the purpose of monitoring and enabling autonomous driving. In recent years, the need to utilize Vision-based cars and pedestrian recognition systems to ensure road safety has significantly increased [14]. Automated vehicle visibility enhancement and pedestrian identification and tracking systems must be developed to address meteorological conditions that can change visibility, such as dusty and foggy weather.

4.2 Adverse Weather Conditions Detection

Detecting adverse weather conditions is an important occupation in computer vision, particularly for outside applications such as autonomous cars, surveillance, and environmental monitoring. Accurately detecting objects in difficult weather circumstances, such as fog, rain, dust, or snow. Obtaining distinct characteristics from weather

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images or videos is exceedingly challenging because of the wide range of weather conditions [15].

Al-Haija et al., [28], present a detection system based on deep learning (DL) to classify weather conditions for autonomous cars in both unfavorable and regular settings. The system employs the transfer learning approaches and the powerful Nvidia GPU to assess the efficacy of the three deep convolutional neural network models (CNNs): Squeeze Net, ResNet-50, and Efficient Net. The created models have been assessed using weather imaging datasets, specifically DAWN2020 and MCWRD2018.

Rajabi et al., [29], the authors suggested an approach that utilizes transfer learning and fine-tuning techniques to implement EfficientNet-B0 and EfficientNet-B4 convolutional neural networks (CNN). Additionally, two comparative models, ResNet-50 and ResNet-101, are employed with transfer learning. The suggested model is assessed using a compiled composite dataset, which consists of five distinct datasets and encompasses five meteorological circumstances: rain, snow, fog, clouds, and dusty particles. The occurrence of Incorrect labeling has been decreased in the merged dataset.

Deepak et al. [15], the authors suggested an approach that utilizes a combination of Histogram of Gradient (HOG) and deep features, as well as feature selection/reduction and classification. it conducted thorough tests on the benchmark datasets, employing different approaches for feature extraction and selection/reduction, in combination with multiple classifiers. The comprehensive experimental evaluation shows that combining HOG and DenseNet-161 features with a linear SVM classifier provides the highest classification accuracy of 99.65% and 95.2% for the MCWRD and MWI datasets, respectively

To summarize, these studies discuss crucial obstacles in weather sensing for autonomous vehicles. The first study primarily addresses the concepts of robustness and real-time inference, whereas the second paper places greater emphasis on multi-modal inputs and interpretability. The last approach emphasizes the integration and selection of features to improve the accuracy of weather detection from individual images. The proposed approach attains a high degree of accuracy but individual images may not include all necessary visual clues for weather identification. For example, a sky filled with clouds may resemble fog or haze in a static image [15].

4.3 Unsupervised Learning Visibility Enhancement

Unsupervised Learning Visibility Enhancement is an interesting field of study that seeks to enhance the appearance and overall quality of images without the need for paired training data. Unsupervised procedures utilize the inherent characteristics of the data itself, compared to supervised methods which rely on a large number of labeled samples [16]. Low-light image improvement approaches based on deep learning often necessitate a large amount of paired training data, which is not feasible to get in real-world situations. In recent times, there has been a focus on investigating unsupervised methods to reduce the need for paired training data. Nevertheless, their performance in many real-world situations is inconsistent because of the lack of past knowledge [17]. Extensive research has been conducted on conventional methods to improve video visibility when fog and dust are present below:

1. Image filtering is a technique used to decrease noise and improve important characteristics in an image. The conventional methods
2. Median Filtering: Eliminates salt-and-pepper noise resulting from the presence of dust particles.
3. Gaussian Filtering: This applies a smoothing effect to the image, minimizing the visibility of graininess caused by fog.
4. Bilateral Filtering: Maintains the integrity of edges while simultaneously decreasing noise [18].

Also, many studies use contrast enhancement techniques to improve visibility by reducing dust and fog, and many techniques and approaches for enhancing visibility have been suggested in previous studies.

Al-Ameen [14], the author present an approach that employs optimized fuzzy intensification operators, is proposed to handle low-quality images taken in adverse dusty weather conditions efficiently.

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More precisely, it excelled in delivering satisfactory color reproduction and revealing intricate features in the processed images.

The authors in the references [19] Suggest a rapid and efficient system for improving images in sand-dust weather circumstances. Initially, adjust due to the decrease in the blue channel's value. Next, a white balancing technique is employed to rectify the image's hue, which has been degraded by sand particles. Guided filtering of images is employed for improve image contrast and edge precision. An adaptive approach is utilized to determine the scaling factor of the detail layer, hence enhancing the level of detail in the image

Whereas, in reference [17] the authors present an unsupervised low-light image-enhancing method using the histogram equalization prior (HEP) is proposed. It creates a HEP with abundant texture and brightness data. When embedded in a Light Up Module (LUM), it decomposes low-light images into illumination and reflectance maps, which can be considered restored images. Reflectance maps are corrupted by noise, as shown by the Retime theory derivation. it also developed a Noise Disentanglement Module (NDM) to separate noise and content in reflectance maps using unpaired clean images. The histogram equalization prior and noise disentanglement enable this method to enhance detail recovery and reduce noise in low-light situations.

[20] present an enhancement technique to achieve a chromatic histogram that aligns perfectly. It proposes a pixel-adaptive color correction technique that utilizes the mean and standard deviation of chromatic histograms. The adjustment of pixel values for each color component is determined by the statistical properties of the green component. Furthermore, a color normalization technique that preserves the mean of the green channel is introduced. Nevertheless, employing the average of the red and blue components as the average of the green component can yield an unfavorable result since the red or blue components of several sand-dust images possess a narrow histogram with a prominent peak. To tackle this issue, we suggest implementing a histogram shifting technique that maximizes the alignment between the red and blue histograms with the green histogram. By implementing this approach, the occurrence of bluish or reddish artifacts in the improved image can be minimized. Ultimately, image modification is utilized to enhance the brightness of the sand-dust image.

A fog model that effectively eliminates fog from hyperspectral images has been proposed in [21]. Initially, a fog density map is computed by distinguishing the averaged bands that belong to the visible and infrared spectral ranges. Subsequently, the level of haze in various spectral bands is determined by analyzing the pixel reflectance of two selected pixels with varying degrees of haze. Ultimately, the superior hyperspectral image is recovered through the resolution of the defogging model.

Li et al. [23] A hazy image improvement strategy based on dark channel priority is introduced. The program first improves the clarity of the transmitted light and then enhances the value of the outside light. It then translates the restored image to the HSV color space. Furthermore, the MSRCR technique, strengthened by bilateral filtering, improves the brightness V component. Additionally, the adaptive stretching algorithm enhances the saturation S. Eventually, the image undergoes a conversion from HSV color space to RGB color space to finalize the process of image improvement. The novel approach effectively addresses the issues of uneven color distribution in broad areas and even overall darkening the image while applying the old dark channel technique for fog removal.

4.4 Supervised deep Learning Visibility Enhancement

In recent years, there has been considerable interest in the use of supervised deep learning for improving visibility. Investigators have investigated several neural network structures and methods of measuring error to enhance the clarity of images in difficult situations, such as low lighting or bad weather conditions [24].

Zahra et al., [9] present a method for enhancing the visibility of foggy and hazy images by using a Conditional Generative Adversarial Network (CGAN). The CGAN consists of dual networks, namely the generator and discriminator, which have different characteristics. The generator network produces clear images from images containing fog, whereas the discriminator network differentiates between restored and original images without fog.

Lv et al., [25] Introduce the multi-branch low-light enhancement network (MBLLEN). The main concept is to extract diverse and specific characteristics at many levels. This allows us to enhance the image using numerous subnetworks and ultimately generate the output image through the fusion of multiple branches.

Ding et al. [22], the authors enhance the resolution of compressed surveillance video frames. Enhancing visual perception and ensuring precise analysis are crucial in surveillance applications. A Residual Squeeze-and-Excitation Network (RSE-Net) is proposed to address the challenge of frame augmentation. The problem at hand is a regression problem, where the objective is to consider frame enhancement as a regression work. The goal is to predict high-quality frames based on the compressed ones. The approach used for this task is called RSE-Net. The network design includes residual connections and squeeze-and-excitation blocks. These components aid in capturing pertinent characteristics and improving the quality of the frame. This showcases enhanced video resolution, making it highly helpful for monitoring purposes

Li et al., [24], the authors introduced the Improved Deep Network for Convolutional Low-light Images Enhancement (EDLLIE-Net) to improve the quality of low-light images. The EDLLIE-Net improves the process of identifying and extracting characteristics using the MSR technique yet it fails to preprocess the original color image. This lack of preprocessing may affect further segmentation in the absence of an improvement in the feature representation. from the beginning.

Liu et al., [26], Based on the CycleGAN network idea, created a learning system that utilizes unpaired fog and fog-free training images, adversarial discriminators, and cycle consistency losses to autonomously build a fog removal system. Our method, like CycleGAN, consists of two transformation paths. One line converts fog images into a fog-free image domain, while the other path converts fog-free images into a fog image domain. Our method employs a two-step mapping strategy in each transformation path, rather than a single-stage mapping, to improve the efficacy of fog removal. In addition, it incorporates prior knowledge into the networks by incorporating the atmospheric deterioration concept and a sky prior. This allows us to map fog-free images to the fog image domain.

4.5 Image Quality Evaluation in Low-Light Conditions

The researchers used numerous criteria to evaluate and compare the selected approaches for enhancing low-light images.

A qualitative assessment: Human perception is used to compare the augmented image to the low-light image for qualitative evaluation. It usually involves showing people the same low-illumination image processed by several algorithms and asking them to choose the best method based on visual judgment. However, external influences can contribute to subjectivity and make it difficult to set a norm in qualitative evaluation. Personal aesthetics, color preferences, and observation angles can affect decision-making. These subjective considerations make standardized and scientific subjective judgment difficult. Qualitative evaluation can reveal the visual impression and overall preference for enhanced images, but it has limitations and biases. Thus, it is typically used with quantitative evaluation methods like PSNR and SSIM, which provide more standardized and measurable criteria for evaluating image enhancement systems [27].

Quantitative Assessment: evaluates image enhancement techniques using certain criteria and measurements. This evaluation approach uses mathematical models to compare original and improved images and create image quality indicators. The simplicity, computing efficiency, and ability to deliver quantitative assessments based on known models make quantitative evaluation procedures stable and reproducible. This article compares PSNR and SSIM evaluation indicators. These quantitative evaluation metrics allow direct comparisons and performance analysis of image-enhancing methods [27].

5 Analysis and discussion

In this research, we have mentioned adverse weather conditions image detection, and enhancement for improving autonomous navigation in fog and dust. The primary objectives of image enhancement are to improve the contrast among various elements in images, suppress irrelevant features, enhance image quality, increase the amount of information, enhance image interpretation and recognition, and fulfill the requirements of specific analysis. We give the latest comprehensive evaluation on video and image improvement in low light using two primary groups: classical and deep learning techniques also numerous studies have been offered for detecting adverse weather. Essentially, it is essential to comprehend the influence of fog and dust on various sensors to create resilient visibility detection systems. We explored different image enhancement methods, along with the challenges, constraints, advantages, and drawbacks associated with using these techniques throughout the past five years. Specifically, it focused on three aspects: supervised algorithms, unsupervised algorithms, and quality evaluation.

Our study distinguishes itself from the previous studies by considering that we use a video dataset that is not available at the ultimate time and collect the dataset by ourselves which is specified for Iraq and the Middle East. Also, we use deep transfer learning with specific parameters to train this dataset and detect the two types of low-light video weather and finally, we use unsupervised learning models to enhance the video dataset. As shown in Table 2 a comparison among several surveys.

Table: 2 Comparison of several surveys on visibility enhancement

Existing surveys	Use deep learning	Unsupervised learning	Dataset	Comparison among different mechanism
Al-Ameen et al. [14]	*	Fuzzy	DAWN	*
Deepak et al. [15]	DL	HOG	benchmark datasets	HOG and DenseNet-161 features with a linear SVM classifier
Qasem et al. [17]	TL	*	DAWN2020 and MCWRD2018	*
Farshid [18]	TL& fine-tuning	*		ResNet-50 and ResNet-101
YAQIAO et al. [19]	*	Blue channel value & white balance technique	*	*
Zhang et al. [17]	*	low-light image enhancing	*	*
Tae et al. [20]	*	pixel-adaptive color correction	*	*
Xudong et al. [21]	*	defogging model	*	*
Dan et al. [20]	*	dark channel priority	*	*
Feifan et al. [25]	MBLLEN	*	*	*
Ding et al. [22]	RSE-Net	*	*	*
Ke et al. [24]	EDLLIE-Net	*	*	*
Wei et al. [26]	CycleGAN network	*	*	*
Ghulfam et al. [9]	CGAN	*	*	*
Our study	TL to classify video dataset	Use different models of unsupervised learning (multispectral, lowlight video enhancement, fog rectification video enhancement)	Collect datasets from Iraq and the Middle East	Comparison between different unsupervised learning models

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6 Conclusion

Improving the visibility of video and images taken in dusty weather using a fine-tuned tri-threshold method. Fuzzy Intensification Operators focus on the problem of degraded image quality resulting from adverse dusty weather conditions. Additionally, it enhances the process of darkening images and prevents any type of distortion across several file formats such as TIFF, JPEG, BMP, GIF, PNG, and PSD.

When compared to other enhancement algorithms such as CLAHE (Contrast Limited Adaptive Histogram Equalization), DCP (Dark Channel Prior), SSR (Single-Scale Retinex), MSR (Multi-Scale Retinex), and MSRCR (Multi-Scale Retinex with Color Restoration), it demonstrates superior performance as measured by PSNR, SSIM, and IE.

The objective of the Fast Sand-Dust Image Enhancement Algorithm is to enhance image quality taken in sand-dust weather conditions. This is achieved through the use of blue channel compensation and guided image filtering techniques.

Investigation on improving the quality of haze images using the dark channel method. The results of the Prior Algorithm in Machine Vision. It suppresses noise amplification and reduces edge blur. Retains edge details. Exhibits high performance in PSNR, SSIM, and IE assessment metrics. This method is both adaptable and stable for enhancing extremely contaminated haze images.

The application of Deep Neural Networks to enhance the visibility of scene images degraded by foggy weather conditions provides a reasonable approximation of the fog function, resulting in improved visibility and safety.

MBLLEN: Enhancing Images and Videos in Low-Light Conditions Utilising Convolutional Neural Networks (CNNs) yields significantly superior results compared to the most advanced approaches available. It can be expanded to accommodate footage captured in low-light conditions.

Conventional and industrial applications depend on low-light image improvement. For this challenge, deep learning technology is powerful. However, deep learning-based techniques have limitations. The intensive use of training data, which takes time to acquire and interpret, is a downside. To cover a wide range of situations and classifications, the dataset must be carefully chosen, complicating the training process. Some deep learning algorithms for low-light image enhancement focus on model performance, which may compromise practicality and generalizability. Addressing these restrictions and proposing solutions for higher-level image processing is critical. Develop methods that use less training data and train faster while producing high-quality outcomes. Prioritize the upgraded images' practicality and universality. Researchers can develop more efficient and effective low-light image enhancement approaches for real-world image processing jobs by tackling these problems.

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