# Enhancing the Unseen: Deep Learning Architectures for Robust Image Quality Improvement in Severe Weather

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## Abstract

The main objective of this research study is the development and design of an innovative deep learning-based framework to enhance image in adverse weather conditions to enhance the quality and visibility of the image and the fineness of the details in a variety of settings and uses. In snow, rain, and fog, the works through the precipitation, of dispersing light to widely angled sides, which creates the dangers of death and accidents. The deep-learning-based architecture is required to provide enhanced imaging power in low-visibility backgrounds. To enhance the quality of the pictures, this model utilised techniques such as generative adversarial networks (GANs), convolutional neural network (CNN) models, edge-optimised YOLO tea, and ViT-Tea vision transformer to solve the issue of low light, snow, rain, and fog weather conditions. The literature review suggests a number of deep-learning models helpful in improving the details of the images in the case of untimely adverse weather conditions, and helps in improving the performance of the real situations in terms of performance and visibility. The research highlights the significant benefits of deep-learning techniques, which are needed for increasing image quality in unfavourable environments such as fog, haze and smoke. It plays a critical role in several industries such as satellite imaging, intelligence, transportation, agriculture and outdoor surveillance.

**Keywords:** Deep Generative Adversarial Network, De-hazing, YOLO

## 1. Introduction

### 1.1 Background

Reliable vision is crucial for agricultural surveillance systems to ensure the transportation and navigation of crops. However, the water hazards, including fog, negatively reduce visibility in the agricultural sections. During snow, rain and fog, due to precipitation, light scattering occurs over wide angles, leading to increased risks of fatalities and accidents. Hence, a deep-learning-based framework is required for powerful image enhancements under unfavourable weather situations. The framework will improve the image quality with the help of techniques like generative adversarial networks (GANs), convolutional neural network (CNN) models, edge-optimised Yolo tea and ViT-Tea vision transformer that address issues like snow, rain, low light and fog ( Vandana et al. 2024).

### 1.2 Research Aim and Objectives

**Aim**

This research aims to develop and create a novel deep learning-based framework for robust image enhancement under adverse weather circumstances, to enhance the quality of the image, visibility, and detail conservation across diverse environments and applications.

**Objectives**

- To create and invent a novel deep learning framework capable of effectively enhancing images captured under various weather conditions (e.g., sunny, rainy, foggy, snowy).
- To enhance the quality and visibility of degraded images while preserving fine details and the actual scene range.
- To examine and incorporate advanced deep learning methods, such as Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), and transfer learning, to complete state-of-the-art image enhancement.
- To create a relaxed and robust framework flexible to different weather conditions, image classes, and enhancement tasks (e.g., dehazing, deraining, denoising, and super-resolution).
- To evaluate the proposed framework through comprehensive experiments and comparisons with existing methods, using standard performance metrics and benchmark datasets.
- To explore real-world applications of the framework in fields such as computer vision, robotics, autonomous driving, surveillance, and remote sensing.
- To contribute to the advancement of deep learning-based image enhancement research by providing new insights, methodologies, and experimental findings.

### 1.3 Research Questions

- How can a deep learning framework be designed to effectively enhance images degraded by diverse adverse weather conditions?
- What strategies can be employed to improve image visibility and quality while ensuring that fine details and scene content are preserved?
- How can different deep learning techniques (e.g., CNNs, GANs, transfer learning) be integrated to achieve superior image enhancement performance?
- To what extent can a single flexible framework adapt to multiple enhancement tasks such as dehazing, deraining, denoising, and super-resolution?
- How does the proposed framework perform in comparison to existing state-of-the-art methods across various benchmark datasets and evaluation metrics?
- What potential benefits and applications can enhance images provide in domains such as autonomous driving, robotics, surveillance, and remote sensing?
- How can this research contribute to advancing the broader field of deep learning-based image enhancement?

### 1.4 Research rationale

The research rationale lies in the growing need for accurate visual data across various real-world industries, including agriculture, intelligent transportation systems, outdoor surveillance, and satellite imaging, by enhancing image clarity, data extraction, and object detection. In agricultural areas, it supports better crop monitoring. By highlighting the benefits of image dehazing techniques, this research will ensure preservation of picture detail, adaptability and high visibility restoration through enhancing safety, performance and decision making in vision-focused aspects.

## 2. Literature review

### 2.1 Introduction

The literature review will highlight recent advances in deep learning-based image enhancement methods adjusted for unfavourable weather conditions. It will consider challenges of retaining visibility, cutting-edge models and architectural inventions that will manage the gap of standard vision-taking methods.

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2.2 Analysis of deep learning methods for image enhancements

Deep learning methods such as generative adversarial networks (GANs) and convolutional neural network (CNN) models have been highly considered as image enhancements under challenging weather conditions (Hu et al., 2021). Recent advancements, including edge-optimised YOLO tea and ViT-Tea vision transformer, are also showing their accuracy in detailed prevention of agricultural imaging. Noticing early detection of crop diseases such as Potato leaf blight (PLB) is important for yield management.

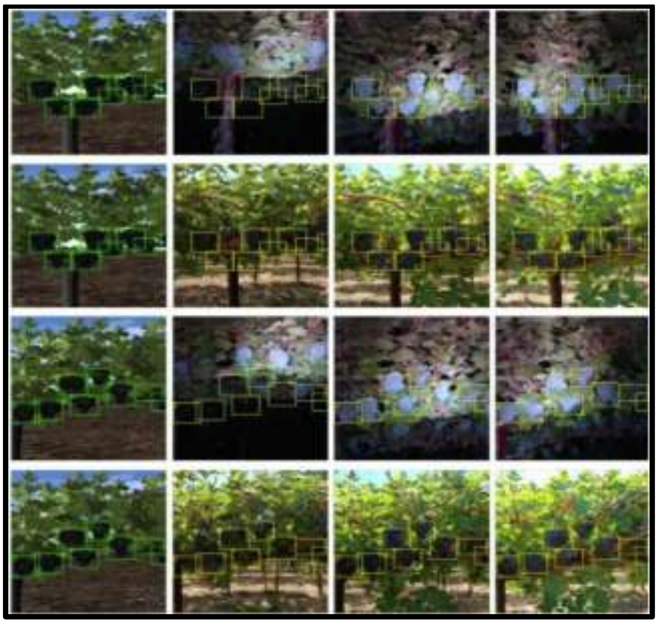

Figure 2.1: GAN aspects in agricultural areas

(Source: Lu et al., 2022)

Hu et al. (2021) highlight that CNN and GAN-focused frameworks may positively increase spot images on leaves that are degraded by water hazards. Hu et al. (2019) state that addressing accurate symptoms, including blighting edges, brown spots and leaf necrosis, these transformer-based critters excel and edge-optimised departures not only improve plant health but also support precision agriculture by providing accurate safeguarding on crop sustainability and timely intervention for increased productivity.

**2.3 Techniques that help to preserve image quality and scene details**

Contemporary inventions based on complicated intervention and visibility rehabilitation help to maintain image quality and screen details. Techniques focused on object-based image analysis (OBIA) and the Novel Coefficient model can be employed to see potato diseases in agricultural areas. Shi et al. (2022) state that CroconNet is a cutting-edge deep learning framework that is developed for the diagnosis of potato late blight by UAV-based hyperspectral images. Such techniques charge deviations in canopy structures and convert the image by accounting for and rotating invariance to feature diseases (Shi et al., 2022). Hence, it performs approximately 98% accuracy in the image quality and screen details (Shi et al., 2022).

Similarly, Siebring et al. (2019) opined that object-based image analysis is primarily utilised to obtain low-altitude-based RGB images to notice pathogen and attribute retrieval characteristics in farming areas. By segmenting these plant-based pictures into individual objects, OBIA addresses issues of pixel-focused image analysis and improves picture visibility (Ishengoma et al. 2021). Applying an arbitrary forest category, OBIA particularly handles pathogens such as PVY and Erwinia. It sustains accurate farming and shares images with high-resolution enhancements.

Together, these techniques demonstrate the procedure of state-of-the-art deep learning and image analysis methods that restore visibility, reduce artefacts and maintain details for monitoring dedicated farming conditions

 

**2.4 Adaptability based on diverse weather**

Adaptable deep learning frameworks for image enhancements under diverse weather conditions incorporate adaptive and modular images (Saleh et al., 2025). By involving processes such as degraining, dehazing, super-resolution and denoising across diverse areas, it manages weather-focused components and claims particular models for immediate detection. Techniques such as domain transformation and attention agencies improve flexibility that allows standards to generalise across unstable conditions without retaining. Moreover, integrating the transfer knowledge aspect allows quick transformation of scalable resolutions and supplies rapid enhancements of implementation based on variations of weather and image sources (Chen et al., 2023). Such image sources are important for remote sensing in real-life applications.

**2.5 Evaluation on real-life applications**

A meaningful evaluation of a deep learning based image enhancement framework relies on diverse areas, including structural similarity index (SSIM), Peak signal-to-noise ratio (PSNR) and learned perceptual image patch similarity (LPIPS), which can completely benefit to develop image quality, perceptual authenticity and structural adherence. Benchmark databases such as RESIDE for examining dehazing, SOTS that demonstrates degradation of various weather elements and Rain100L for managing deranging are beneficial to resemble standardised models of pictures and difficulty conception established on water hazards (Karavarsamis et al., 2022).

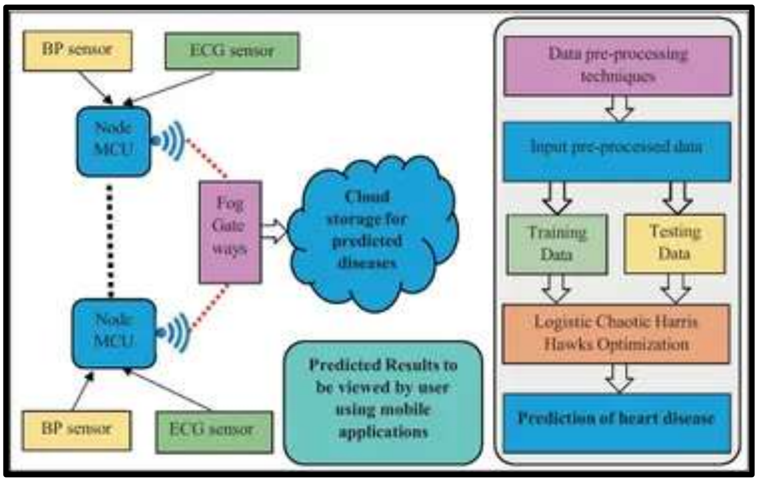


Figure 2.2: Deep learning framework for picture enhancement in foggy weather
(Source: Abirami and Poovammal, 2024)

In practical areas, improved imaging aspects positively navigate through visual translucency for detecting rain, fog and snow. Wang et al. (2025) argued that in traditional methods, recognising the small sensors in PLB areas is challenging to differentiate from natural leaf patterns. In agricultural areas, these leaves have matching colours, such as brown and green, that can imitate PLB assumptions (Shi et al., 2022). Hence, the utilisation of deep learning based frameworks arises because it leverages data-focused procedures, such as CNN, to remove features on layers. Accordingly, CNNs foreshadow complex relations between degraded and hazy images and interpret accurate, improved pictures. To increase safety (Tang et al., 2020). Moreover, surveillance techniques aim to increase visibility by supporting valid monitoring in adverse domains, hazard detection and increasing protection.

Integration of such metrics is developing cutting-edge frameworks for rising effectiveness and reliability across current-day scenarios.

**2.6 Theoretical perspectives**

Socio-technical systems theory can connect with the deep learning based image enhancement concept as it highlights the interconnection of advanced technology (CNNs, GANs and others )and social contents, including agriculture, remote sensing and surveillance. It offers weather-focused designs to indicate image degradation across diverse environmental conditions (Johnson et al., 2021). It highlights that improved image enhancement needs detailed observation, feature extraction and artefact minimisation by attention mechanisms and spatial learning (Tang et al., 2020). The theory indicates designing frameworks that help to manage technical performances, including high image production in complex weather conditions, to address social needs and usability. It ensures that innovation can be used in both socially and technically responsible real-life applications.

### 2.7 Research Gap

The core limitations of a deep learning based framework are its high dependence on high-quality inputs, PLB-certain detection issues and general optimisation (Guerri et al., 2024). The existing deep learning models, such as CNNs, generative adversarial networks (GANs) and others, are mostly trained for giving high-resolution images, and it is less applied in real-world agricultural areas. Sometimes, Hawaldar et al. (2024) argued that PLB symptoms in agriculture occur in blurry and small forms that make detection difficult for models such as YOLO5.

### 2.8 Summery

The literature review advances diverse deep learning frameworks that help to increase image details under adverse weather conditions and help to improve real-world application performance and visibility.

## 3. Methodology

### 3.1 Research philosophy

It will use interpretivism as a research philosophy, which will combine with a deep learning established image enhancement study by comprehending its complex and context-focused qualities of visual information under various weather situations. It examines how findings of deep learning models are comprehended by users and educates on the impressionistic understanding of improved images, specifically concentrating on the accuracy of objectives. For example, a GAN-focused system may be associated with a generator network which adjusts a degraded image into a restored image, and it prepares the users to discover the distinction between improved and degraded images (Porkodi et al., 2022).

### 3.2 Research approach

It will use an indicative research approach because utilising the deep learning-based frameworks to explore extensive data sets of images will allow capturing the practices of formulated images in various weather aspects. By uncovering understandings and conventions, it will attach to the improved image enhancement processes and details of photographs. The inductive approach starts with particular statements, including blurry images and more elaborate standards such as a deeper learning framework that describes the examined designs (Kang et al., 2018).

### 3.3 Research design

An exploratory research design has been used. By employing an exploratory research design, this research illustrates the urgency to utilise deep learning established frameworks for potent image enhancements under unfavourable weather conditions. In addition, by generating and experimenting with potential solutions, it describes a cycle of exploration, model designation and evaluation to get the effects based on the framework.

### 3. 4 Data collection method

This research tracks secondary data collection as the various image-based datasets have been apprehended from real-world origins such as surveillance cameras, UAVs and public image repositories. Chen et al. (2023b) opined that the knowledge of data administration techniques, such as noise accumulation, variation in brightness and rotation of images, has been gathered from secondary journals, books and others.

### 3.5 Data analysis

Thematic data analysis has been established on the qualitative data, as it allows for the examination of the connections and importance of research objectives. It recognises the key designs based on weather-based degradation influences, modifications in image quality and results of degradation. Themes will be concentrated on environmental variability, component conservation and antique removal.

**3.6 Ethical consideration**

Ethical considerations established in the research ensure the solitude of the picture data and investigate the required approvals for data collection. Translucency has been observed to control appropriations while conducting in diverse domains. The ethical deployment of improved imaging techniques in liberated driving and public surveillance regions has aimed to provide responsibility and security.

## 4. Data analysis

**4.1 Theme 1: Analysis of deep learning methods for image enhancements**

Hu et al. (2021) reveal that deep learning methods such as GANs and CNNs are the most effective approaches that help in image enhancement under hard weather, significantly in the case of agricultural imaging. Hu et al. (2021) highlight that ViT tea vision transformers and edge-optimised YOLO tea aspects are showing advancements in the detailed examination, and it is important for preventing the early disease symptoms of crops, for example, potato leaf blight. It finds that these frameworks help to bring improvements in the quality of spot pictures that have been degraded through water hazards. Hu et al. (2019) state that other transformer-based models positively address the symptoms of potato leaf blight. The leaf necrosis, blotting edges and brown spots are the primary symptoms of potato leaf bulging diseases. By timely and accurate intervention, precision agriculture can be supported, and it is needed to increase crop sustainability.

**4.2 Theme 2: Techniques that help to preserve image quality and scene details**

Theme 2 indicates that contemporary advancements in image enhancements positively leverage diverse interventions, including OBIA, and novel coefficient models. These models improve picture visibility and detail preservation. Shi et al. (2022) introduce the usage of CropdocNet, which is a cutting-edge deep learning framework. It is designed to address the potato late blight issues and uses UAV-focused hyperspectral imagery to identify the preliminary issues. Shi et al. (2022) enlighten the effectiveness of CropdocNet approaches as it gives 98% accuracy in detail preservation and picture quality. Siebring et al. (2019) talk about the usage of OBIA that takes RGB aerial pictures in low-altitude areas. Focusing on segmentations in plant images, it dissects the plant images and enhances the visibility of details. On the other hand, Ishengoma et al. (2021) identify that OBIA can be used by combining with random forest classifiers to significantly address the PVY and Erwinia pathogens. These factors help to bring contributions to crop health and support accurate, sustainable actions in agricultural practices.

**4.3: Theme 3: Adaptability based on diverse weather**

Saleh et al. (2025) describe that by applying adaptive processing techniques, including dehazing, degrading and denoising, adaptable deep learning frameworks can help to gain excellent image enhancements in different weather conditions. This process provides modification and develops attention mechanisms to enable immediate restoration and detection under environmental cases. Chen et al. (2023) explain that integrating transfer learning values in the facilitation of rapid adaptation and scalability in diverse weather conditions, and give upgraded image sources. By delivering high-quality images, it helps users to be beneficial in remote sensing and other real-life scenarios.

**4.4 Summary of key findings**

In summary, several deeper learning frameworks such as GANs, CNNs, domain adaptation and traffic are significantly helpful to provide high-quality images under different weather conditions. It considers preliminary detection of issues and quickly takes adaptive solutions for certain scenarios. It gives high-quality image production, flexibility and accuracy of image that is used in the surveillance of agricultural areas and remote sensing in real-life.

**4.5 Discussion**

These findings are consistent with the socio-technical systems theory that highlights the need for technology and results to be streamlined with social practices and innovation. Wang et al. (2018) highlight that GANs such as *super-resolution generative adversarial network (SRGAN)* help to improve image quality by capturing under different weather conditions by increasing its resolution and lowering its artefacts, which are caused by unfavourable weather. Through generating realistic details and textures, SRGAN may significantly remove blur and noise coming from water hazards and give clearer and more visible images (Maqsood et al., 2021). Shermeyer and Etten (2018) state that deep learning models permit the capture of lower altitude-based and closed pictures of leaves, cars and others by offering flexibility in creative applications. These enhanced images are developed through improving resolution, changing colour palette and removing noise and are often indistinguishable to human eyes.

Chen et al. (2022) opined that the state-of-the-art models regarding deep learning develop peak-signal-to-noise (PSNR) improvements of 2 to 5 dB. In addition, novel modes such as CropdocNet give 98% accuracy to detect diseases on the trees (Shi et al., 2022). However, Yao et al. (2022) indicated that weather-degraded datasets can include only 22-30dB PSNR ranges and give high-quality images. Pahwa (2024) stated that different image restoration methods, such as dehazing, desnowing and serening, are mostly applied to remove the weather degradation impacts and improve image quality. However, these methods increase images in the 22-30 dB range and improve the quality of original pictures (Pahwa, 2024).

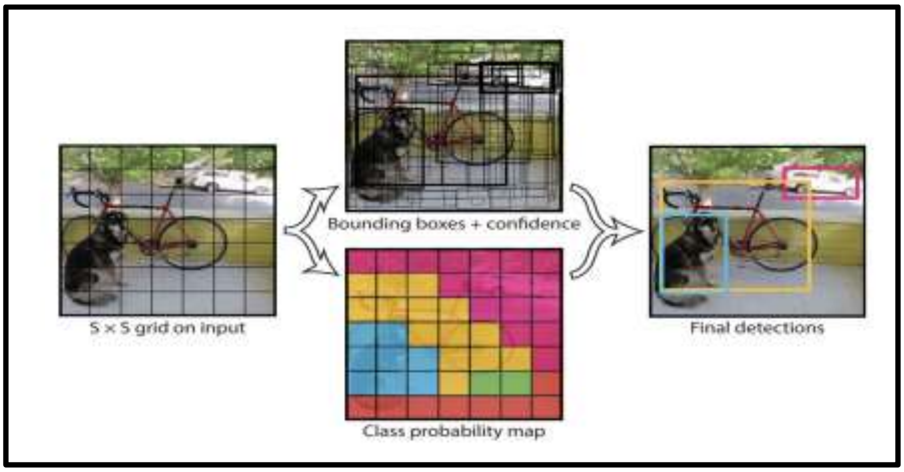


**Figure 4.5.1: YOLO model in picture extraction**

(Source: Noor et al., 2021)

In addition, Chen et al. (2020) indicate the applications of YOLOv3 as it is developed for spread and it makes pictures suitable for fast detection of objects, including fast driving cars, robotics and surveillance. By operating object detection, it is significantly predicting bounding boxes from the entire pictures with a single pass and using neural network aspects. Chen et al. (2020) also talk about its accuracy, as despite focusing on speed, YOLOv3 provides a high level of accuracy to detect objects. Utilising an excellent network such as Darknet-53, it extracts the robust factors from the image.

In summary, the discussion shows the effectiveness of different deep learning models, such as YOLOv3 and SRGAN, to increase the image quality in adverse weather. Improving the noise and resolution, it gains high PSNR values and accuracy for real-life aspects.

## 5. Conclusion and recommendations

### 5.1 Conclusion

The research highlights the significant benefits of deep-learning techniques, which are needed for increasing image quality in unfavourable environments such as fog, haze and smoke. It plays a critical role in several industries such as satellite imaging, intelligence, transportation, agriculture and outdoor surveillance. By improving image clarity, data extraction, object detection, and deep learning based techniques, it supports better detailed monitoring and increases safety through improved object identification. The research enlightens the limitations and benefits of traditional dehazing techniques and highlights the urgency for continued research to produce more effective and application-focused techniques. Improved dehazing may lead to better decision-making and performance across diverse industries.

### 5.2 Recommendations

- ***Develop a technological CNN architecture***

It would be possible to employ the use and application of an innovative convolutional neural network (CNN) model like DenseNet, VGG and MobileNet, which has been widely used in image analysis and efficiency in data surveillance (Ahmed et al. 2021). It will serve to provide better information regarding negative environmental conditions. In a situation where unfavorable weather condition is detected, the photographs will refine their photographs and increase high-resolution photographs to be accurate.

- ***Integration with multimodal aspects***

Vandana et al. (2024) suggested that Amalgamate data from various sources, including combined RCB pictures with distracted images, can help to recover lost details in low-visibility conditions such as darkness and snow.

- ***Develop targeted and diverse datasets based on diverse environmental conditions.***

Develop datasets that have diverse areas of unfavourable weather conditions such as snow, fog, rain and sand. It needs to ensure that all of this data contains both high-quality and low-quality images to work with effectively in supervised models. In addition, developing advanced data augmentation methods can make more suitable datasets for training and covering diverse artefacts and degradation levels in images (Ahmed et al. 2021). It will make the deep-learning techniques more improved and accurate.

- ***Implement suitable invasion metrics.***

As suggested by Sharma et al. (2022), using suitable models to examine the performance of models is important. By examining accuracy, recall and precision, a knowledge of adverse weather conditions can be achieved successfully.

### 5.3 Future Studies

The future studies on deep learning based frameworks for robust image enhancements under adverse weather conditions may focus on enhancing their abilities in real-life scenarios. An extension of the framework to video enhancement can cover the challenges of video capture in various weather conditions, optical flow and investigation of time consistency (Hu et al., 2025). In addition, the framework can be optimised to enable real-time improvements within the edge device, including drones, smartphones and vehicles, supporting embedding of further information (Lee et al. 2022). In the future, physical models of weather formation and image-forming might be included as part of the deep learning framework in order to make it even more realistic and accurate. Potential effects of the suggested framework on down-flows ascertain computers can guide to gain familiarity on picture fragmentation, following segment process and actualizing discernment. Moreover, taking the framework as an open-sourced library can build a standard of multi-weather image enhancements and inspire the cooperation of societies.

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