SINGLE IMAGE RAIN REMOVAL USING BILATERAL FILTERING AND U-NET BASED GENERATIVE ADVERSARIAL NETWORK WITH PATCHGAN DISCRIMINATOR

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Abstract - *Rain streaks in outdoor images significantly reduce visual quality and can negatively affect the performance of many computer vision systems. Applications such as autonomous driving, surveillance, traffic monitoring, and remote sensing rely on clear images to accurately interpret visual scenes. However, images captured during rainy conditions often contain streak-like artifacts that obscure important details such as edges, textures, and objects. To address this problem, this paper proposes a deep learning–based image de-raining approach using a Generative Adversarial Network (GAN). The proposed framework employs a U-Net based generator to learn the mapping between rainy images and their corresponding clean images. To improve the realism of the generated outputs, a PatchGAN discriminator is used to evaluate local image regions and enforce texture consistency. In addition, bilateral filtering is applied during preprocessing to reduce rain noise while preserving important structural information in the image. The model is trained using a combination of reconstruction loss, adversarial loss, and total variation loss to ensure effective rain removal and stable image reconstruction. An additional output enhancement stage consisting of contrast enhancement, sharpening, and noise reduction filters is applied to further improve the visual clarity of the reconstructed images. Experimental results evaluated using Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) show that the proposed method effectively removes rain streaks while preserving fine image details. The developed approach can be applied to enhance images captured in rainy environments and improve the reliability of outdoor vision systems.*

Key Words **Image De-raining, Rain Streak Removal, Generative Adversarial Network (GAN), U-Net, PatchGAN Discriminator, Bilateral Filtering, Image Restoration, Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM).**

1. INTRODUCTION

Digital images have become an essential source of information for many modern computer vision applications, including autonomous driving, intelligent transportation systems, surveillance monitoring, remote sensing, and outdoor robotics [1], [2]. These systems rely heavily on clear and high-quality visual data to accurately detect objects, analyze scenes, and make reliable decisions. However, images captured in outdoor environments are often affected by adverse weather conditions such as rain, fog, haze, and snow. Among these conditions, rain is one of the most common factors that significantly degrades image quality.
Rain streaks appear as bright or semi-transparent lines in images due to the reflection and scattering of light by falling raindrops [1], [2]. These streaks obscure important scene details such as edges, textures, and object boundaries, which can negatively impact the performance of computer vision algorithms. For example, rain-degraded images may reduce the accuracy of object detection systems in autonomous vehicles, make surveillance footage harder to analyze, or affect the reliability of environmental monitoring systems. Therefore, developing effective techniques for removing rain streaks from images is an important research problem in the field of image restoration.

Early approaches for rain removal mainly relied on traditional image processing techniques such as filtering methods, frequency-domain analysis, and matrix decomposition [6], [7]. Although these methods can remove certain rain patterns, they often struggle to distinguish rain streaks from background textures. As a result, they may produce blurred images or fail to completely remove rain artifacts, especially in complex scenes with dense rain.
With the rapid advancement of deep learning, more powerful methods have been developed for image restoration tasks. Convolutional Neural Networks (CNNs) have demonstrated strong capability in learning complex image patterns directly from large datasets. Recently, Generative Adversarial Networks (GANs) have shown remarkable success in various image-to-image translation tasks, including image denoising, super-resolution, and artifact removal [21], [24]. A GAN framework consists of two networks: a generator that produces improved images and a discriminator that evaluates their realism. Through adversarial training, the generator learns to produce visually convincing outputs that closely resemble real images.
Motivated by the success of GAN-based image restoration techniques, this paper proposes a deep learning–based framework for single-image rain streak removal using a U-Net based generator and a PatchGAN discriminator. In the proposed approach, bilateral filtering is first applied as a preprocessing step to reduce rain noise while preserving important image edges. The filtered image is then processed by the generator network, which uses an encoder–decoder architecture with skip connections to learn multi-scale image

features and reconstruct a rain-free image. A PatchGAN discriminator is employed to evaluate the generated outputs at the patch level, encouraging the generator to produce more realistic textures and detailed structures.
The proposed model is trained using a combination of reconstruction loss, adversarial loss, and total variation loss to improve the quality of the restored images. Experimental evaluation using Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) demonstrates that the proposed approach effectively removes rain streaks while preserving important structural information. The developed method can improve the visual quality of images captured in rainy environments and enhance the performance of outdoor vision systems.

2. RELATED WORK

Single-image rain streak removal has been an active research topic in image processing and computer vision due to its importance in outdoor vision applications [3], [7], [15]. Over the years, several approaches have been proposed to address this problem, ranging from traditional image processing techniques to advanced deep learning–based methods.
Early research on rain removal mainly focused on image decomposition and filtering techniques. Kang et al. proposed a rain removal method based on image layer separation, where a rainy image is decomposed into a low-frequency background layer and a high-frequency rain layer [6]. The rain streaks were then removed using sparse dictionary learning techniques. Although this approach was able to reduce rain artifacts, it required complex optimization procedures and often failed in scenes with dense rain patterns.
Later, Luo et al. introduced a discriminative sparse coding approach to separate rain streaks from background images by learning dictionaries for rain and non-rain components [7]. Similarly, Li et al. proposed a method based on Gaussian Mixture Models (GMM) to model rain streak distributions and separate them from the background [9]. While these methods improved rain removal performance compared to simple filtering approaches, they relied heavily on handcrafted features and assumptions about rain patterns, which limited their generalization capability.
With the rapid advancement of deep learning, Convolutional Neural Networks (CNNs) have been widely adopted for image restoration tasks. Eigen et al. introduced one of the early CNN-based methods for rain removal, where the network learns the mapping between rainy images and clean images [14]. Fu et al. later proposed the Deep Detail Network (DDN), which focuses on learning high-frequency detail layers to remove rain streaks while preserving background structures [15]. Similarly, Zhang et al. developed Density-aware Multi-stream Dense Networks (DID-MDN) to handle rain streaks of different densities by incorporating multi-stream feature extraction [18].
In recent years, Generative Adversarial Networks (GANs) have shown promising results in image restoration and enhancement tasks. GAN-based models use a generator–discriminator framework to improve the visual realism of generated images [21]. Conditional GAN architectures have been applied to image de-raining by learning the transformation between rainy images and rain-free images [24]. These methods produce visually convincing results and preserve fine textures better than traditional CNN-based approaches.

Yang et al. proposed a rain removal method that combines bilateral filtering with a Generative Adversarial Network, where the bilateral filter is used to separate high-frequency rain components from the background before feeding the image into the network [5]. Their approach demonstrated improved rain removal performance on benchmark datasets by focusing the learning process on rain-related features.
Despite these advancements, several challenges remain in rain removal tasks. Many existing methods suffer from high computational complexity, over-smoothing of image details, or incomplete removal of rain streaks in complex scenes. In addition, some models struggle to preserve fine textures while removing rain artifacts.

To address these limitations, this paper proposes a GAN-based image de-raining framework that combines bilateral filtering, a U-Net generator, and a PatchGAN discriminator. The bilateral filtering stage suppresses rain noise while preserving structural details, while the U-Net architecture enables effective multi-scale feature extraction and reconstruction through skip connections. Furthermore, an output enhancement stage is introduced to improve the visual clarity of the reconstructed images. This integrated framework enables more effective rain streak removal while maintaining important structural details in the restored image.

3. PROPOSED METHOD

The proposed image de-raining framework aims to remove rain streaks from a single image while preserving important structural details and textures. The overall system is based on a **Generative Adversarial Network (GAN)** architecture consisting of a **U-Net based generator** and a **PatchGAN discriminator**. In addition, **bilateral filtering** is applied during preprocessing to reduce rain noise while preserving image edges. The proposed framework learns the relationship between rainy images and their corresponding clean images through supervised training.

The overall workflow of the system begins with a rainy input image that contains rain streak artifacts. The input image is first processed using bilateral filtering to reduce high-frequency rain noise while maintaining important structural information. The filtered image is then passed to the generator network, which predicts the rain residual component and reconstructs an initial rain-free image. During training, the generated output is evaluated by the PatchGAN discriminator to ensure that the reconstructed image is visually realistic and contains consistent textures. After the rain removal process, the reconstructed image is further refined using an output enhancement stage to improve contrast, edge sharpness, and overall visual clarity.

Through adversarial training between the generator and discriminator networks, the system gradually improves its ability to remove rain streaks while maintaining natural image appearance. Finally, the reconstructed image is refined using output enhancement filters to produce the final rain-free image with improved visual quality.

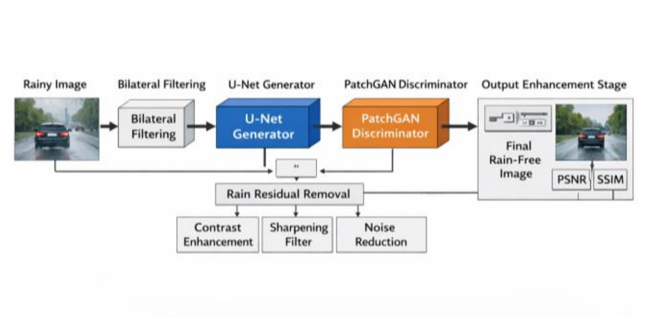

Fig 1: Overall architecture of the proposed rain removal framework

3.1 Bilateral Filtering for Preprocessing

Before feeding the rainy image into the deep learning model, bilateral filtering is applied as a preprocessing step. Bilateral filtering is an edge-preserving smoothing technique that removes noise while maintaining important image structures such as edges and textures.

Unlike traditional linear filters, bilateral filtering considers both the **spatial distance between pixels** and the **intensity difference between pixel values**. This allows the filter to smooth regions with similar intensity values while preventing smoothing across object boundaries.

In the context of rain removal, rain streaks often appear as high-frequency noise patterns. Bilateral filtering helps suppress these unwanted patterns while preserving structural details that are important for accurate image reconstruction. By applying this filtering step before the deep learning model, the network receives a cleaner input image, which improves the efficiency of feature extraction and enhances the overall rain removal performance.

3.2 U-Net Based Generator

The generator network is responsible for removing rain streaks from the input image and generating a clean rain-free output. In the proposed system, the generator is implemented using a **U-Net architecture**, which has proven effective in various image restoration tasks.

The U-Net architecture consists of two main components:

1. **Encoder (Contracting Path)**
2. **Decoder (Expanding Path)**

The encoder extracts hierarchical features from the input image using multiple convolutional layers and pooling operations. These layers capture important patterns such as rain streak structures, textures, and edges.

The decoder then reconstructs the output image by progressively increasing the spatial resolution using up-sampling layers. The decoder combines the extracted features to generate a rain-free image.

One of the key advantages of the U-Net architecture is the use of **skip connections** between corresponding encoder and decoder layers. These skip connections transfer feature maps directly from the encoder to the decoder, preserving spatial information and preventing the loss of important image details during down-sampling.

Through this architecture, the generator learns to identify rain streak patterns and reconstruct the underlying scene while preserving important structural information.

Fig 2 : Architecture of the U-Net

3.3 PatchGAN Discriminator

The discriminator network plays a crucial role in improving the realism of the generated images. Instead of evaluating the entire image at once, the proposed system uses a **PatchGAN discriminator**, which focuses on small local patches of the image.

The PatchGAN discriminator divides the image into multiple overlapping patches and classifies each patch as real or fake. By evaluating smaller regions, the discriminator can better detect local inconsistencies such as remaining rain streaks or unrealistic textures.

The discriminator consists of multiple convolutional layers that progressively extract image features. These features are then used to determine whether the input image is a real clean image or a generated rain-free image produced by the generator.

During training, the generator attempts to produce images that can fool the discriminator, while the discriminator attempts to correctly classify real and generated images. This adversarial learning process improves the quality and realism of the generated outputs.

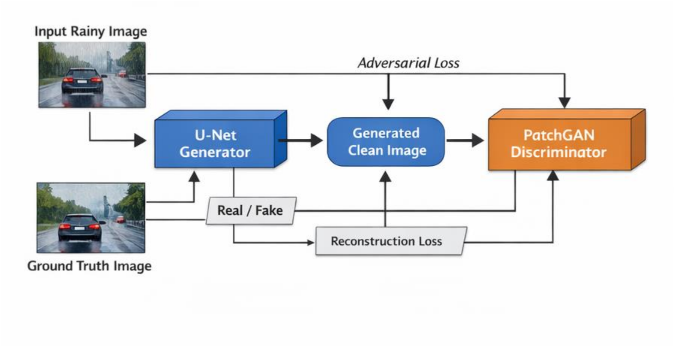

Fig 3 : Architecture of the PatchGAN discriminator.

3.4 Residual Learning Strategy

Instead of directly predicting the entire clean image, the proposed system adopts a **residual learning strategy**. In this approach, the generator learns to estimate the **rain component (residual image)** present in the input image.

The final rain-free image is obtained by subtracting the predicted rain residual from the original rainy image.

This approach simplifies the learning task for the network because the model only needs to learn the rain streak patterns rather than reconstructing the entire image from scratch. As a result, the training process becomes more efficient and the reconstructed images retain more background details.

3.5 Loss Functions

To train the proposed GAN-based model effectively, multiple loss functions are used to guide the learning process.

L1 Reconstruction Loss

The L1 loss measures the pixel-wise difference between the generated image and the ground truth clean image. This loss ensures that the reconstructed image remains close to the original clean image.

Adversarial Loss

Adversarial loss is used to train the generator and discriminator networks in a competitive manner. The generator attempts to produce realistic rain-free images, while the discriminator tries to distinguish between real and generated images.

Total Variation Loss

Total variation loss encourages smoothness in the generated images by reducing unwanted noise and artifacts. This helps improve the visual quality of the reconstructed output.

The final loss function is a combination of these losses to ensure accurate rain removal while preserving important structural details.

3.6 Output Enhancement

Although the U-Net based GAN effectively removes most rain streak artifacts, the generated output may still contain slight intensity variations or reduced contrast due to the learning process. To further improve the visual quality of the reconstructed image, an **output enhancement stage** is applied after the rain removal process.

In this stage, several image enhancement filters are used to refine the generated image and improve its visual appearance. These enhancement operations help increase image clarity, improve contrast, and reduce any minor artifacts remaining after the GAN reconstruction.

First, a **contrast enhancement operation** is applied to improve the visibility of image details and balance the overall brightness of the image. This step enhances the intensity distribution and makes the reconstructed image visually clearer.

Next, a **sharpening filter** is used to strengthen image edges and fine structures that may have been slightly smoothed during the rain removal process. Sharpening helps recover important features such as object boundaries and textures.

Finally, a noise reduction filter is applied to remove small residual artifacts while preserving important structural information to remove small residual artifacts while preserving important structural information. These enhancement operations ensure that the final output image has improved clarity, contrast, and natural appearance.

The combination of rain removal using the GAN model and post-processing enhancement filters results in higher visual quality and more realistic rain-free images.

4. IMPLEMENTATION AND TRAINING

This section describes the implementation environment, dataset preparation, and training configuration used for the proposed rain removal framework.

4.1 Implementation Environment

The proposed image de-raining framework was implemented using **MATLAB**. The model development and training were performed using the **Deep Learning Toolbox**, which provides built-in support for designing convolutional neural networks and training deep learning models. Image preprocessing operations and evaluation metrics were implemented using the **Image Processing Toolbox**.

To accelerate the training process, **GPU-based computation** was enabled through MATLAB's **Parallel Computing Toolbox**, which significantly reduced the training time during model optimization.

The system was implemented on a workstation equipped with standard computational resources suitable for deep learning experiments. The overall implementation pipeline includes image preprocessing, model training, rain removal inference, and quantitative evaluation using image quality metrics.

4.2 Dataset Preparation

The proposed model was trained using paired rainy and clean images obtained from the **RL100 and RH100 datasets**. These datasets contain clean ground-truth images along with synthetically generated rain streak variations.

In this work, **100 clean images** were used as base images. Each image was combined with **14 different rain streak patterns**, resulting in a total of **1400 paired training samples**. These pairs consist of a rainy input image and its corresponding clean ground-truth image.

Before training, all images were resized to a uniform resolution and normalized to ensure consistent input to the neural network. The dataset was then divided into training and validation sets to evaluate the model performance during training.

Fig 4 : Sample rainy images from the dataset used for training and evaluation of the proposed rain removal model.

4.3 Training Configuration

The proposed GAN model was trained in a supervised manner using paired rainy and clean images. During training, the **U-Net generator** learns to predict the rain residual component from the rainy input image. The predicted rain component is subtracted from the input image to generate the final rain-free output.

The **PatchGAN discriminator** evaluates the generated image by analyzing small local patches and determines whether the output image is real or generated.

This adversarial process encourages the generator to produce realistic and high-quality images. The model was trained for **50 epochs**, where each epoch contained **175 iterations** based on the dataset size and batch configuration.

The main training parameters used in this work are summarized in Table 1.

Table 1 : Training parameters

Parameter	**Value**
Epochs	50
Batch Size	8
Training Samples	1400
Iterations per Epoch	175
Total Training Iterations	8750

4.4 Loss Function Optimization

To effectively train the proposed GAN framework, a combination of multiple loss functions was used to guide the optimization process.

The **L1 reconstruction loss** measures the pixel-wise difference between the generated image and the ground truth clean image, ensuring accurate rain removal.

The **adversarial loss** is used to train the generator and discriminator networks in a competitive manner, encouraging the generator to produce visually realistic images that can fool the discriminator.

In addition, **total variation loss** is used to reduce unwanted artifacts and improve the smoothness of the generated image.

The combination of these loss functions enables the network to achieve a balance between accurate rain removal and preservation of visual realism.

5. EXPERIMENTAL RESULTS AND ANALYSIS

This section presents the experimental results obtained using the proposed rain removal framework. The performance of the system was evaluated using both **qualitative visual analysis** and **quantitative image quality metrics**. The proposed method was tested on rainy images from the RL100 and RH100 datasets to evaluate its ability to remove rain streaks while preserving image structures.

5.1 Evaluation Metrics

To measure the effectiveness of the rain removal system, two widely used image quality metrics were employed: **Peak Signal-to-Noise Ratio (PSNR)** and **Structural Similarity Index Measure (SSIM)**.

Peak Signal-to-Noise Ratio (PSNR)

PSNR measures the reconstruction quality of the generated image compared to the ground truth clean image. A higher

PSNR value indicates better image restoration performance and lower reconstruction error.

The PSNR is calculated using the Mean Squared Error (MSE) between the generated image and the ground truth image.

PSNR is calculated as:

$$PSNR = 10\log_{10}\left(\frac{MAX^2}{MSE}\right)$$

where MAX represents the maximum pixel value and MSE represents the mean squared error between the reconstructed image and the ground truth image.

Structural Similarity Index (SSIM)

SSIM evaluates the similarity between two images by comparing their luminance, contrast, and structural information. Unlike PSNR, which focuses only on pixel differences, SSIM measures how well the structural information of the image is preserved.

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$

where μ_x and μ_y represent the mean intensities, σ_x^2 and σ_y^2 represent the variances, and σ_{xy} represents the covariance between the two images.

Higher SSIM values indicate better structural similarity between the reconstructed image and the ground truth image.

5.2 Visual Results

The proposed model successfully removes rain streaks while preserving important image details such as edges, textures, and object boundaries. After the rain removal process, the reconstructed images exhibit improved clarity, reduced rain streak artifacts, and better preservation of structural details compared to the original rainy images.

The U-Net generator effectively learns rain streak patterns and reconstructs the underlying scene, while the PatchGAN discriminator helps maintain local texture consistency. As a result, the generated images appear more natural and contain fewer artifacts.

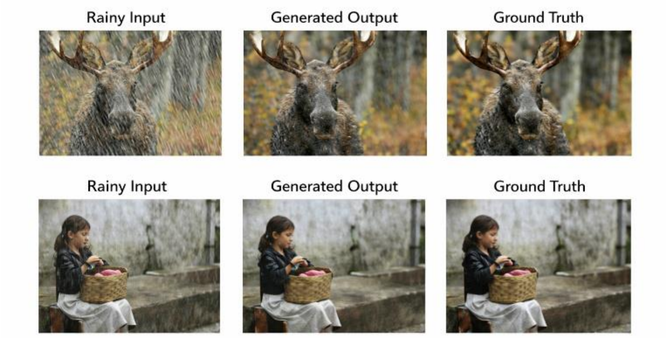

Fig 5 :Visual comparison between rainy input images, generated rain-free outputs, and corresponding ground truth

5.3 Quantitative Results

The quantitative performance of the proposed rain removal framework was evaluated using Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM). These metrics measure the reconstruction accuracy and structural similarity between the generated rain-free images and the corresponding ground truth images.

The statistical distribution of PSNR and SSIM values obtained across the evaluated test images is shown in Fig. 0 and Fig. 0. The PSNR values are mostly concentrated around the mid-range region, indicating consistent reconstruction performance across different scenes. Similarly, the SSIM values are distributed in the higher range, demonstrating that the proposed method effectively preserves structural information in the restored images.

Overall, the quantitative analysis confirms that the proposed GAN-based rain removal framework improves image quality while maintaining structural similarity with the ground truth images.

5.4 Histogram Analysis

To further analyze the performance of the proposed rain removal framework, statistical distributions of the Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) were examined across the evaluated test images. These distributions provide insights into the overall reconstruction quality and structural preservation achieved by the model.

Statistical distributions of PSNR and SSIM values were analyzed to evaluate the overall performance of the proposed rain removal framework.

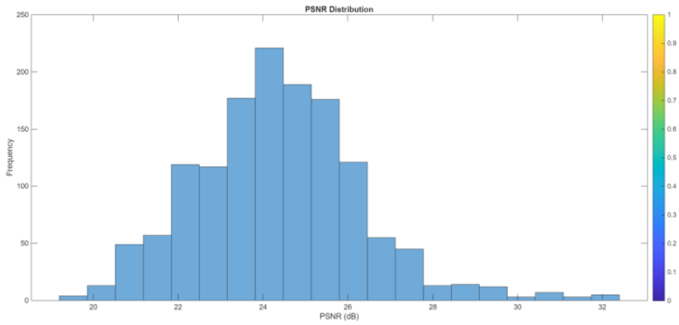

Fig 6 : Distribution of PSNR values obtained for the evaluated test images, indicating the reconstruction quality achieved by the proposed rain removal model.

The PSNR distribution illustrates the frequency of different PSNR values obtained during evaluation. Most of the PSNR values are concentrated around the mid-range region, indicating consistent restoration performance across multiple test samples. This suggests that the proposed method is capable of maintaining stable image reconstruction quality under varying rain conditions.

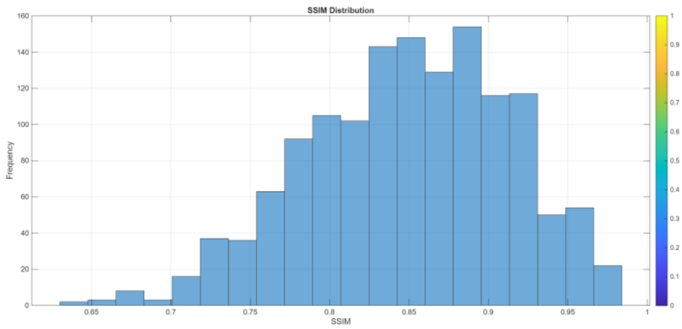

Fig 7: Distribution of SSIM values showing the structural similarity between the reconstructed images and the ground truth images.

Similarly, the SSIM distribution demonstrates how well the structural information of the images is preserved after rain removal. The majority of SSIM values lie in the higher range, indicating that the generated images maintain strong structural similarity with the ground truth images. This confirms that the proposed method effectively removes rain streak artifacts while preserving important image structures such as edges and textures.

Overall, the distribution analysis of PSNR and SSIM values demonstrates that the proposed model achieves stable and reliable performance across different test images.

6. APPLICATIONS AND DISCUSSION

The proposed rain removal framework can be applied in various real-world computer vision systems where image quality is affected by rainy weather conditions. Removing rain streak artifacts improves visual clarity and enhances the performance of vision-based systems operating in outdoor environments.

One important application area is **surveillance systems**. Outdoor CCTV cameras often capture footage during rainy weather, which can significantly reduce visibility and make scene interpretation difficult. By removing rain streak artifacts from surveillance footage, the proposed method can enhance image clarity and assist in more accurate monitoring and security analysis.

Another important application is **autonomous driving systems**. Self-driving vehicles rely heavily on cameras and sensors to detect road conditions, pedestrians, traffic signals, and surrounding vehicles. Rain streaks may obscure these visual cues and negatively impact object detection accuracy. The proposed rain removal approach helps improve road scene visibility, which can enhance perception and decision-making capabilities in autonomous vehicles.

The proposed framework can also be beneficial for **remote sensing and aerial image analysis**. Rain streak artifacts may degrade aerial or satellite images used for environmental monitoring, disaster management, and geographical analysis. Removing these artifacts improves the quality of captured images and enables more reliable interpretation of remote sensing data.

n addition, the method can support **robotics and drone-based vision systems** that operate in outdoor environments. Robots and drones frequently rely on visual sensors for navigation and obstacle detection. Improving image clarity in rainy conditions can enhance the reliability of visual perception and improve navigation accuracy.

Although the proposed GAN-based rain removal framework demonstrates effective rain streak suppression and structural detail preservation, some challenges remain. In particular, extremely dense rain conditions may still introduce residual artifacts that are difficult to completely remove. Future work may focus on improving the robustness of the model by incorporating attention mechanisms or advanced deep learning architectures to further enhance rain removal performance.

Overall, the experimental results demonstrate that the combination of **bilateral filtering, U-Net generator, and PatchGAN discriminator** enables effective rain streak removal while maintaining natural image structures. The proposed framework therefore provides a practical solution for improving image quality in outdoor vision applications.

7. CONCLUSION

In this paper, a deep learning–based framework for single-image rain streak removal was proposed using a Generative Adversarial Network (GAN). The proposed method integrates bilateral filtering, a U-Net based generator, and a PatchGAN discriminator to effectively remove rain streak artifacts while preserving important image structures and textures. Bilateral filtering is applied as a preprocessing step to suppress rain noise while maintaining edge information. The filtered image is then processed by the U-Net generator, which learns hierarchical features and predicts the rain residual using an encoder–decoder architecture with skip connections. The PatchGAN discriminator evaluates the generated images at the patch level, encouraging the generator to produce visually realistic outputs with consistent textures.

The model is trained using a combination of reconstruction loss, adversarial loss, and total variation loss to ensure both rain removal accuracy and image smoothness. Experimental evaluation on the RL100 and RH100 datasets demonstrates that the proposed approach improves image quality by effectively removing rain streaks while preserving structural details. The performance was evaluated using PSNR and SSIM metrics, which indicate improvements in both numerical reconstruction quality and visual image clarity.

The results suggest that the proposed framework provides an effective solution for enhancing images captured under rainy conditions. This method can improve the reliability of various outdoor computer vision systems such as surveillance monitoring, autonomous driving, remote sensing, and robotic vision systems.

Future work may focus on extending the proposed approach to handle heavy rain conditions and video-based rain removal. Additionally, integrating advanced deep learning techniques such as attention mechanisms and lightweight network architectures may further improve the efficiency and robustness of the system.

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