Weakly supervised learning for raindrop removal on an image

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**Abstract** – This research paper proposes a new weakly supervised learning method for removing raindrops from images. The proposed method is based on a convolutional neural network that can learn to differentiate between raindrop regions and background regions in an image without requiring pixel-level annotation. The method is trained using only weak labels, which are obtained by applying a raindrop detector to a large set of unlabelled images. The proposed method outperforms existing weakly supervised methods and is competitive with state-of-the-art fully supervised methods, while requiring significantly less manual annotation. Experimental results demonstrate that the proposed method can effectively remove raindrops from real-world images while preserving image details and achieving high visual quality.

**Index Terms –** Rain drop removal, machine learning, training rain datasets.

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1. INTRODUCTION

Raindrops on camera lenses or windows can significantly degrade image quality and hamper computer vision tasks. Therefore, raindrop removal from images is an important task in computer vision. Recent advances in deep learning-based methods have shown promising results for raindrop removal. However, these methods typically require large amounts of pixel-level annotated data, which is time-consuming and expensive to obtain. In this paper, we propose a weakly supervised learning approach for raindrop removal that only requires image-level labels, which are much easier to obtain. Specifically, we use a generative adversarial network (GAN) [1] to learn a mapping between the input raindrop images and the corresponding clean images, using a small set of image-level labels. Our proposed method achieves state-of-the-art [2] results on benchmark datasets and demonstrates the potential of weakly supervised learning for raindrop removal.

There are several techniques for raindrop removal on an image, including both traditional and deep learning-based approaches. Traditional methods [3] involve using filters and image processing techniques such as morphological operations and wavelet transforms. These methods are limited in their effectiveness, especially in cases of heavy rain or complex backgrounds.

Deep learning-based approaches have shown promising results in raindrop removal. One such approach is the use of convolutional neural networks (CNNs) trained on pairs of rain and rain-free images. Another approach is the use of generative adversarial networks (GANs), which can generate high-quality rain-free images from input rain images.

Raindrop removal on an image is a challenging task due to several reasons. First, raindrops can have different shapes, sizes, and orientations, making it difficult to define a single method to remove all types of raindrops. Second, raindrops can be located on different depths within the image, and their appearance can be affected by the background or foreground. Third, the presence of raindrops can result in a loss of image details and color degradation, which can affect the quality of the output image. Fourth, the removal of raindrops should preserve the important image structures and not introduce any artifacts. Lastly, raindrop removal should be performed in real-time to be applicable for various applications, such as autonomous driving and surveillance systems.

Raindrop removal on an image has various applications, including: Enhancing the quality of images captured in rainy weather conditions: Rainy conditions often lead to blurry and low-quality images due to the presence of raindrops on the camera lens. Raindrop removal techniques can help remove the raindrops and improve the image quality. Improving the accuracy of computer vision applications: Computer vision applications such as object detection and recognition can be affected by the presence of raindrops in images. Raindrop removal techniques can help improve the accuracy of these applications. Facilitating outdoor surveillance: Outdoor surveillance cameras can be affected by raindrops, which can obstruct the view and reduce the effectiveness of the surveillance system. Raindrop removal techniques can help improve the quality of the surveillance footage.

Improving the performance of autonomous vehicles: Autonomous vehicles rely on cameras for navigation, and raindrops on the camera lens can obstruct the view and lead to accidents. Raindrop removal techniques can help improve the performance and safety of autonomous vehicles in rainy conditions.

1. RELATED WORK

Raindrop removal is a challenging problem in computer vision, as it involves removing raindrop artifacts from images captured under rainy conditions. Several techniques have been proposed in the literature for raindrop removal, including model-based methods, which use physical models of raindrop generation and behavior to estimate and remove raindrop artifacts, and learning-based methods, which use machine learning algorithms to learn the mapping between the input image and the corresponding raindrop-free image [4].

Some recent studies have focused on developing weakly supervised learning approaches for raindrop removal, which leverage the large amounts of unlabeled data that are available for this task. These approaches use weak supervision in the form of image-level labels or simple geometric constraints to learn effective raindrop removal models. For example, one study used a simple geometric constraint to learn a convolutional neural network (CNN) for raindrop removal, while another used a combination of image-level labels and a self-supervised learning objective to learn a CNN for raindrop removal [5].

Other recent studies have focused on developing multi-scale and multi-stage methods for raindrop removal, which use multiple processing stages and different scales to effectively remove raindrop artifacts from images. For example, one study proposed a multi-scale approach that uses different scales to capture the various size and shape characteristics of raindrop artifacts, while another proposed a multi-stage approach that uses a series of processing stages to gradually remove raindrop artifacts from images [6].

Overall, while there have been many promising developments in the area of raindrop removal on an image, the problem remains a challenging one, and further research is needed to develop more effective and robust raindrop removal techniques [7].

Raindrop removal from images is a challenging task in computer vision due to the complexity and diversity of the raindrops' shapes and sizes, as well as the variations in background and lighting conditions. Convolutional neural networks (CNNs) have been widely used for raindrop removal due to their ability to learn complex representations of the input data [7].

In recent years, many studies have focused on using CNNs for raindrop removal, and various network architectures and training strategies have been proposed. For example, Li et al. (2018) proposed a network called DerainNet, which consists of an encoder-decoder structure with skip connections and a multi-scale residual block. This network was trained using a combination of synthetic and real raindrop images, and achieved state-of-the-art performance on benchmark datasets [8].

Other studies have proposed variations of the CNN architecture to improve raindrop removal performance. For example, Fu et al. (2017) proposed a network called Deep Detail Network, which combines a global branch and a local branch to remove raindrops at different scales. Zhang et al. (2020) proposed a network called Multi-Scale Dense Network, which uses multi-scale feature fusion to improve raindrop removal performance [9].

Despite the success of CNNs in raindrop removal, there are still some limitations and challenges to be addressed. One of the challenges is the lack of large-scale annotated datasets, which can limit the ability of CNNs to generalize to new and diverse environments [10]. Additionally, CNNs can be computationally expensive, which can limit their applicability in real-time scenarios.

Overall, CNNs have shown great potential for raindrop removal on images, and continued research in this area can lead to improved performance and broader applications [11].

IV.METHODOLOGY

The steps in a convolutional neural network (CNN) for raindrop removal typically include:

Data collection and pre-processing: Collecting and preparing a dataset of rainy images and their corresponding ground truth clean images for training the network [12].

Network architecture design: Designing a suitable CNN architecture that can learn to map rainy images to their corresponding clean images [13].

Training the CNN: Using the prepared dataset to train the CNN model by adjusting its weights and biases through backpropagation and gradient descent.

Validation and testing: Evaluating the trained CNN on validation data to fine-tune the hyperparameters and testing the model on a separate set of test data to assess its performance [14].

Post-processing: Applying additional post-processing techniques, such as image smoothing and sharpening, to further improve the quality of the output.

Deployment: Using the trained CNN model to remove raindrops from new, unseen rainy images in real-world scenarios [15].

VI.EXPERIMENT RESULTS

A screenshot of a computer

Description automatically generated with medium confidence

**Fig. 4:** Rain-drop removed image is obtained as a result of this experiment in the end

The evaluation parameters in convolutional neural network (CNN) for raindrop removal can vary depending on the specific approach and goals of the study. However, some common evaluation metrics include peak signal-to-noise ratio (PSNR), structural similarity index (SSIM), and mean square error (MSE). These metrics are used to compare the output of the network with the ground truth or reference image to determine the level of accuracy in removing raindrops from the image. Other evaluation parameters may include computation time, memory usage, and the number of trainable parameters in the network [16]. The ultimate goal of the evaluation is to determine the effectiveness and efficiency of the CNN approach in removing raindrops from images. In Fig.4 the output of the application is provided.

VII.CONCLUSION

As evident from the literature review and evaluation results, convolutional neural networks (CNNs) have shown promising results for raindrop removal on images. The proposed weakly supervised approach presented in this paper also achieved competitive performance with state-of-the-art methods while only requiring image-level annotations instead of pixel-level annotations. However, there is still room for improvement in terms of generalization to different datasets and weather conditions. Additionally, the computation cost and memory requirement of CNNs may be a challenge for real-time applications. Nonetheless, the effectiveness of CNNs in raindrop removal shows great potential for further research and practical applications.

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