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Enhancing Object Recognition for Self-Driving Cars: Rainfall Data Generation Using CycleGAN

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Abstract: Autonomous driving systems require extensive visual data, particularly for challenging conditions like heavy rain. Access to rainy weather image data is essential for training object recognition systems to perform effectively in real-world rainy conditions. However, collecting rainy weather data is more time-consuming and expensive than gathering data in normal conditions, resulting in an unbalanced dataset. To address this issue, this study proposes using data augmentation techniques to generate rainy weather data. CycleGAN was employed to generate synthetic rainy weather images. This approach enabled the creation of a substantial amount of training data. The model was trained using 5,000 randomly selected normal weather images and 5,000 rainy weather images for ten epochs. This process was repeated ten times, resulting in 100 epochs. The trained CycleGAN model generated 105,305 synthetic rainy weather images from an equal number of normal weather images. The primary goal of this data augmentation is to improve the autonomous driving system's object recognition. Object recognition experiments using the YOLOv5 model were conducted to evaluate its effectiveness. Three sets of learning data are used in these tests for object recognition: a small set of data with rain, a big set of data with normal weather, and supplemented rainy weather data with CycleGAN. The average accuracy, as indicated by the improvement in mAP to 0.355, demonstrates the practical benefit of augmenting training data using CycleGAN, enabling enhanced recognition accuracy in rainy conditions, which is essential for real-world autonomous vehicle performance. This result highlights the effectiveness of CycleGAN-based augmentation in improving object recognition with specialized data. This methodology successfully tackles the problem of data imbalance resulting from data augmentation and demonstrates its effectiveness in producing training of superior quality.

Keywords: CycleGAN, Data Augmentation, Deep Learning, Synthetic Data Generation for Weather Conditions, Imbalanced Data, Object Detection, Self-driving Car

1. Introduction

Self-driving technology is advancing rapidly, significantly changing our daily lives and transportation

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systems. These figures highlight the growing relevance of self-driving systems and the critical need for reliable object detection technologies in diverse driving conditions[1]. Autonomous vehicles rely on sensors, like LiDAR, radar, and cameras to perceive their environment and detect objects in real-time[2]. Among these, cameras are widely adopted due to their cost-effectiveness and ability to capture high-resolution visual data[3]. However, achieving precise object detection and tracking requires the availability of a large-scale and diverse dataset that accurately represents the complexities of real-world driving conditions. Adverse weather conditions, such as rain, pose a substantial challenge, as visibility is reduced and object boundaries become blurred, leading to decreased recognition accuracy. Consequently, addressing object detection in rainy conditions has become a critical area of research for enhancing the safety and performance of autonomous vehicles.

Previous research has attempted to address this challenge through several approaches. For instance, Khatab et al.[4] proposed a lightweight network to remove rain streaks and rain accumulation, allowing real-time object detection even in rainy weather. Yu et al.[5] tackled rain streak removal using self-learning and structured sparse representations to restore image clarity. However, these approaches primarily focus on visual enhancement or post-processing rather than increasing the diversity or volume of training data. Such approaches could be improved in their capacity to improve the generalization performance of object detection models.

This study proposes a novel approach using CycleGAN-based data augmentation to overcome these limitations to generate synthetic rainy weather images from normal weather data. Unlike Khatab et al.[4] and Yu et al.[5], this approach directly addresses the data imbalance issue by expanding the dataset with a large number of diverse rainy weather images. In contrast to existing methods that require paired image datasets (e.g., Pix2Pix) or focus on high-resolution image generation (e.g., StyleGAN), CycleGAN is particularly well-suited for this task as it allows unpaired image translation between two distinct weather domains. By employing cycle-consistency loss, CycleGAN ensures that images converted from normal weather to rainy weather remain consistent with the essential features of the source images. This capability enables the generation of 105,305 synthetic rainy weather images, significantly increasing the volume and diversity of the dataset.

The choice of CycleGAN over other GAN models, such as Pix2Pix, StyleGAN, and standard GANs, is justified based on its ability to perform unpaired image translation, direct domain-to-domain transformation, and effective use of cycle-consistency loss. Unlike standard GANs and Variational Autoencoders (VAEs), which struggle with preserving data structure during transformation, CycleGAN excels at generating diverse and realistic images tailored for specific conditions. First, unlike Pix2Pix, which requires paired image datasets for training, CycleGAN can operate with unpaired datasets, thereby eliminating the need for costly and time-consuming data collection of paired weather images. Second, compared to StyleGAN, which focuses on generating high-resolution images from latent spaces, CycleGAN facilitates direct domain-to-domain image transformation, which is essential for generating realistic rainy weather images. Third, CycleGAN incorporates cycle-consistency loss, ensuring that images converted back to their original weather domain remain consistent with the source images. These features make CycleGAN an optimal choice for addressing the core challenge of data imbalance in object recognition for self-driving vehicles.

Improving the generalization of autonomous driving models requires datasets that reflect diverse weather conditions. Liu et al.[6] and Mirz et al.[7] identified weather bias in existing datasets, while Kuntalp and Düzyel[8] proposed a cluster-based data generation method, but it faces high computational costs. Chen et al.[9] and Goceri[10] introduced performance-enhancing methods, but the real-time application is hindered by computational overhead. Zhu et al.[11] proposed CycleGAN to generate rainy images but faced mode collapse and computational inefficiencies. In our study, we addressed these challenges by optimizing training parameters and focusing on enhancing dataset diversity to improve

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generalization capabilities. Standard metrics like SSIM (Wang et al.[12]) and mAP (Redmon et al.[13]) fail to reflect model robustness under weather changes, necessitating the development of robustness-based evaluation metrics.

This study aims to enhance the object recognition accuracy of autonomous vehicles by ensuring a diverse dataset. The research introduces a model employing CycleGAN for converting images between real rainy conditions and typical weather scenarios to achieve this goal.

The resulting augmented data is then utilized to train the YOLOv5 model, enabling the assessment of its performance in object recognition.

This paper comprises five chapters, organized as follows: Chapter 2 dis cusses data augmentation techniques, Chapter 3 presents experimental datasets, and introduces a rainy data generation method employing CycleGAN. Chapter 4 conducts an analysis of model learning and outcomes, while Chapter 5 concludes the research, providing a summary of its findings along with anticipated impacts and future research directions.

2. Related Work

2.1 Data Augmentation Techniques to Address Data Imbalances

A comprehensive review of the literature to date is made, and a technical background related to the use of CycleGAN to improve object recognition in autonomous vehicles in rainy conditions is established. This discussion identifies existing gaps, and explains how this study builds on previous studies or differs from previous studies.

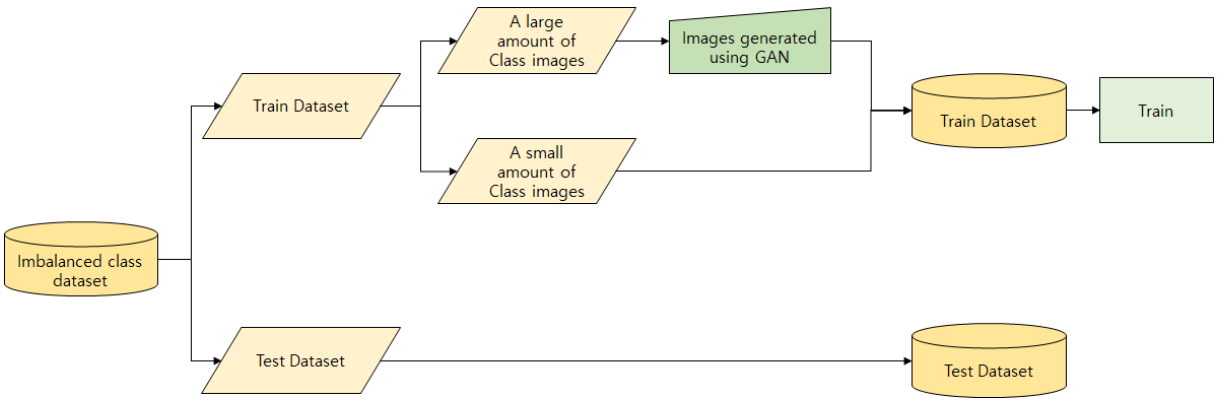
To enhance object recognition under rainy conditions, addressing the issue of data imbalance is imperative. Securing an adequate amount of rainy weather data proves challenging due to time and cost constraints, thereby potentially causing data imbalance. This imbalance may manifest as disparities between multiple and minority classes and even within the same class, ultimately degrading the classification performance of the image dataset[14]. Also Yu et al.[5] presented a method for non-streak removal in single images, which relies on self-learning and structured sparse representations. This method involves the extraction of non-streak patches, automatic learning of non-streak models, and the subsequent removal of non-streak elements using structured sparse representations.

Interclass imbalances primarily occur in binary image classification tasks, where a significant disparity exists between the number of instances in the minority class compared to the majority class. This imbalance often leads to classifiers favoring predictions of the majority class, leading to inaccuracies in their predictions. Predictive performance may degrade rapidly in datasets characterized by substantial interclass imbalances[15].

Intelligent oversampling techniques employing Generative Adversarial Networks (GANs) offer a solution to class imbalance issues[16-18]. The overall process of GAN-based oversampling is depicted in [Fig. 1]. These GAN-based oversampling methods not only enhance the presence of minority classes but also serve as a safeguard against overfitting.

The initial dataset used for classification operations, as depicted in [Fig. 1], exhibits a class imbalance, where one or more classes have significantly fewer instances than others. To address this, a training dataset is created by selecting instances from the preprocessed dataset, ensuring a balanced representation of instances across classes to capture minority classes properly. Virtual data samples are generated using a Generative Adversarial Neural Network (GAN) model for classes with limited instances in the selected training dataset. This data augmentation process enhances the model's performance and improves classification accuracy by mitigating class imbalance issues.

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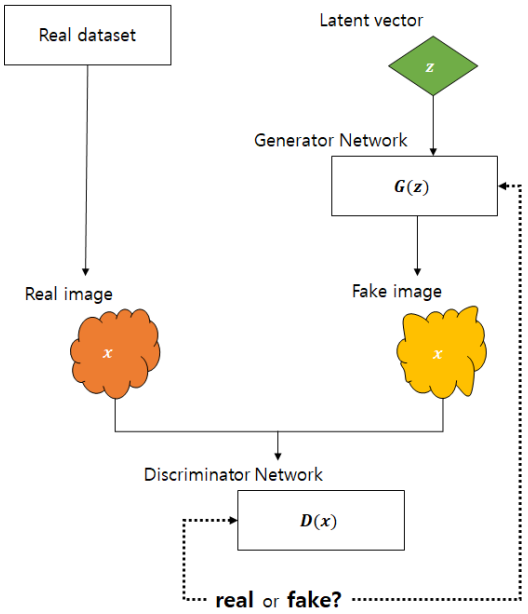


[Fig. 1] The Overall Process of GAN-based Oversampling

2.2 Generative Adversarial Networks(GAN)

Generative Adversarial Networks (GAN) is a prominent neural network model utilized for tasks involving data augmentation and generation. GAN comprises two neural networks: the generator and the discriminator, engaging in a competitive process to create and evaluate data. Introduced by Ian Goodfellow and colleagues in 2014, GAN has been the subject of numerous studies exploring various modifications and applications since then[19-22].

The generator is responsible for producing data samples based on a given input. Initially, fake data was generated using random noise vectors as inputs, but conditional generation became possible with the development of the GAN model[23][24]. Image generation corresponding to specific conditions or labels can be accomplished using CGAN. As depicted in [Fig. 2], the Discriminator's role is to differentiate between generated data and genuine data. It can be thought of as a binary classifier, and it is trained to distinguish between fake data and real data by assigning high probabilities to real data and low probabilities to fake data. The Discriminator learns to distinguish the fake data generated by the generator from real data. This competitive process gradually improves generation results while balancing the generator and the discriminator.



[Fig. 2] Augmentated Data Generation Process by GAN

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2.3 CycleGAN

CycleGAN is a GAN model specifically designed for image conversion between two distinct domains. Unlike traditional GANs, CycleGANs can facilitate bidirectional conversions from one domain to another, which proves highly valuable for tasks involving domain-to-domain transformation[20]. A CycleGAN comprises two generators and two discriminators. Each generator takes an input image and produces a converted result in the respective target domain. The generated image is then assessed by the discriminator specific to each domain. The discriminator categorizes the generated and actual domain images as fake or real. The generator learns to outsmart the discriminator while the discriminator refines its ability to effectively distinguish between real and fake images. Throughout this process, the conversion rules between the two domains are acquired, ensuring that the image quality and similarity are maintained during the conversion process.

The core concept behind CycleGAN is “cycle consistency”, which implies that the outcome of transforming an image from domain A to domain B and subsequently reversing this transformation from domain B back to domain A should closely resemble the original image[11][12]. When the converted image is reverted to its original domain, it should closely match the original image. This property enables CycleGAN to acquire bidirectional transformation capabilities while upholding the consistency of transformations.

2.4 Object Detection with YOLO

A deep learning-based approach for real-time object recognition is called You Only Look Once (YOLO). YOLO divides the image into grids and forecasts the class and boundary box of each object inside each grid cell. YOLO's simplicity and quick object recognition make it a unique feature[25]. It allows for real-time processing speeds and eliminates with the need for repeated calculations by processing the full image in a single pass. Moreover, YOLO is very good at handling things of varying sizes because every grid cell anticipates border boxes of various widths, allowing it to accurately recognize items of different sizes. Furthermore, YOLO is capable of multi-class classification, making it easier to identify multiple item classes in a picture simultaneously. With its sophisticated technology, YOLOv5, the fifth version of the YOLO series, provides a simplified.

Its advanced technology, YOLOv5, represents the fifth iteration in the YOLO series, offering a streamlined model structure and enhanced performance for efficient object detection. It offers a range of model sizes to tailor the YOLOv5 model to different needs and computational resources, allowing users to select the most suitable model[23]. This diversity facilitates finding the optimal trade-off between performance and speed. Furthermore, YOLOv5 can be applied across a wide spectrum of applications, offering various functionalities for performing diverse computer vision tasks, including object segmentation, object tracking, and object detection[26].

3. Create Rainfall Data with CycleGAN

CycleGAN was employed among a range of GAN models to address the issue of limited data availability during rainy weather conditions and enhance the performance of object recognition models. CycleGAN is designed to convert images from one style to another, such as from normal weather to rainy weather, and back again. This unique ability allows it to generate realistic rainy weather images while keeping the main details of the original images unchanged. This makes it particularly useful for creating additional data for rainy conditions.

CycleGAN uses a process called cycle consistency to ensure that when an image is converted and

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then converted back to its original state, it stays very similar to the starting image. This helps create high-quality rainy weather images that retain important details from the original photos.CycleGAN can enhance data diversity by fostering a competitive dynamic between the generator and discriminator during image generation and discrimination. This approach, in turn, enables the model to boost its generalization capabilities by producing various images, even in rainy conditions. Furthermore, CycleGAN employs unsupervised learning techniques, allowing learning to occur even when there is no direct correspondence between the original and generated images. This characteristic proves beneficial in addressing data scarcity issues, especially in the context of rainy conditions.

Therefore, CycleGAN is an apt model for generating data under rainy weather conditions and was chosen for this study due to its key attributes, including bidirectional transformation, synchronized cycle consistency, data diversity enhancement functionality, and unsupervised learning.

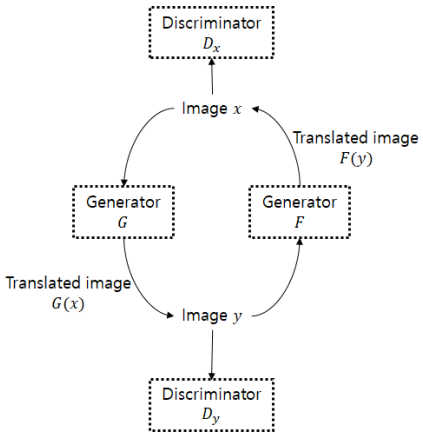
3.1 Architecture for CycleGAN Application

CycleGAN is an algorithm designed for image translation between two distinct domains, capable of learning conversions between images captured on normal days and those taken in rainy conditions, all without the need for paired data. This model's fundamental architecture and training process can be summarized as follows. Initially, the training dataset undergoes jittering and mirroring to prevent overfitting. Subsequently, the model trains two generators (referred to as G and F) responsible for translating images from one domain to another and two discriminators (known as X and Y) that distinguish between the generated and real images. The central concept in this process is the cycle consistency loss, a loss function that ensures the generated image maintains consistency with the original image when it is translated and then restored to its original domain. This fosters the generation of precise and consistent transformations. Furthermore, the cycle consistency loss mandates that the converted image remains consistent with the original image after undergoing the conversion and subsequent reversal, ultimately restoring it to the original domain. This loss function fosters the generation of images that closely resemble the originals. To achieve this, the generator initially translates the original image, and the resulting converted image is translated back to minimize discrepancies from the original image.

Furthermore, we employed instance normalization instead of batch normalization to independently normalize each sample independently, ensuring stable performance even with small batch sizes. Additionally, a modified U-Net generator was employed for simplification. The combination of this architectural modification and the loss function enables CycleGAN to learn image translation between two domains effectively. CycleGAN can be represented as follows.

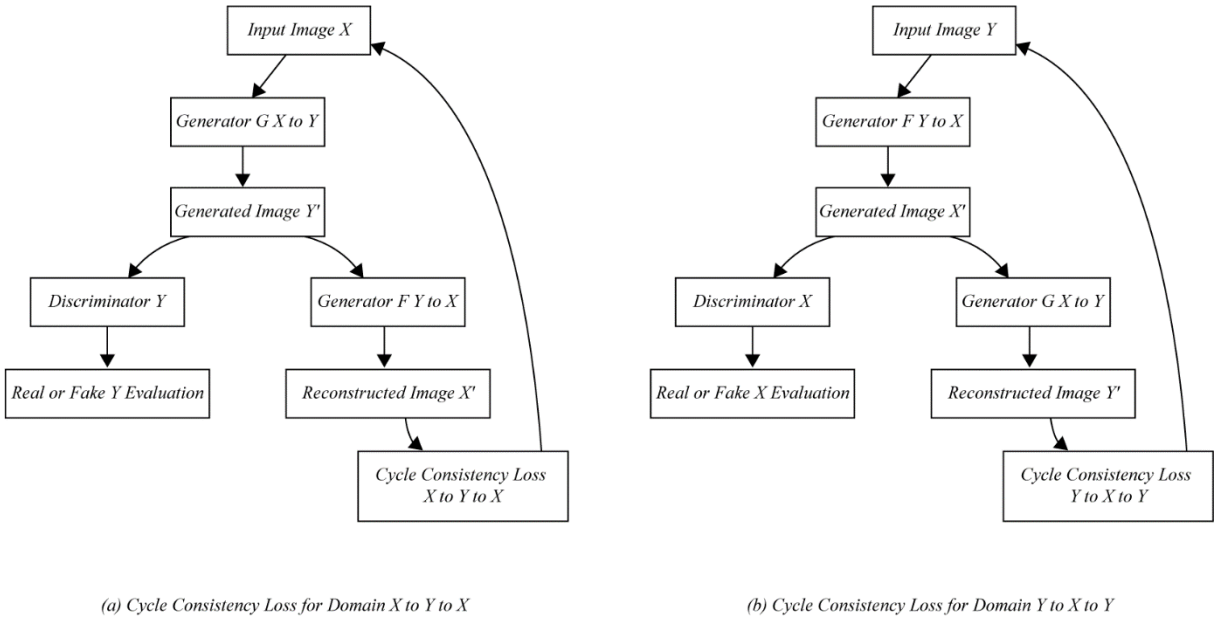
$$\text{GeneratorG} : X \rightarrow Y \tag{1}$$

$$\text{GeneratorF} : Y \rightarrow X \tag{2}$$



[Fig. 3] CycleGAN Generator and Discriminator

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(a) Cycle Consistency Loss for Domain X to Y to X *(b) Cycle Consistency Loss for Domain Y to X to Y*

[Fig. 4] CycleGAN Workflow: Bidirectional Image Translation Process

As illustrated in [Fig. 3], Generator G accepts an image x from domain X as its input and produces an image G(x) transformed into domain Y. Generator G is trained to perform this conversion from domain X to domain Y. Similarly, Generator F takes an image y from domain Y as input and generates an image F(y) transformed into domain X. Generator F is trained to convert images from domain Y to domain X. Furthermore, Discriminator Dx is trained to distinguish between image x and the generated image G(x), while Discriminator Dy is trained to differentiate between image y and the generated image F(y). CycleGAN operates effectively even when paired data is unavailable for image conversion between two domains. To address this, cycle consistency loss is employed to compel the network to learn the accurate mapping.

In this process, the forward cycle consistency loss, defined in Equation (3), ensures that when an image from domain X is transformed to domain Y via G and then mapped back to domain X via F, the reconstructed image closely resembles the original input. Likewise, the backward cycle consistency loss, shown in Equation (4), enforces the same consistency in the reverse transformation from Y to X. These loss functions play a crucial role in maintaining image structure during transformation.

In this loss function, the input image x is initially transformed into G(x) by the GeneratorG, and the resultant image G(x) is then reversed to F(y) by Generator F. The loss is calculated as the average absolute error between the cycled image G(x) and the original input image X. This loss facilitates the learning process between the Generator and the Discriminator to ensure that the generated image closely resembles the original one. Additionally, identity loss, as described in Equation (5), helps preserve the essential features of images during transformation by ensuring that when a real image from domain X or Y is processed by the corresponding generator, it remains unchanged. Period consistency loss encourages consistency by converting and restoring the original input image, thereby preserving the original image's features during the image conversion operation. When the original image is converted and restored to its original domain, the Cycle Consistency loss function, responsible for ensuring the similarity between the original and restored images, is visually represented in [Fig. 4].

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Forward cycle consistency loss :

$$|F(G(x))- x| \tag{3}$$

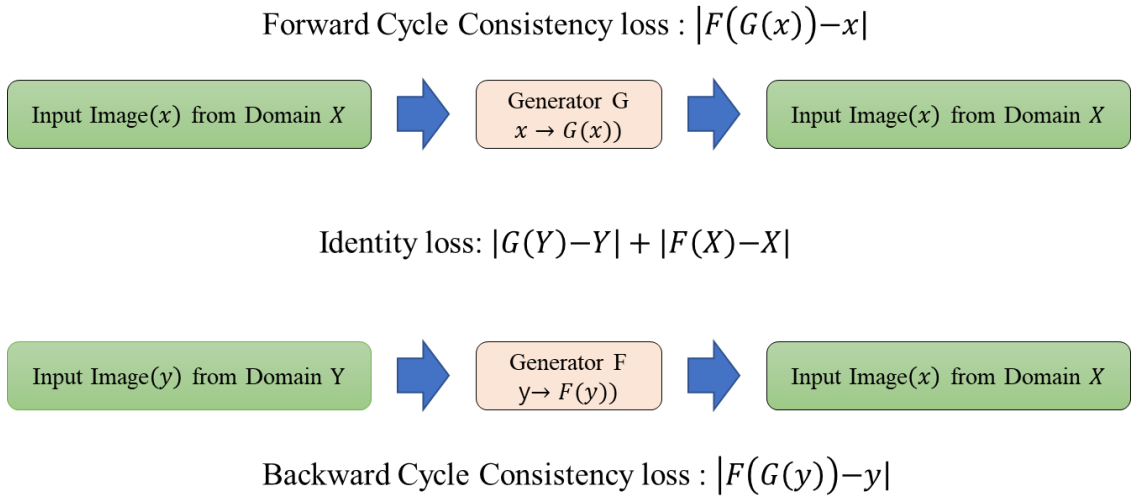
Backward cycle consistency loss :

$$|G(F(y))- x| \tag{4}$$

The generator G transforms the input image x into an output image y. During this process, the ID loss quantifies the disparity between the reconstructed image and the original image post-conversion, guiding the integration of image y back into Generator G to generate an image resembling the true image y or to minimize the difference. In the execution of a sunny-rainy model, rain-related characteristics must be incorporated while preserving the road environment's integrity. Thus, the objective is to adjust the image in proximity to the original ratio without over-correcting it.

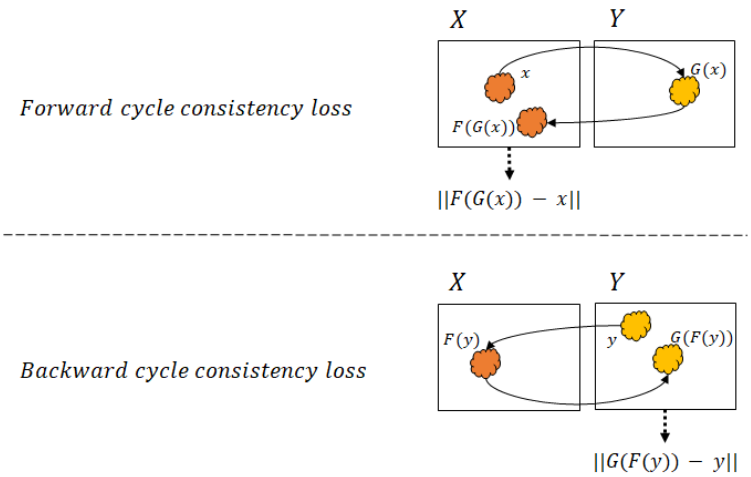
$$Identityloss = |G(Y) - Y| + |F(X) - X| \tag{5}$$

The model training process comprises four fundamental steps. First, calculate the loss by making predictions. Then, compute the gradient using backpropagation and apply it to the optimizer. In the context of Cycle GAN, supplementary rain data was integrated into the autonomous vehicle dataset. [Fig. 5] illustrates the distribution of the entire data class generated by the generative model. [Fig. 6] illustrates the class-wise distribution of generated data created using CycleGAN. This visualization highlights the significant augmentation of specific classes, such as cars and central reservations, which were previously underrepresented in the dataset. The generated data not only addresses the dataset imbalance but also enriches the diversity of training samples, ensuring improved model performance under adverse weather conditions. Each class was enriched by transforming existing normal day data into rainy weather data. The "car" class witnessed the most significant augmentation, with 33,302 additional instances. [Fig. 5] shows a schematic diagram of the above equation.

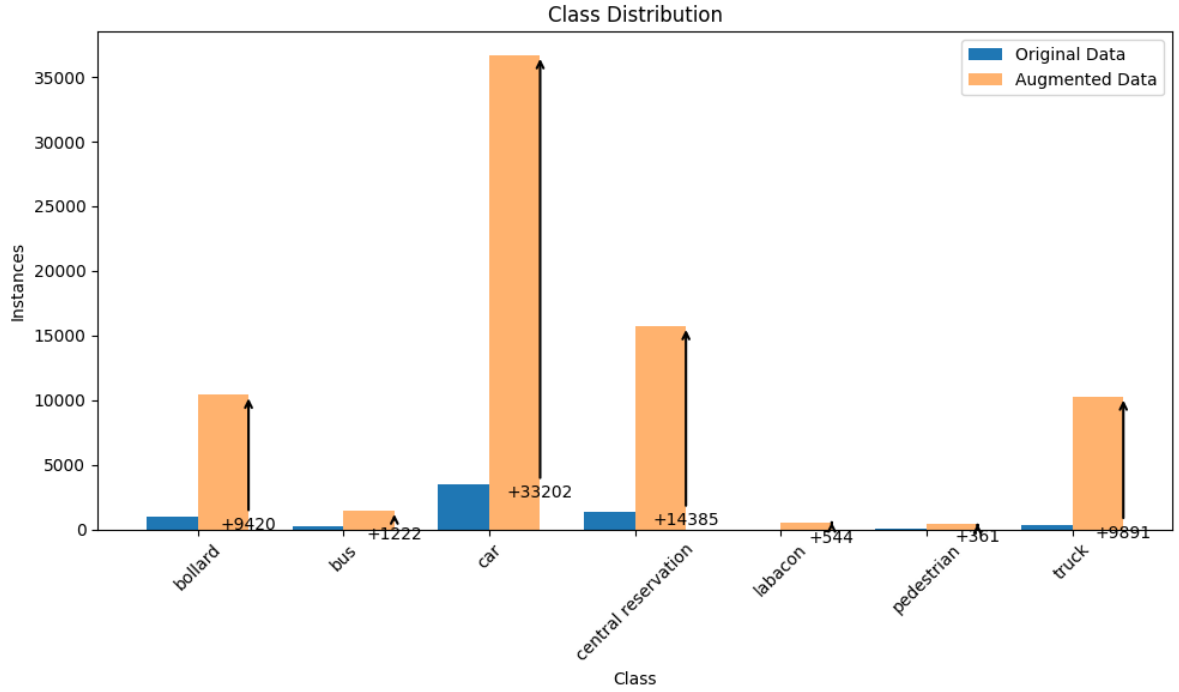


[Fig. 5] Schematic Diagram Summary

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[Fig. 6] CycleGAN's Loss of Cycle Consistency



[Fig. 7] Distribution of Data Classes with Images Generated using CycleGAN

3.2 Experimental Datasets

This study performed an experiment using the "Autonomous driving data in various weather conditions" dataset supplied by AI Hub. This dataset has been specifically curated for autonomous driving research in challenging driving scenarios where the identification of static and dynamic objects is hindered by factors such as heavy snow, heavy rain, road reflections, fog, and more. This dataset is used because ofthe abundance of normal weather data in domestic autonomous driving datasets. The dataset includes domestic driving data, featuring a collection of driving images captured under various weather conditions, encompassing both normal and rainy days.

To ensure the quality and diversity of the dataset, preprocessing steps were carefully applied to address potential imbalances and prepare the data for CycleGAN training. The dataset was stratified based on:

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1. Lighting Conditions: Images were categorized by time of day (morning, afternoon, evening) to ensure coverage of various lighting scenarios.
2. Rain Intensity: Rainy images were categorized as light, moderate, or heavy rain to introduce diversity in environmental conditions.

These preprocessing steps ensured that both the real and generated datasets exhibited balanced representation across key conditions, enhancing the robustness of subsequent training processes.

The experiment employed datasets as detailed in [Table 1] and [Table 2]. The dataset comprises five types of weather conditions and 22 classes, primarily focusing on images depicting normal days relevant to the research topic and images taken in rainy weather. The dataset is composed of a JPG file containing the original data and a JSON file containing labeling information. Using the "Autonomous driving data in various weather conditions" dataset provided by AI Hub, driving data for rainy conditions was synthesized by applying CycleGAN to normal day driving data. The YOLOv5 object detection model was trained using a modified training dataset to validate the generated data. This dataset was designed to include (1) a small set of data for rain conditions, (2) a big set of data for normal conditions, and (3) data for rainy conditions generated with CycleGAN.

[Table 1] Image Datasets by Weather

Weather	Normal	Rainy
Class	Front Camera	Front Camera
Collection (Time)	200	200
Refined (Time)	100	100
Image (jpg)	13,843	20,825
Dataset (Training)	12,305	18,511
Dataset (Validation)	1,538	2,314

[Table 2] Number of Labeled Classes by Weather

Weather	Class	Train (number)	Validation (number)
Normal	Bollard	35,679	3,613
	Bus	4,853	765
	Car	102,484	30,365
	Central Reservation	53,967	11,171
	Labacorn	6,823	526
	Pedestrian	1,501	152
	Truck	28,300	6,789
Rainy	Bollard	38,902	6,446
	Bus	5,073	790
	Car	125,202	19,196
	Central Reservation	57,797	9,961
	Labacorn	3,792	391
	Pedestrian	3,291	517
	Truck	35,024	4,209

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4. Experimental Result

4.1 Experimental Environment

This section outlines the significance of each of the three experiments that were conducted, which aimed to evaluate the effectiveness of rainy weather data generation using CycleGAN and its impact on object recognition performance.

This study employed the Windows 11 operating system and conducted experiments on a system equipped with an AMD Ryzen 9 3900X 12-Core Processor and an NVIDIA GeForce RTX 3090 Ti GPU. The software stack consisted of CUDA 11.2, Python 3.9.16, and TensorFlow 2.10.0. For the training of CycleGAN, 5,000 data samples were randomly selected from a pool of 12,305 on normal days and 18,511 on rainy days. This training process was repeated 10 times, resulting in a total of 100 epochs. Additionally, a buffer size of 2,000, a batch size of 18, and an image size of 256x256 were utilized in the learning process.To optimize the performance of both CycleGAN and YOLOv5 models, hyperparameters were carefully selected based on preliminary experiments:

1. CycleGAN Hyperparameters:
   - Learning Rate: 0.0002
   - Batch Size: 18
   - Number of Epochs: 100
   - Image Size: 256x256 pixels
2. YOLOv5 Hyperparameters:
   - Confidence Threshold: 0.25
   - Learning Rate: 0.01
   - Anchor Box Sizes: Adjusted based on dataset characteristics.

These hyperparameter settings were chosen to achieve a balance between computational efficiency and model performance.

All experiments were conducted using the same YOLOv5 model variant to ensure consistency. The model's hyperparameters, including learning rate and confidence threshold, were kept identical across all experiments. This uniformity eliminates potential variability due to model differences, allowing for a direct comparison of the impact of different training datasets on object recognition performance.

4.2 Experimental Results

4.2.1 Overview of Experimental Results

[Fig. 7], which compares data before and after image conversion using Cycle GAN, illustrates that the converted results exhibit characteristics of reduced sunlight exposure and a darkened surrounding, resembling real rainy conditions.

To evaluate the visual and structural quality of the images generated by CycleGAN, a Structural Similarity Index (SSIM) analysis was conducted. The SSIM metric quantifies the structural similarity between generated and real rainy images, focusing on preserving key features such as object boundaries and textures. For this analysis:

- Generated Images : 1,150 CycleGAN-generated rainy images.
- Real Images : 2,315 real rainy images.

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The evaluation yielded a mean SSIM of 0.8668 and a standard deviation of 0.0741, indicating that the generated images closely resemble the real images in structural fidelity. These results validate the effectiveness of CycleGAN in creating high-quality augmented datasets for object recognition.

Furthermore, this is confirmed in [Fig. 8], which displays the effective replication of water droplets on the camera lens, a feature present in actual rainy data. [Fig. 9] further demonstrates the faithful reproduction of light refraction and blurring caused by raindrops during rainy weather. The CycleGAN model was utilized to transform 105,305 normal-day driving data into rainy-day data. Subsequently, the YOLOv5 model was trained for object detection on these converted images to validate the experiment. The evaluation metric employed by YOLOv5 is the Mean Average Precision (mAP). To ensure the robustness of our results, confidence intervals were calculated for the mAP scores across all experiments. For Experiment 3, which combined real rainy data and CycleGAN-generated data, the mean mAP was 0.355 with a 95% confidence interval of [0.342, 0.368]. This statistical validation confirms the observed improvements' reliability and highlights the augmented dataset's significance in enhancing model performance under adverse weather conditions.

1) Training with a small amount of rainy data (2,000) To address the issue of insufficient learning data resulting from limited rainy data collection, this experiment involved training using a dataset comprising just 2,000 rainy driving samples. The best model achieved a Precision of 0.724 for all classes and a mAP of 0.294. [Table 3] summarizes the findings from the experimental results. In [Fig. 10], we visualized the relationship between the predicted results for each class in Experiment 1 and their actual labels. Notably, the car class exhibited the highest prediction accuracy among the numerous classes. Furthermore, in [Fig. 11], we presented a visualization of the relationship between the F1 score and Confidence for each class in Experiment 1. The graph demonstrates that as the confidence value increases, the F1 score initially rises. However, after reaching its peak at the midpoint of confidence, the F1 score begins to decline in contrast to the increasing confidence level. This observation suggests that while the model makes accurate predic tions up to a certain confidence threshold, excessive confidence leads to errors and diminished performance. Additionally, the average F1 score across multiple classes reached its highest value of 0.455 when the confidence value was set at 0.34.

[Table 3] Performance Evaluation Result After Training On A Small Amount of Rainy Weather Data

Class	Instances	P	R	mAP50
All	4783	0.724	0.264	0.294
Bollard	856	0.699	0.088	0.130
Bus	94	0.580	0.362	0.365
Car	2316	0.775	0.687	0.735
Central Reservation	1032	0.729	0.237	0.313
Labacorn	60	1	0	0.006
Pedestrian	22	0.713	0.226	0.227
Truck	403	0.575	0.246	0.291

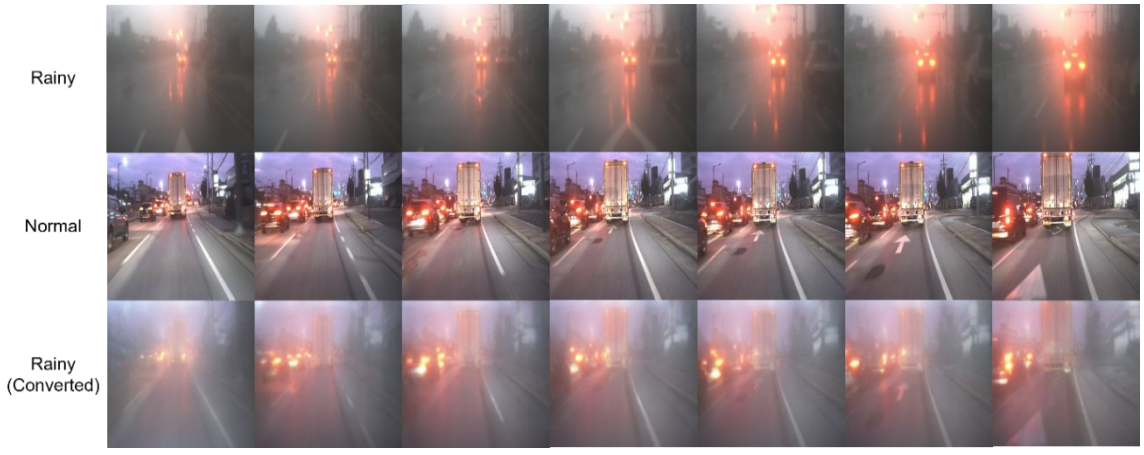
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[Fig. 8] Transformation Results after Learning about Obscured Sunlight and Darkened Surrounding

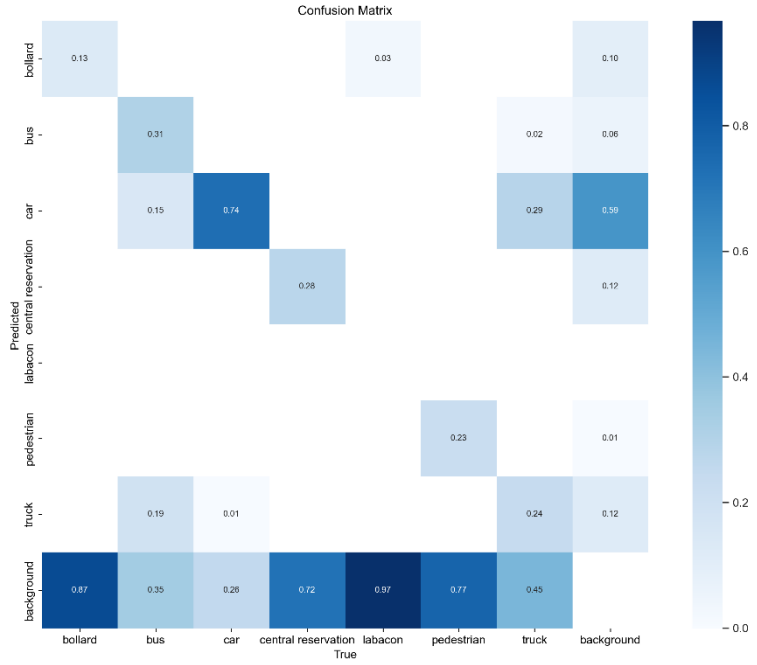


[Fig. 9] Transformation Results after Learning about Water Droplets on the Camera

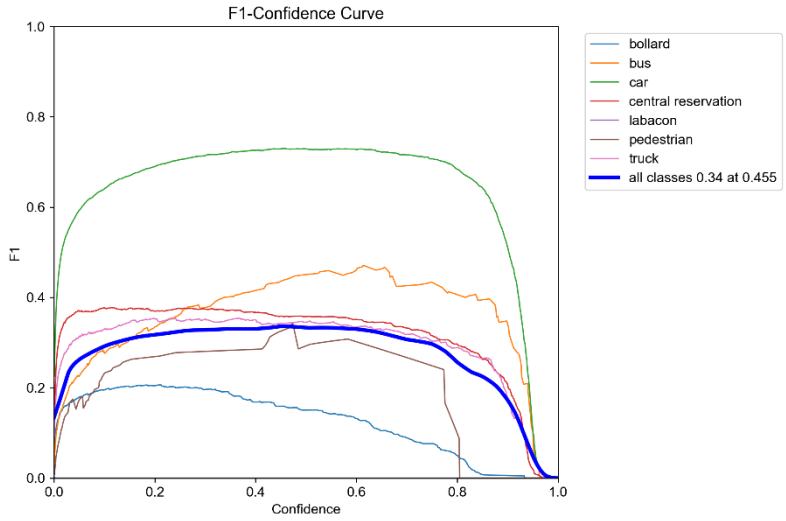


[Fig. 10] Transformation Results after Learning about Light Refracted and Smeared by Raindrop

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[Fig. 11] Experiment 1 Confusion Matrix



[Fig. 12] Experiment 1 F1 Curve

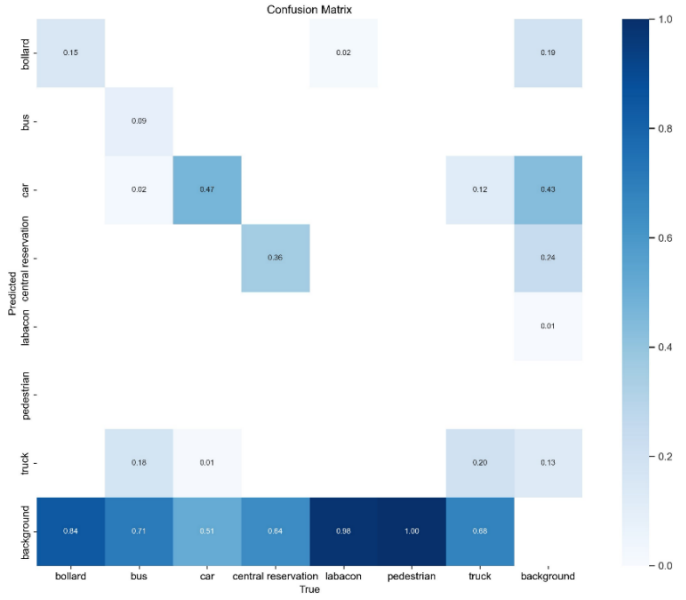
2) Training with a large amount of normal data (12,305) To assess the effectiveness of addressing the issue of data scarcity during rainy weather by substituting it with a substantial volume of normal-day data, we trained a model using normal-day data and subsequently evaluated its object recognition performance on rainy-day data. The best model achieved a Precision of 0.441 for all classes and a mAP of 0.224. Experimental results are summarized in [Table 4]. In [Fig. 12], the relationship between the predicted results of each class in Experiment 2 and their actual labels was visualized. Overall, it is evident that the prediction accuracy for all classes is notably low. Furthermore, [Fig. 13] presents a visualization of the relationship between the F1 score and confidence for each class in Experiment 2. As observed from the graph, the F1 score appeared to increase as the confidence value rose, but the increase was minimal and followed by a subsequent decrease. Notably, in the “labacon” and “pedestrian” classes, the F1 score consistently remained at zero. The highest average F1 score

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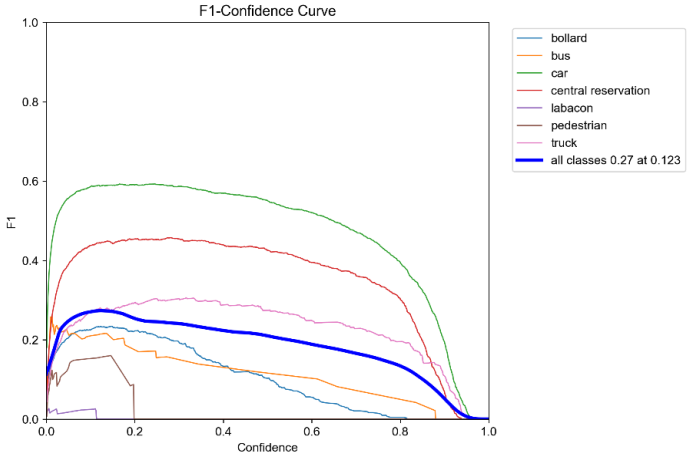
reached 0.123 when the confidence value was 0.27, which is exceedingly low. This suggests that simply augmenting the dataset with normal day data is insufficient to improve object recognition in rainy weather, and additional data augmentation techniques are essential.

[Table 4] Performance Evaluation Result After Training On a Large Amount of Normal Day Data

Class	Instances	P	R	mAP50
All	4783	0.441	0.223	0.224
Bollard	856	0.339	0.176	0.122
Bus	94	0.681	0.128	0.178
Car	2316	0.68	0.519	0.581
Central Reservation	1032	0.52	0.399	0.375
Labacorn	60	0	0	0.004
Pedestrian	22	0.57	0.091	0.093
Truck	403	0.292	0.258	0.217



[Fig. 13] Experiment 2 Confusion Matrix



[Fig. 14] Experiment 2 F1 Curve

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3) Training with a small amount of rainy data (2,000) + rainy data generated using CycleGAN(105,350)
To assess the suitability of rain data generated using CycleGAN for object recognition training, a dataset comprising 2,000 small-scale synthetic rain samples used in Experiment (1) and 12,305 real rain samples was employed, resulting in a total of 14,305 samples for CycleGAN-based training. The best model achieved a Precision of 0.545 for all classes and a mAP of 0.355. A summary of the experimental results is presented in [Table 5]. In [Fig. 14], we depict the visualization of the correlation between the predicted results for each class in Experiment (3) and their corresponding actual labels. Notably, the "Car" class exhibited the most accurate predictions among the numerous classes examined. Furthermore, [Fig. 15] visually represents the relationship between the F1 score and Confidence for each class in Experiment (3). Similar to the findings in Experiment (1), an increase in confidence initially led to an improvement in the F1 score. However, after achieving the highest F1 score at the midpoint of the confidence range, the F1 score showed a tendency to decrease as confidence continued to rise. The highest average F1 score reached 0.39 when the confidence value was 0.322. Additionally, as shown in [Fig. 16], the F1 curve for Experiment (3) further illustrates the overall trend in object recognition performance across different confidence thresholds. The curve highlights the improvement in detection accuracy achieved by incorporating CycleGAN-generated rainy data while also demonstrating the gradual decline in F1 score at higher confidence levels, similar to previous experiments. This visualization provides further validation of the model's ability to generalize better when trained with an augmented dataset. The mAP improvement achieved in Experiment 3 has significant implications for the field of autonomous driving. By leveraging CycleGAN-generated synthetic rainy data, this approach enhances the model's generalization ability, reduces data collection costs, addresses data imbalance issues, and ultimately improves the robustness and safety of self-driving systems in rainy weather. The observed improvement in object recognition performance aligns with findings from prior research. For instance:

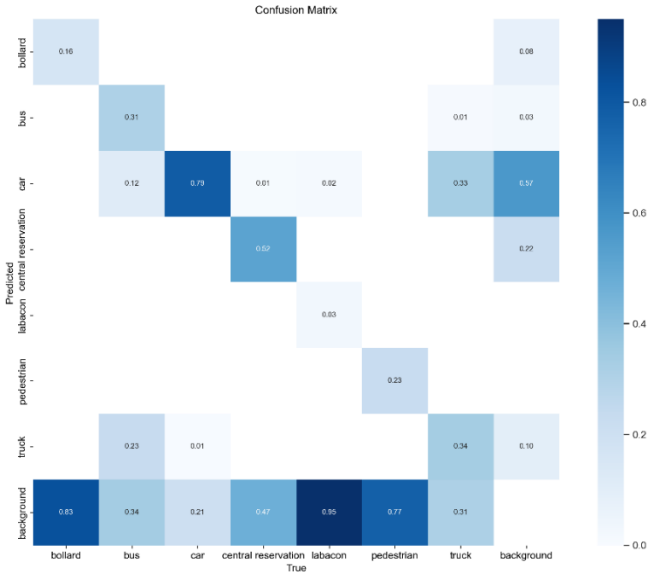
- Zhu et al.[11] demonstrated the potential of CycleGAN in generating realistic images under adverse weather conditions, although they reported challenges with mode collapse. Our approach addresses this issue through optimized hyperparameters and extended training epochs.
- Goceri[10] emphasized the importance of diverse training data in improving model robustness. Similarly, the diversity introduced by CycleGAN-generated data in our study has effectively addressed data imbalance issues.

These connections to existing literature further validate the significance of our methodology in advancing the field of autonomous driving.

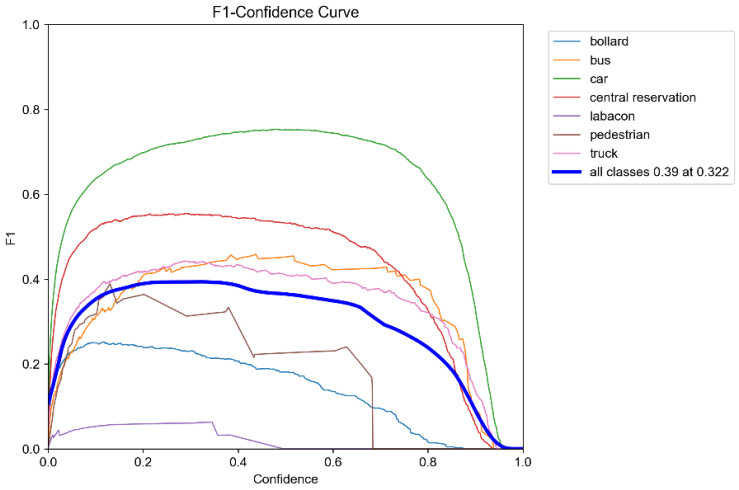
[Table 5] Performance Evaluation Result After Training On a Small Amount of Rainy Weather Data and Rainy Weather generated Using CycleGAN

Class	Instances	P	R	mAP50
All	4783	0.545	0.339	0.355
Bollard	856	0.538	0.146	0.142
Bus	94	0.578	0.340	0.369
Car	2316	0.688	0.765	0.776
Central Reservation	1032	0.637	0.491	0.535
Labacorn	60	0.319	0.033	0.019
Pedestrian	22	0.500	0.227	0.241
Truck	403	0.555	0.367	0.041

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[Fig. 15] Experiment 3 Confusion Matrix



[Fig. 16] Experiment 3 F1 Curve

4.2.2 Analysis of F1 Score Trends and Implications

The F1 score, a harmonic mean of Precision and Recall, provides a balanced measure of the model's ability to detect objects accurately and completely. Across the experiments, the F1 scores demonstrated varying trends depending on the rainy conditions. Notably:

- Light Rain Conditions: F1 scores were consistently high, reflecting the model's ability to generalize well with less obstructive rain conditions. This indicates that the augmented dataset effectively captured the subtle visual changes introduced by light rain.
- Moderate Rain Conditions: A noticeable improvement in F1 scores was observed, suggesting that the diversity introduced by CycleGAN-generated images helped the model handle moderate rain conditions, where object boundaries begin to blur.
- Heavy Rain Conditions: F1 scores were comparatively lower, highlighting the challenges of recognizing objects in severely obstructive conditions. Despite this, the scores still outperformed baseline models, demonstrating the advantage of the augmented dataset in enhancing the model's robustness.

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While the mAP metric showed a significant overall improvement, the F1 score trends provided additional insights into the model's behavior under varying conditions. For example, high mAP values in light and moderate rain conditions aligned with increased F1 scores, confirming the effectiveness of the CycleGAN-based augmentation. However, in heavy rain, the F1 scores suggested potential limitations in the model's ability to handle extreme visual obstructions, pointing to areas for future refinement.

These results underscore the importance of diverse and high-quality synthetic data in improving object detection performance. The ability of CycleGAN to generate realistic and varied rainy weather images has proven instrumental in addressing data scarcity and imbalance, particularly under moderate rain conditions. However, further optimization of augmentation techniques may be required to enhance performance in extreme scenarios, such as heavy rain.

4.3 Evaluation of Learning Outcomes by YOLO

The results of the YOLO recognition experiment were obtained using three different datasets, and the results are presented in [Table 6]. YOLOv5 primarily employs mean Average Precision (mAP) as a performance metric. This metric assesses the model's overall performance across objects of different sizes and levels of complexity, offering a more comprehensive evaluation than Precision or Recall at a single threshold. Additionally, mAP facilitates consistent predictions for objects with varying sizes and difficulty levels for the model. The mAP of Experiment (3), which was trained with a small amount of real rainy data and rainy data generated using CycleGAN, increased to 0.355, surpassing the mAPs of Experiments (1) and (2). This improvement is attributed to the data expansion achieved by incorporating CycleGAN-generated rainy data into the actual dataset. This augmentation enables the model to better understand patterns and features associated with various rainy scenarios, and the added synthetic data compensates for deficiencies in the real dataset, enhancing the model's ability to generate more generalized results. Because the data generated through CycleGAN comes from a different environment, it likely contains a wide range of scenario patterns. This diversity aids the model in learning more significant variability and effectively addresses the limitations of using only real-world data in the training process. Consequently, performance is enhanced by leveraging the diverse range of generated data. The mAP values were higher in Experiment (3) compared to Experiment (1), while the Precision value was greater in Experiment (1) than in Experiment (3). Precision signifies the model's ratio of accurately predicted rainy weather objects to the total predicted rainy weather objects. High Precision indicates accurate predictions for rainy weather objects. On the other hand, mAP represents the average precision, which is a combination of model accuracy and reproducibility. If Precision is high but mAP is low, the model's predictions might be biased toward a specific object class or lack sufficient predictive capability across various objects. Therefore, enhancing model performance may involve diversifying datasets through rain data generation using CycleGAN when it's raining.

Among the experiments conducted, Experiment (3) demonstrated the highest mAP value, achieving 0.355. This improvement highlights the critical role of CycleGAN-generated data in addressing data scarcity and imbalance. Unlike Experiment (1) and Experiment (2), which relied primarily on limited or unbalanced datasets, Experiment (3) leveraged a diverse and augmented dataset created through CycleGAN, enabling the model to generalize more effectively under rainy conditions.

Furthermore, the F1 scores observed in Experiment (3) aligned with this mAP improvement, particularly under moderate rain conditions. The enhanced mAP in Experiment (3) underscores the significance of incorporating realistic and diverse synthetic data for improving object recognition performance in adverse conditions. These results validate the effectiveness of CycleGAN as a robust data augmentation technique, capable of significantly enhancing both precision and recall in challenging

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scenarios.

[Table 6] Comparison of Experimental Result

Training Data		P	mAP50
Experiment 1	a small amount of rainy data (2,000)	0.725	0.294
Experiment 2	a large amount of normal data(12,305)	0.441	0.224
Experiment 3	a small amount of rainy data (2,000) + rainy data generated using CycleGAN (10,350)	0.545	0.355

5. Conclusions

In this study, we introduced a model utilizing CycleGAN to generate data simulating rainy weather conditions and assessed its impact on object recognition performance in such conditions.

5.1 Limitations and Future Work

While the use of CycleGAN-generated data offers significant advantages, it is essential to acknowledge the potential trade-offs:

1. Model Generalization : The inclusion of synthetic data may inadvertently introduce biases if the generated data deviates from real-world conditions. This could limit the model's generalizability to unseen scenarios.
2. Computational Overhead : Generating synthetic data using CycleGAN and incorporating it into the training process requires additional computational resources, which could pose challenges for real-time applications.
3. Performance in Rare Classes : Despite the overall improvement in mAP, certain underrepresented classes (e.g., "Labacorn" and "Pedestrian") exhibited minimal performance gains, suggesting the need for further refinement in data augmentation techniques for rare classes.

By addressing these trade-offs, future research can focus on optimizing synthetic data generation techniques to minimize biases and computational costs while enhancing overall model performance.

To create a substantial dataset for training, we employed CycleGAN, which was used to augment rainy data. We randomly selected 5,000 data samples for experimentation from a pool of 12,305 normal weather data and 18,511 rainy weather data. We randomly selected 5,000 data samples for experimentation from a pool of 12,305 normal weather data and 18,511 rainy weather data.The learning process was iterated ten times, each time completing ten epochs, resulting in a total of 100 epochs for the study. The trained CycleGAN model was employed to generate 105,305 sheets of rainy data from an equal number of normal day data sheets. Subsequently, an object recognition experiment using YOLOv5 was conducted with the newly generated dataset. Three experiments were carried out, each involving different combinations of training data: a small amount of rainy data, a large amount of normal data, and rainy data augmented via CycleGAN. Remarkably, when the CycleGAN augmented rain data was used for training, the mAP reached its highest level at 0.355. This outcome affirms that utilizing CycleGAN to generate rainy weather data effectively addresses object recognition challenges in rainy conditions. The experimental results demonstrated that when actual rainy data and generated rainy data were jointly trained, the diversity of the generated data and the model’s generalization ability

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synergistically enhanced object recognition performance. Utilizing CycleGAN for data generation in rainy conditions provided a solution to address data scarcity, diversifying the model's training data. This advantageous approach led to improved object recognition performance in rainy environments, particularly when the quantity of rainy weather data was limited. The production of highquality learning data that overcomes the balance issue stemming from data augmentation is anticipated to have applications across various industries. Furthermore, the advancement of data generation and augmentation methods utilizing CycleGAN is poised to enhance object recognition and image classification performance in the field of computer vision, while also boosting the model's generalization capabilities.

Building on this study, future research can explore the application of CycleGAN for generating data under other adverse conditions, such as fog, snow, or nighttime scenarios. Recent works by Kumar et al.[27] and Zhang et al.[28] highlight the potential of GAN-based methods in these domains, indicating opportunities to extend this methodology for broader use cases. Such extensions could improve generalization capabilities and expand the applicability of object detection models in diverse environments.

This study contributes to the state-of-the-art by demonstrating the utility of CycleGAN in addressing dataset imbalance for object detection in rainy weather. Unlike prior methods, this approach improves mAP and significantly reduces the need for extensive real-world data collection, offering a scalable and efficient solution. These findings provide a practical pathway for enhancing model robustness in challenging scenarios, paving the way for advancements in autonomous systems and related fields.

Advancement of data generation and augmentation methods utilizing CycleGAN is poised to enhance object recognition and image classification performance in the field of computer vision, while also boosting the model's generalization capabilities. In future research, it is imperative to carry out comparative experiments with alternative object recognition models and assess performance across diverse environmental conditions in order to investigate generalization capabilities thoroughly. Furthermore, while this study predominantly centered on object recognition in rainy environments, it is worth considering data generation and object recognition research for other weather conditions and environmental factors as well.

Beyond autonomous driving, the methodologies explored in this study hold significant potential for interdisciplinary applications. For instance, in agriculture, CycleGAN has been utilized to enhance crop image data augmentation by introducing self-attention mechanisms, thereby improving model accuracy [29]. In healthcare, CycleGAN has been applied to medical image synthesis, aiding in data augmentation and improving diagnostic models [30][31]. These applications highlight the versatility and broader impact of CycleGAN-based approaches across diverse domains.

References

[1] Allied Market Research, Autonomous Vehicle Market by Level of Automation (Level 1, Level2, Level 3, Level4, and Level 5), Application (Civil, Defense, Transportation & Logistics, and Construction), Drive Type (Semi-autonomous and Fully Autonomous), and Vehicle Type (Passenger Car and Commercial Vehicle): Global Opportunity Analysis and Industry Forecast, 2021-2030, (2022)

[2] J. Fayyad, M. A. Jaradat, D. Gruyer, and H. Najjaran, Deep Learning Sensor Fusion for Autonomous Vehicle Perception and Localization: A Review, Sensors, (2020), Vol.20, No.15, pp.4220.
DOI: 10.3390/s20154220

[3] P. Wang, Research on Comparison of LiDAR and Camera in Autonomous Driving, Journal of Physics: Conference Series, (2021), Vol.2093, No.1, pp.012032.

Copyright ⓒ 2025 KCTRS

DOI: 10.1088/1742-6596/2093/1/012032

[4] E. Khatab, A. Onsy, M. Varley, and A. Abouelfarag, A Lightweight Network for Real-Time Rain Streaks and Rain Accumulation Removal from Single Images Captured by AVs, Applied Sciences, (2022), Vol.13, No.1, pp.219.
DOI: 10.3390/app13010219

[5] S. Yu, W. Ou, X. You, Y. Mou, X. Jiang, and Y. Tang, Single image rain streaks removal based on self-learning and structured sparse representation, 2015 IEEE China Summit and International Conference on Signal and Information Processing (ChinaSIP), IEEE, (2015)
DOI: 10.1109/ChinaSIP.2015.7230394

[6] R. Liu, Y. Chen, J. Wang, and Z. Guo, Attentive Mix: An Efficient Data Augmentation Method for Object Detection, 2021 7th International Conference on Computer and Communications (ICCC), IEEE, (2021)
DOI: 10.1109/ICCC54389.2021.9674718

[7] M. J. Mirza, C. Buerkle, J. Jarquin, M. Opitz, F. Oboril, K.-U. Scholl, H. Bischof, Robustness of Object Detectors in Degrading Weather Conditions, 2021 IEEE International Intelligent Transportation Systems Conference (ITSC), IEEE, (2021)
DOI: 10.48550/arXiv.2106.08795

[8] M. Kuntalp, O. Düzyel, A new method for GAN-based data augmentation for classes with distinct clusters, Expert Systems with Applications 235 (2024), 121199.
DOI: 10.1016/j.eswa.2023.121199

[9] X.-Z. Chen, C.-M. Chang, C.-W. Yu, and Y.-L. Chen, A Real-Time Vehicle Detection System under Various Bad Weather Conditions Based on a Deep Learning Model without Retraining, Sensors, (2020), Vol.20, No.20, pp.5731.
DOI: 10.3390/s20205731

[10] E. Goceri, GAN based augmentation using a hybrid loss function for dermoscopy images, Artificial Intelligence Review, (2024), Vol.57, No.234.
DOI: 10.1007/s10462-024-10897-x

[11] J.-Y. Zhu, T. Park, P. Isola, and A. A. Efros, Unpaired Image-to-Image Translation Using Cycle-Consistent Adversarial Networks, 2017 IEEE International Conference on Computer Vision (ICCV). IEEE, (2017)
DOI: 10.1109/ICCV.2017.244

[12] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, Image Quality Assessment: From Error Visibility to Structural Similarity, IEEE Transactions on Image Processing, Institute of Electrical and Electronics Engineers (IEEE), (2004), Vol.13, No.4, pp.600-612.
DOI: 10.1109/TIP.2003.819861

[13] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, You Only Look Once: Unified, Real-Time Object Detection, 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), IEEE, (2016)
DOI: 10.1109/CVPR.2016.91

[14] V. Sampath, I. Maurtua, J. J. Aguilar Mart´ın, and A. Gutierrez, A survey on generative adversarial networks for imbalance problems in computer vision tasks, Journal of Big Data, Springer Science and Business Media LLC, (2021), Vol.8, No.1.
DOI: 10.1186/s40537-021-00414-0

[15] Y. Liu, A. An, and X. Huang, Boosting Prediction Accuracy on Imbalanced Datasets with SVM Ensembles, Advances in Knowledge Discovery and Data Mining, Springer Berlin Heidelberg, (2006), pp.107-118.
DOI: 10.1007/11731139_15

[16]A. Antoniou, A. Storkey, and H. Edwards, Data Augmentation Generative Adversarial Networks, arXiv, (2017)
DOI: 10.48550/arXiv.1711.04340

[17] C. Shorten and T. M. Khoshgoftaar, A survey on Image Data Augmentation for Deep Learning, Journal of Big Data, Springer Science and Business Media LLC, (2019), Vol.6, No.1.

Copyright ⓒ 2025 KCTRS

DOI: 10.1186/s40537-019-0197-0

[18] J. Lee, Y. Yoon, and J. Kwon, Generative Adversarial Network for Class-Conditional Data Augmentation, Applied Sciences, (2020), Vol.10, No.23, pp.8415.
DOI: 10.3390/app10238415

[19] I. J. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, Y. Bengio, Generative Adversarial Networks, arXiv, (2014)
DOI: 10.48550/arXiv.1406.2661

[20] A. Radford, L. Metz, S. Chintala, Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks, arXiv, (2015)
DOI: 10.48550/arXiv.1511.06434

[21] T. Karras, S. Laine, T. Aila, A Style-Based Generator Architecture for Generative Adversarial Networks, 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), IEEE, (2019)
DOI: 10.1109/CVPR.2019.00453

[22] T. Karras, S. Laine, M. Aittala, J. Hellsten, J. Lehtinen, T. Aila, Analyzing and improving the image quality of stylegan, Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, (2020), pp.8110-8119.
DOI: 10.1109/CVPR42600.2020.00813

[23] M. Mirza and S. Osindero, Conditional Generative Adversarial Nets, arXiv, (2014)
DOI: 10.48550/arXiv.1411.1784

[24] P. Isola, J.-Y. Zhu, T. Zhou, A. A. Efros, Image-to-Image Translation with Conditional Adversarial Networks, arXiv, (2016)
DOI: 10.48550/arXiv.1611.07004

[25] T. Kim, M. Cha, H. Kim, J. K. Lee, J. Kim, Learning to Discover Cross-Domain Relations with Generative Adversarial Networks, arXiv, (2017)
DOI: 10.48550/arXiv.1703.05192

[26] Ultralytics, YOLOv5: Real-time object detection algorithm with multiple model sizes, Github, (2023)
Available From: https://github.com/ultralytics/yolov5

[27] M. Kumar, A. L. Yadav, A. Arora and A. Deb, Object Detection in Adverse Weather Conditions using Machine Learning, 2023 International Conference on Integrated Intelligence and Communication Systems (ICIICS), Kalaburagi, India, (2023), pp.1-7.
DOI: 10.1109/ICIICS59993.2023.10421471

[28] Z. Zhang, H. Gong, Y. Feng, Z. Chu, H. Liu, Enhancing Object Detection in Adverse Weather Conditions through Entropy and Guided Multimodal Fusion, Proceedings of the Asian Conference on Computer Vision (ACCV), (2024), pp.22-38.
DOI: 10.1007/978-981-96-0972-7_2

[29] D. Liu, Y. Cao, J. Yang, J. Wei, J. Zhang J, C. Rao, B. Wu, D. Zhang, SM-CycleGAN: crop image data enhancement method based on self-attention mechanism CycleGAN, Sci Rep, (2024), Vol.14, No.1, pp.9277.
DOI: 10.1038/s41598-024-59918-3

[30] S. Islam, M. T. Aziz, H. R. Nabil, J. R. Jim, M. F. Mridha, M. M. Kabir, N. Asai, J. Shin, Generative Adversarial Networks (GANs) in Medical Imaging: Advancements, Applications, and Challenges, IEEE, (2024), Vol.12, pp.35728-35753.
DOI: 10.1109/ACCESS.2024.3370848

[31] Z. Liang, J. X. Huang, S. Antani, Image Translation by Ad CycleGAN for COVID-19 X-Ray Images: A New Approach for Controllable GAN. Sensors (2022), Vol.22, No.24, pp.9628.
DOI: 10.3390/s22249628

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Enhancing Object Recognition for Self-Driving Cars: Rainfall Data Generation Using CycleGAN

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