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Multi-Modal Fusion for Robust Vehicle Detection in Adverse Weather and Low-Light Scenarios using Deep Learning Techniques

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ABSTRACT
In autonomous cars and intelligent transportation systems, vehicle identification and tracking are crucial components. Unfavorable weather conditions, such as intense snow, fog, rain, dust storms, or sandstorms, as well as low-light scenarios, pose a serious threat to the functionality of cameras since they impair driving safety by lowering visibility. The proposed system combines the strengths of the YOLO (You Only Look Once) algorithm, known for its real-time vehicle detection, with cutting-edge computer vision techniques. In response to adverse weather intricacies such as fog, rain, and reduced visibility, the study employs advanced defogging algorithms and the Cycle Generative Adversarial Network to enhance image clarity. Additionally, the research introduces a real-time adaptive defogging mechanism that dynamically adjusts its parameters based on the severity of fog or adverse weather conditions, ensuring continuous and optimal performance. This hybrid architecture capitalizes on the unique strengths of different algorithms, combining the speed of YOLO, the accuracy of Faster R-CNN, and the adaptability of Efficient Net. The implications of this research extend beyond advancing computer vision, with tangible applications in promoting road safety and minimizing traffic accidents. With critical applications in autonomous driving, surveillance, and transportation safety, this research paves the way for advancements that have a positive impact on public safety and transportation efficiency.

Keywords
You Only Look Once; Cycle Generative Adversarial Network; Faster Region-Based Convolutional Neural Network; EfficientNet; Autonomous Driving; Surveillance

1. INTRODUCTION
In today's dynamic landscape, in the realm of autonomous vehicles and intelligent transportation systems, the accurate detection of vehicles faces formidable challenges when exposed to adverse weather conditions and low-light scenarios. The efficacy of technologies pivotal to autonomous driving, traffic management, and collision avoidance hinges on the precision and consistency of vehicle detection. However, these challenges become pronounced when confronted with real-world conditions dominated by adverse weather intricacies such as fog, rain, and reduced visibility. The proposed system leverages the strengths of the YOLO (You Only Look Once) algorithm, known for its real-time vehicle detection capabilities, and combines them with advanced computer vision methodologies. In response to adverse weather intricacies, including fog and low-light conditions, the study introduces novel defogging algorithms, notably the CycleGAN architecture, to enhance image clarity. Moreover, a real-time adaptive defogging mechanism dynamically adjusts its parameters based on the severity of adverse weather conditions, ensuring continuous optimal performance.

Beyond the technical intricacies, the broader aspiration of this research is to catalyze a transformative shift in the integration of AI technologies, particularly in autonomous vehicles, surveillance systems, and transportation safety. The goal is not merely to overcome impediments but to spearhead advancements that fortify the resilience, dependability, and safety of these groundbreaking technologies. This exploration extends beyond technological innovation; it embodies a holistic endeavor to sculpt a future where autonomous systems seamlessly navigate through the complexities of real-world conditions. The ultimate aim is to create an ecosystem where safety, efficiency, and dependability converge, laying the groundwork for a transportation landscape where the boundaries between the challenges of adverse weather and cutting-edge technology blur into insignificance. The contributions of this paper are summed up as follows;

Significantly improving the visibility of vehicles in low-light and adverse weather conditions, including fog and rain. The proposed methodology employs advanced defogging techniques, specifically using CycleGAN, to enhance image clarity and mitigate the challenges associated with reduced visibility.

- Introducing a powerful vehicle identification method based on efficientnet, faster R-CNN, and YOLOv7.

This method addresses the shortcomings of individual algorithms by combining their strengths to ensure accurate vehicle recognition in the improved photos.

- Pioneering a fusion strategy that combines the outputs of YOLO, Faster R-CNN, and EfficientNet. This fusion-driven approach aims to achieve higher accuracy in vehicle detection by capitalizing on the unique strengths of each algorithm, resulting in a more comprehensive and reliable detection system.
- Implementing a real-time vehicle detection system capable of continuous monitoring and identification of vehicles in low-light and adverse conditions. This contribution ensures the practical applicability of the system in dynamic scenarios, such as traffic management and surveillance.

This article's remaining sections are arranged as follows; Section II contains related works. Section III provides an explanation of data collection and its issues. Section IV provides an explanation of the proposed vehicle detection techniques. Section V presents comprehensive experimental results and a detailed evaluation. Lastly, Section VI brings the work to a conclusion.

2. RELATED WORK

Recent research on vehicle detection methods has revealed a number of creative strategies, each of which demonstrates improvements but also has certain drawbacks.

By combining headlight and taillight data, Zhang et al.'s multi-camera system for nighttime vehicle detection made notable advancements and significantly increased tracking accuracy. But it became difficult to localize contours accurately for trucks and other larger vehicles, which resulted in sporadic failures. This limitation arises from challenges in classifying headlights and taillights for larger vehicles in an efficient manner, leading to ambiguities and sometimes false positives. Noisy lighting sources also caused the system to struggle, which affected the accuracy and performance of contours. [1]

When compared to traditional methods, Liu's approach for obstacle detection in foggy weather combined GCANet and feature fusion training, resulting in impressive improvements in precision, recall, and mAP. Though successful, the system's precision was not as high as that of other approaches in situations other than cloudy weather. Its resilience to a range of unfavorable weather conditions, including rainy ones, is still unknown, necessitating more testing to guarantee resilience in these situations. [2]

. In order to achieve a balance between speed and accuracy in real-time vehicle detection using deep networks, Nafiseh Zarei developed the Fast-Yolo-Rec algorithm. Although there were noticeable gains in speed and accuracy, the alternating use of prediction and detection networks added complexity that affected efficiency and real-time performance. Intricacy was increased by stable labeling for position prediction in odd frames, and difficulties may arise from the algorithm's flexibility in dynamic situations. [3]

Reducing vehicle misdetection was a notable outcome of using Wang's Soft-Weighted-Average ensemble method in deep learning vehicle detection. However, its inability to adapt to more complicated scenarios was hampered by its dependence on high-quality labeled training data. Its efficacy in handling more difficult scenarios was called into question by the emphasis on easy-level detection targets, underscoring the need for additional research and development. [4]

Yuanfeng Wu's AFFCM model showed excellent results for aerial vehicle recognition by utilizing multimodal properties. Although it significantly outperformed baseline approaches in terms of mAP, it was limited in its capacity to adapt to settings with a lack of diverse training samples because of its reliance on high-quality labeled data. [5]

When taken as a whole, these developments show how far vehicle identification technology has come, but they also make clear the need for more research to overcome certain obstacles. These include decreasing reliance on high-quality labeled datasets, increasing flexibility to varied weather conditions and difficult scenarios, improving accuracy for bigger vehicles, and guaranteeing stable performance across a range of real-world driving situations.

3. DATA COLLECTION AND CHALLENGES

In this section, we will provide a detailed explanation of the computer vision model and algorithms employed to meet the unique challenges of detecting vehicles in front and behind autonomous vehicles in adverse weather conditions and low-light scenarios. Our model is specifically tailored to process images affected by adverse weather conditions, including rain, fog, and poor visibility, as well as low-light conditions, with the primary goal of improving vehicle detection accuracy and ensuring the safety and reliability of autonomous driving systems.

The research conducted an extensive and diverse experimental study utilizing a robust dataset comprising over 500 videos captured during both day and night scenarios. This dataset provides a comprehensive representation of varying lighting conditions, allowing for a thorough analysis of the proposed system's performance across diurnal cycles. Additionally, the dataset includes a substantial collection of over 500 videos recorded under adverse weather conditions, such as fog and rain, introducing challenges associated with reduced visibility. This diverse dataset enables a comprehensive evaluation of the system's efficacy in adverse weather scenarios, addressing real-world challenges encountered in practical applications. The abundance of videos across different conditions contributes to the reliability and generalizability of the experimental findings, making the research outcomes pertinent to a wide range of environmental situations.

3.1 Addressing Adverse Weather Conditions

The process of detecting vehicles for autonomous vehicles is complex and involves a number of techniques, such as using rain removal techniques and defogging algorithms to improve visibility in cloudy and foggy conditions, integrating thermal cameras and sensor fusion with radar and LIDAR for reliable vehicle detection, deploying sensor cleaning and adaptive lighting systems, training machine learning models on a variety of weather datasets, and putting redundancy and fail-safe mechanisms in place to guarantee safety and dependability in difficult weather situations. All of these methods are continuously monitored for adaptive response, with the goal of improving visibility and preserving the integrity of autonomous driving systems in challenging weather conditions.

Fig. 1. Adverse Weather Dataset

3.2 Addressing Low Light and Nighttime

This involves using infrared illumination and low-light cameras to take pictures in low-light situations, applying denoising and image enhancement algorithms to enhance the quality of the images, incorporating thermal cameras to identify heat signatures for vehicle recognition, making use of active safety features like adaptive headlights to improve visibility, and training machine learning models to adapt to and identify vehicles in low-light and nighttime scenarios. The integration of these methodologies guarantees autonomous cars' capacity to travel and identify things in low-light and nighttime scenarios, hence augmenting safety and dependability.

Fig. 2. Night Time Dataset

4. PROPOSED SYSTEM

To address shortcomings in vehicle identification and recognition, particularly in inclement weather, the suggested system design incorporates state-of-the-art computer vision techniques, with a focus on the YOLO framework. The system's main modules are as follows: the input module collects data from sensors or cameras. Subsequently, the Preprocessing Module refines the input data, and the Defogging Module uses sophisticated algorithms such as CycleGAN to reduce the effect of bad weather on the image quality. With an emphasis on YOLO, the Vehicle Detection Module provides accurate bounding box coordinates and labels while simultaneously identifying and classifying vehicles in real-time. To increase detection accuracy, the Fusion Module intelligently integrates outputs with algorithms such as Faster R-CNN and EfficientNet. Ultimately, the Output Module presents the findings graphically, supporting uses like surveillance and driverless cars by guaranteeing reliable operation even under adverse weather conditions

4.1 CycleGAN

The novel neural network architecture known as CycleGAN, or Cycle-Consistent Generative Adversarial Network, is used for image processing and computer vision. It functions inside the Generative Adversarial Network (GAN) framework and is intended to learn mappings between two different picture domains without requiring paired data for training. "Cycle-consistent" refers to its capacity to provide consistency in domain mapping, enabling conversions like pictures from one domain to another and back.

The transformation process in a CycleGAN unfolds iteratively during training epochs. Initially, both generators, G_AtoB and G_BtoA, randomly initialize their weights. Adversarial training involves the generators attempting to generate realistic images in the target domain, while discriminators D_A and D_B aim to distinguish between real and generated images. The generators adjust their parameters to minimize the adversarial loss, encouraging the production of images that are perceptually authentic. Simultaneously, the cycle-consistency loss enforces that the translation is bidirectional. For an image x in domain A, G_AtoB generates an image G_AtoB(x) in domain B, and then G_BtoA reconstructs it back to the original domain A as G_BtoA(G_AtoB(x)). The cycle-consistency loss penalizes discrepancies between the original input x and the reconstructed image G_BtoA(G_AtoB(x)), ensuring a faithful mapping.

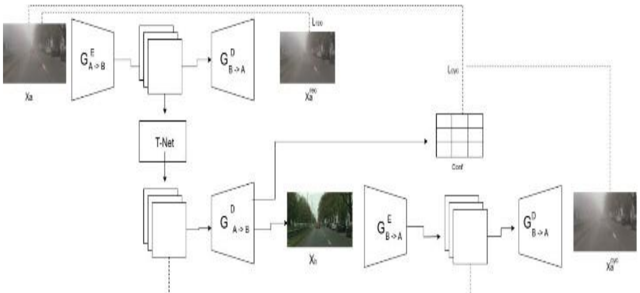

Fig. 3. Structure of CycleGAN

To further enhance the stability of the training, identity mapping loss encourages the generators to preserve key features in the input images. This is achieved by enforcing that applying G_BtoA to an image in domain B results in an image close to the original, and vice versa for G_AtoB.

The discriminators are concurrently trained to accurately classify between real and generated images, contributing to the adversarial training loop. As the training progresses, the generators and discriminators fine-tune their parameters through backpropagation, gradually improving the quality of the generated images. The overall training process continues iteratively until a satisfactory convergence is achieved, where the generators are capable of transforming adverse weather or low-light images of vehicles into clear images with high fidelity. The success of the model can be assessed through quantitative metrics such as PSNR or SSIM and a qualitative evaluation of the generated images against ground-truth clear images. Adjustments may be made to hyperparameters, architecture, or training data based on the observed performance during training and evaluation.

Let Frames from domain A (Adverse weather image) and standard domain B (Clear Image) be represented by the notations $xA \in A$ and $xB \in B$, respectively. Figure 4.1 illustrates the two generators, which are composed of an encoder and a decoder. Specifically, G AtoB =

{GEAtoB},GD AtoB} transforms domain A to B ($A \rightarrow B$), while G BtoA = {G E BtoA,G D BtoA} transforms domain B to A ($B \rightarrow A$). Using the generator $GA \rightarrow B$, the objective of unfavorable weather translation is to successfully synthesize altered picture XB from XA. For stable and balanced optimization, the majority of CycleGAN-based models use a symmetrical opposite translation (B → A → B) in addition to adopting a cyclic translation technique (A→ B → A) to take advantage of cycle-consistency loss.

4.2 Detection Module

The main goal of the fusion-driven approach is to establish a mutually beneficial connection between the three integrated algorithms—YOLO, Faster R-CNN, and EfficientNet—in order to produce a hybrid model that excels in a number of areas that are essential for efficient vehicle recognition. Figure 4 explains the architecture of the proposed methodology. The fusion is a purposeful orchestration that aims for a harmonic combination of qualities rather than just the sum of the individual contributions. This tactical combination aims to strike a balance by tackling certain issues that arise in real-world situations as well as computing efficiency.

1) *YOLO Algorithm:* The most recent iteration of YOLOV7 is chosen as the detection network in order to increase the precision and real-time vehicle identification for autonomous driving in dimly lit and foggy weather situations. Based on a particular level of detection accuracy, the YOLO series is a quick object identification method that is notable for its lightweight and speed. Consequently, when used in low-light, foggy conditions, the chosen YOLO detection technique works well for autonomous car object recognition. From V1 to V7, Yolo's detection accuracy and speed were consistently enhanced. With its emphasis on optimization, YOLOV7 aims to increase the cost of training while maintaining accuracy levels and consuming fewer computing parameters. aforementioned attributes, the same network architecture, and the lost function of YOLOV7. When the object detection module is utilized in low-light or adverse conditions, it combines the aforementioned capabilities with the same network architecture and the absence of the function of YOLOV7. After defogging photos, the algorithm is utilized for vehicle recognition to enhance control choices, increase the safety of autonomous cars in inclement weather, and attain road environment awareness for autonomous driving in low-light and adverse weather situations. Figure 4 displays the YOLOV7 design, which proposes an extended ELAN (E-ELAN) based on ELAN in the system's architecture. By employing techniques like extension and integrating bases, the network's learning capacity is continually improved without affecting the initial gradient route. In the calculation process, group convolution is utilized to expand the bases and channels. The input, backbone, and head are the three components that make up the YOLOV7 network. The whole backbone layer, which is utilized to extract features, is made up of many BConv layers, E-ELAN layers, and MPConvlayers that alternately double the channels, cut the aspect in half, and extract the features. Head is a forecasting layer that is made up of multiple SPPCPC layers, multiple BConv layers, multiple MPConv layers, multiple Concat layers, and a RepVGG block layer that generates three Heads in the end. Following the production of three separate feature maps, the Head proceeds to produce three unprocessed predictions with varying sizes via the three REP and Conv layers.

2) *Integration of Faster R-CNN:* The YOLO (You Only Look Once) algorithm and Faster R-CNN (Region-based Convolutional Neural Network) are strategically combined to maximize the accuracy of vehicle recognition in input footage. Because it divides an image into a grid and predicts bounding boxes and class probabilities for each grid cell in a single forward pass, YOLO is well known for its real-time object recognition capabilities. Faster R-CNN, on the other hand, is a two-stage object identification model that uses a classifier after the region proposal network (RPN) to refine the bounding box suggestions that the RPN first generated. YOLO quickly analyzes the complete image, enabling effective and timely object recognition. However, Faster R-CNN steps in to provide its expertise for cases where better precision is required. Potential bounding box recommendations are generated by the RPN of Faster R-CNN, and these ideas are refined by the succeeding classifier to produce a more precise vehicle localization. In order to get a balanced approach, this integration is important. The speed of YOLO guarantees real-time processing, and the faster R-CNN enhances the accuracy of vehicle identification. The integrated design seeks to offer an ideal solution for vehicle identification jobs by merging the advantages of both models, meeting the needs of situations where speed and accuracy must be balanced.

3) *EfficientNet:* The hybrid architecture's integration of EfficientNet is essential for improving the system's flexibility, especially in resource-constrained settings. A neural network architecture called EfficientNet is intended to scale models efficiently, resulting in significant performance with fewer parameters. The hybrid architecture's EfficientNet component guarantees flexibility in a range of computing settings. The system's simplified architecture makes effective use of the resources at its disposal while maintaining exceptional performance. This flexibility is essential to maintaining the vehicle detection system's effectiveness and dependability under a variety of operational circumstances, particularly in situations where there may be computational limitations. The hybrid design seeks to achieve a compromise between strong vehicle detection capability and computing economy by integrating EfficientNet.

4) *Fusion-Driven Strategy:* The results of each algorithm complement and strengthen one another in a dynamic interaction. This partnership explores the subtle nuances of detection rather than only cooperating on the surface. YOLO quickly gathers real-time data, whereas Faster R-CNN's methodical, precision-focused technique painstakingly refines the output.

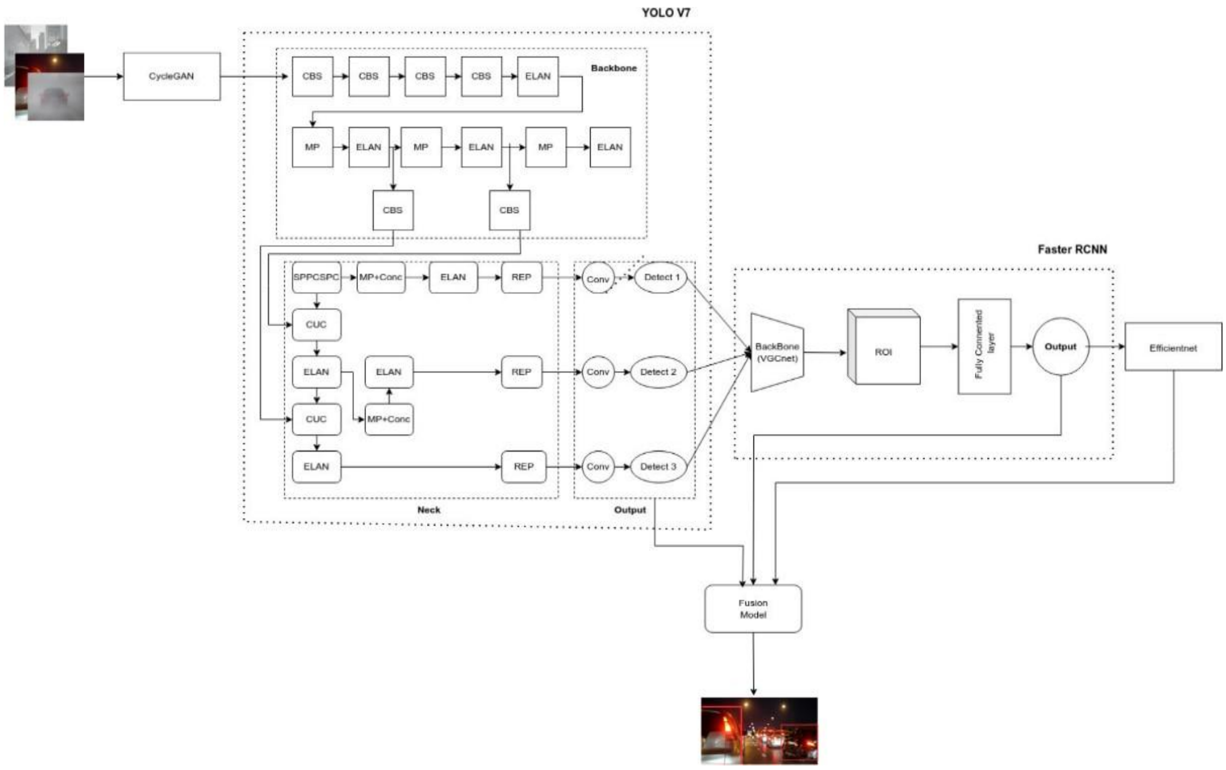

Fig. 4. Schematic structure of neural network used in proposed work

5. EVALUATION AND VALIDATION

A wide range of performance measures are used to evaluate the suggested vehicle detecting system's efficacy. The precision, recall, and F1 score are important measures that offer a detailed picture of the system's car-detecting accuracy. Metrics that capture the accuracy and geographical overlap of identified vehicles, such as intersection over union (IoU) and mean average precision (mAP), also add to a comprehensive assessment.

5.1 Precision

Precision measures the accuracy of the positive predictions made by the system. It is calculated as the ratio of true positive detections to the total number of predicted positives.

P=TP/TP+FP (1)

where TP is the number of true positives (correctly detected vehicles), and FP is the number of false positives (instances where the system incorrectly identified a non-vehicle as a vehicle).

5.2 Recall

Recall, also known as sensitivity or true positive rate, quantifies the system's ability to identify all relevant instances. It is calculated as the ratio of true positives to the total number of actual positives.

R=TP/TP+FP (2)

5.3 Intersection over union(IoU):

IoU measures the spatial overlap between the ground truth bounding box and the predicted bounding box for each detected vehicle. It is computed as the ratio of the intersection area to the union area.

IoU = Area of intersection/Area of Union (3)

5.4 Mean Average Precision(mAP):

mAP is commonly used in object detection tasks and evaluates the precision-recall curve across different confidence thresholds. It involves calculating the average precision for each class and then averaging those values.

Table 1 outlines the performance metrics of a vehicle detection system across different weather conditions. In clear weather, the system demonstrates high accuracy with a recall of 98.1% and precision of 98.81%. As adverse weather intensifies, specifically in moderate conditions, the system maintains strong performance with an 86.79% recall and 87.69% precision. Even under heavy weather, the system retains robustness, achieving a 75.45% recall and 75.89% precision. These metrics collectively emphasize the system's effectiveness in adverse weather scenarios, balancing the ability to detect vehicles (recall) with the accuracy of those detections (precision), crucial for real-world applications.

Table I. Comparison Between different intensity of weather

Weather	**Original Image**		**Adverse weather**	
	Recall	***Precision***	***Recall***	***Precision***
Clear Weather	98.1%	98.81%	-	-
Moderate Weather	80.24%	80.10%	86.79%	87.69%
Heavy Weather	70.13%	71.14%	75.45%	75.89%

Table 2 summarizes the key characteristics and performance metrics of various YOLO-based detection methods and a fusion model. The fusion model, combining YOLO with Faster R-CNN and EfficientNet, utilizes an

ELAN-based backbone at an input size of 416, yielding a remarkable average precision of 0.89, comprising 6.1 million parameters, and achieving the lowest miss rate of 0.05.

Table II. Performance Comparison between YOLO models

YOLO-base detection methods	BackBone	Input Size	Average Precision	Miss Rate
YOLOV2	Darknet19	416	0.6210	0.15
YOLOV3	Darknet53	416	0.6956	0.09
YOLOV4	FCCL	416	0.7843	0.08
YOLOV7	E-ELAN-based	320	0.8289	0.07
Fusion Model (YOLO + FasterRCNN + EfficientNet)	**ELAN-based**	**416**	**0.8999**	**0.05**

The results of the proposed system are shown in figure 5. The fusion model's success lies in its ability to capitalize on the complementary strengths of different architectures, resulting in a synergistic enhancement of detection performance. The research findings position the proposed model as a cutting-edge solution in the field of vehicle detection, showcasing its potential for practical applications in areas such as autonomous vehicles, traffic monitoring, and public safety. The outcomes of this research underscore the model's effectiveness, accuracy, and versatility, making it a valuable contribution to the advancements in computer vision and object detection methodologies.

Fig. 5. Detection using Fusion Method

6. CONCLUSION

Combining YOLO with cutting-edge defogging algorithms—CycleGAN in particular—works well for real-time vehicle recognition in low-light situations. A real-time adaptive defogging module that dynamically adjusts to changing weather severity strengthens the system's flexibility. Evaluation measures demonstrate competitive performance and practical use, confirming the system's effectiveness. Furthermore, integrating real-time meteorological data into the decision-making procedure can improve the model's flexibility by enabling it to dynamically modify its parameters in response to the existing environmental circumstances. In conclusion, our project not only improves computer vision skills but also has a real impact on road safety, especially during inclement weather. The suggested system, which addresses visibility problems in nighttime driving, has potential uses in autonomous driving, surveillance, and transportation safety.

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