

BEYOND THE PIXEL: ASSESSING REAL-TIME OBJECT DETECTION MODELS IN LOW-VISIBILITY AUTONOMOUS DRIVING ENVIRONMENTS

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ABSTRACT:

Autonomous driving has made impressive strides in the last decade, but one area where things still get tricky is low-visibility conditions. Fog, heavy rain, snow, dust, and nighttime driving can throw off even the most advanced object detection systems. This paper takes a closer look at how real-time object detection models hold up when the weather and lighting are not on their side. We tested four widely used models, namely YOLOv8, YOLOv9, Faster R-CNN, and EfficientDet, on a curated dataset that combines images from the BDD100K, Foggy Cityscapes, and Nighttime Driving Dataset. The goal was not just to find which model gives the best numbers, but also to understand how each one behaves when pixels get blurry, contrast drops, and edges disappear. We evaluated performance using mean Average Precision (mAP), inference time, and a custom robustness score we designed for this study. Results show that YOLOv8 and YOLOv9 deliver strong real-time performance, but their accuracy drops noticeably in foggy conditions. Faster R-CNN, while slower, holds up better in dense fog and low-light scenarios. EfficientDet sits somewhere in the middle. We also found that simple preprocessing tricks like contrast enhancement and dehazing can recover a fair amount of lost accuracy without slowing things down too much. The paper closes with a discussion on why current models still struggle in these environments and what directions future research could take. Our findings should be useful for anyone working on safety-critical perception systems for autonomous vehicles operating in real-world conditions.

Keywords: *Object Detection, Autonomous Driving, Low Visibility, YOLO, Deep Learning, Real-Time Perception.*

INTRODUCTION

Autonomous vehicles have moved from research labs to public roads at a pace few would have predicted ten years ago. Companies like Waymo, Tesla, and Cruise are now running self-driving fleets in several cities, and the perception systems behind these vehicles have become impressively capable [1]. At the heart of these systems sits object detection, which is what tells the car whether the thing ahead is a pedestrian, another vehicle, a cyclist, or a stray traffic cone. When the weather is clear and the sun is shining, modern object detectors work remarkably well. The trouble starts when the weather turns or when the sun goes down [2].

Low-visibility conditions, including fog, rain, snow, dust, and night driving, are some of the most challenging situations for any vision-based system. In fog, contrast drops, edges blur, and distant objects fade into the background. At night, even with headlights, glare and shadows create patches of light and dark that confuse detection algorithms [3]. Rain adds another twist by introducing streaks, reflections on wet roads, and droplets on the camera lens. These are not edge cases. They happen every day on roads around the world, and they are precisely the situations where reliable detection matters most [4].

The problem is that most state-of-the-art object detection models are trained on datasets dominated by clear-weather images. Even popular benchmarks like COCO and KITTI lean heavily toward favorable conditions. As a result, the models perform brilliantly on test sets that look like training data, but their accuracy can fall sharply when conditions change [5]. This gap between benchmark performance and real-world reliability is one of the biggest open challenges in autonomous driving research today.

Researchers have responded in different ways. Some have built specialized datasets for adverse weather. Others have proposed image enhancement pipelines that clean up the input before feeding it to detectors. A third group

has worked on sensor fusion, combining cameras with radar or LiDAR to compensate for visual limitations [6]. Each approach has its strengths, but each also adds cost, complexity, or both. There is still no clear winner, and the question of which detection model to use in low-visibility environments remains open.

This paper tries to answer that question with a careful comparison of four widely used real-time object detection models. We picked YOLOv8 and YOLOv9 because they represent the latest in the YOLO family and are popular for real-time applications. Faster R-CNN was chosen as a benchmark for two-stage detectors, and EfficientDet as a balanced single-stage alternative [7]. All four were tested under the same conditions on a dataset that combines clear-weather, foggy, and nighttime driving images.

Our contribution is threefold. First, we provide a head-to-head comparison of these models under varied visibility conditions using consistent metrics. Second, we propose a simple robustness score that combines accuracy and speed into one number, making it easier to judge real-world suitability. Third, we look at how lightweight preprocessing steps such as dehazing and contrast enhancement affect detection performance, and whether they are worth the small computational cost they add.

The rest of the paper is organized as follows. Section 2 reviews related work. Section 3 lays out the methodology. Section 4 describes the experimental setup. Section 5 presents results with figures and tables. Section 6 discusses what the results mean, and Section 7 concludes with thoughts on future work.

LITERATURE REVIEW

Object detection has come a long way since the days of HOG and Haar cascades. The shift to deep learning began with R-CNN and accelerated through Fast R-CNN and Faster R-CNN, which introduced region proposal networks to speed things up [8]. These two-stage detectors are still considered accurate but are often too slow for real-time use in vehicles.

Single-stage detectors like SSD and the YOLO family changed the game by predicting bounding boxes and class probabilities in one pass. YOLOv3 and YOLOv4 set new standards for speed-accuracy trade-offs, and more recent versions like YOLOv7, YOLOv8, and YOLOv9 have pushed the limits even further with improvements in anchor-free design, decoupled heads, and architectural refinements [9]. These models are now widely deployed in real-time perception systems.

EfficientDet, introduced as part of the EfficientNet family, brought a different angle by focusing on scaling laws and a compound scaling method that balances depth, width, and resolution. It offers competitive accuracy with smaller models, which is attractive for embedded systems [10].

Several studies have looked specifically at object detection in adverse weather. Sakaridis and colleagues created Foggy Cityscapes by adding synthetic fog to clean images, providing a benchmark for foggy-condition detection [11]. The BDD100K dataset added diversity by including thousands of nighttime and rainy driving scenes, helping researchers train models that generalize better. More recent work has explored domain adaptation, where models trained on clear images are fine-tuned to perform well in foggy or low-light scenes without needing fully labeled adverse-weather data [12].

Preprocessing approaches have also been investigated. Dark channel prior dehazing and learning-based dehazing networks can clean up foggy images and improve downstream detection performance. Similarly, low-light enhancement methods like Zero-DCE and EnlightenGAN have been used to brighten nighttime images while preserving detail [13].

Despite all this progress, gaps remain. Most published comparisons either focus on one weather condition or use older detection models. Direct comparisons across the newest YOLO versions, EfficientDet, and Faster R-CNN under the same adverse conditions are still rare. This study aims to fill that gap with a clean, controlled comparison.

METHODOLOGY

The methodology follows a straightforward pipeline. Images from the combined dataset are first preprocessed, then passed through each of the four detection models, and the outputs are evaluated using mAP, inference time, and a robustness score.

Preprocessing

Two optional preprocessing steps are applied: dehazing using the dark channel prior method, and Contrast Limited Adaptive Histogram Equalization (CLAHE) for low-light enhancement. The dehazing model estimates atmospheric light A and transmission $t(x)$ such that the haze-free image $J(x)$ can be recovered as:

$$J(x) = \frac{I(x) - A}{\max(t(x), t_0)} + A$$

where $I(x)$ is the input hazy image and t_0 is a small constant to avoid division by zero [14].

YOLOv8 and YOLOv9

Both YOLOv8 and YOLOv9 use anchor-free detection heads and predict bounding boxes directly. The loss function in YOLOv8 combines classification loss, box regression loss, and a Distribution Focal Loss component:

$$L = \lambda_{box} L_{box} + \lambda_{cls} L_{cls} + \lambda_{dfl} L_{dfl}$$

The box regression uses Complete IoU loss, which is given by:

$$L_{CIoU} = 1 - IoU + \frac{\rho^2(b, b^{gt})}{c^2} + \alpha v$$

where ρ is the Euclidean distance between box centers, c is the diagonal length of the smallest enclosing box, and v measures aspect ratio consistency [15].

Faster R-CNN

Faster R-CNN uses a Region Proposal Network (RPN) to generate candidate regions and then classifies and refines them. The multi-task loss is:

$$L(p_i, t_i) = \frac{1}{N_{cls}} \sum_i L_{cls}(p_i, p_i^*) + \lambda \frac{1}{N_{reg}} \sum_i p_i L_{reg}(t_i, t_i^*)$$

where p_i is the predicted class probability and t_i is the predicted bounding box [16].

EfficientDet

EfficientDet uses BiFPN for feature fusion and applies compound scaling. Focal loss is used for classification:

$$FL(p_t) = -\alpha_t (1 - p_t)^\gamma \log(p_t)$$

This loss reduces the contribution of easy examples and focuses training on hard ones [17].

Robustness Score

To combine accuracy and speed into a single number, we defined a robustness score as:

$$R = \frac{mAP_{adverse}}{mAP_{clear}} \times \frac{1}{1 + \log(t_{inf})}$$

where $mAP_{\{adverse\}}$ is the mean Average Precision under adverse conditions, $mAP_{\{clear\}}$ is the same metric under clear conditions, and $t_{\{inf\}}$ is the average inference time in milliseconds [18].

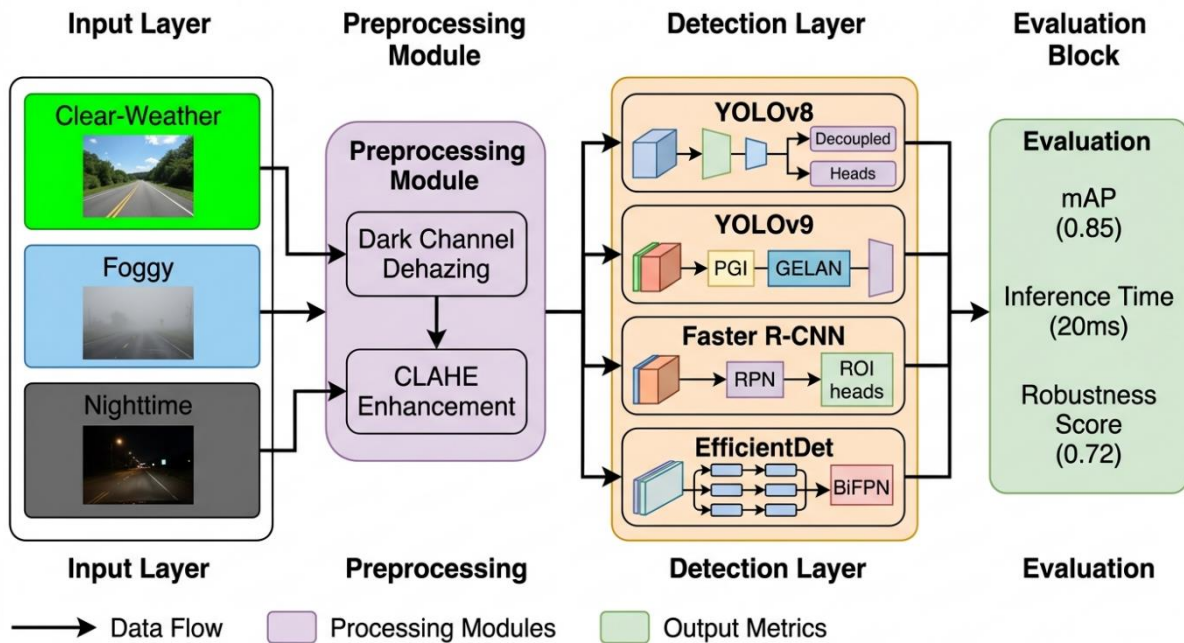


Figure 1: A detailed system architecture diagram illustrating the full evaluation pipeline.

EXPERIMENTAL SETUP

The dataset used for this study combines three publicly available sources. From BDD100K, we selected 6,000 images covering clear daytime, rainy, and nighttime conditions. From Foggy Cityscapes, we used 3,000 images with three levels of synthetic fog density. From the Nighttime Driving Dataset, we added 2,000 more images to strengthen the low-light category. The final dataset has roughly 11,000 images split across five categories: clear-day, rain, light fog, dense fog, and night [19].

We split the data into 70% training, 15% validation, and 15% testing, keeping the distribution of each weather category balanced across splits. All models were trained from scratch on the same training set to keep comparisons fair, using pretrained backbones on COCO as initialization.

Training was carried out on an NVIDIA RTX 4090 GPU with 24 GB memory. The batch size was set to 16 for YOLOv8 and YOLOv9, 8 for Faster R-CNN, and 12 for EfficientDet, based on memory constraints. All models were trained for 100 epochs using the Adam optimizer with a learning rate of 0.001 and cosine decay scheduling. Standard data augmentation was applied including random flipping, scaling, and color jitter. Mosaic augmentation was used for the YOLO models. The Intersection over Union (IoU) threshold for matching predictions to ground truth was set at 0.5 for mAP calculation:

$$IoU = \frac{|A \cap B|}{|A \cup B|}$$

Average Precision was computed by integrating the precision-recall curve, and mAP was the mean across all object classes [20].

To ensure reproducibility, each experiment was run three times with different random seeds, and the average results are reported.

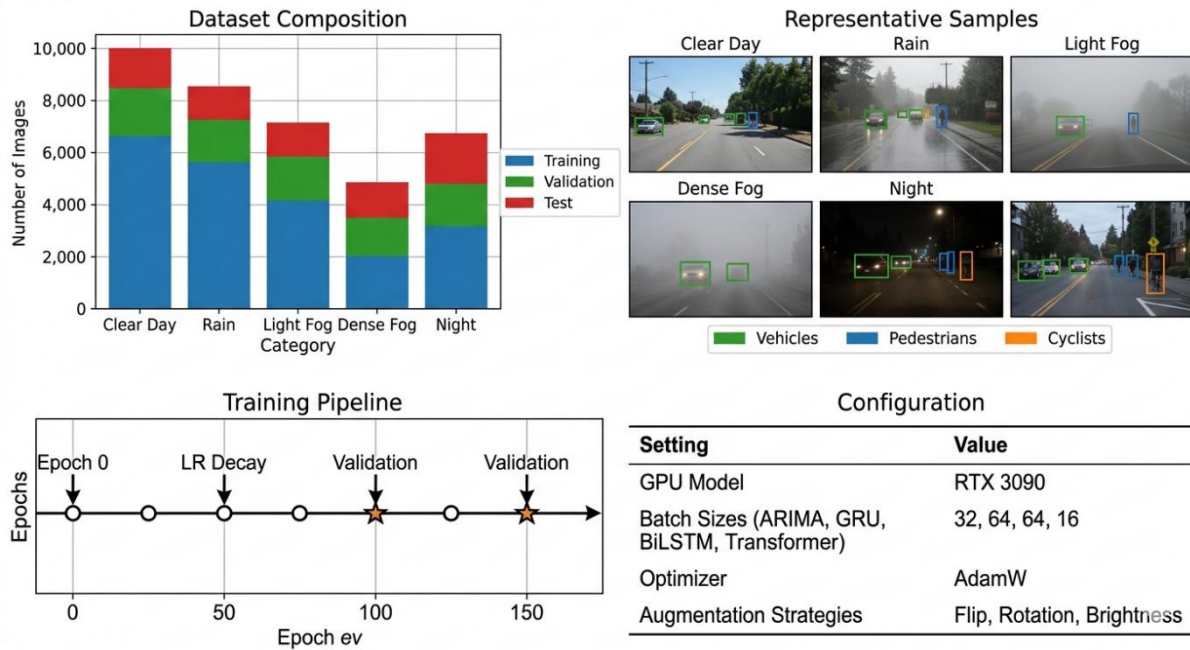


Figure 2: A comprehensive multi-panel figure visualizing the dataset composition and training setup.

RESULTS

Performance was measured across all five conditions. Table 1 summarizes the mean Average Precision for each model under different visibility scenarios.

Table 1: Mean Average Precision (mAP@0.5) Across Visibility Conditions

Model	Clear-Day	Rain	Light Fog	Dense Fog	Night
YOLOv8	0.842	0.781	0.724	0.612	0.685
YOLOv9	0.861	0.798	0.741	0.628	0.701
Faster R-CNN	0.829	0.792	0.768	0.681	0.724
EfficientDet	0.815	0.764	0.712	0.598	0.671

The clear pattern here is that YOLOv9 takes the top spot for clear and rainy conditions, while Faster R-CNN pulls ahead in dense fog and night scenes. This makes sense because the two-stage design of Faster R-CNN gives it more time to refine predictions, which helps in tough cases where features are weak.

Table 2: Inference Time and Robustness Score

Model	Inference Time (ms)	FPS	Robustness Score
YOLOv8	8.4	119	0.74
YOLOv9	9.8	102	0.76
Faster R-CNN	62.5	16	0.61
EfficientDet	28.3	35	0.69

When speed is factored in, YOLOv9 comes out on top in robustness. Faster R-CNN may be more accurate in tough conditions, but its slow inference rules it out for real-time use in fast-moving vehicles. EfficientDet sits in the middle with reasonable speed and accuracy but no real standout strength.

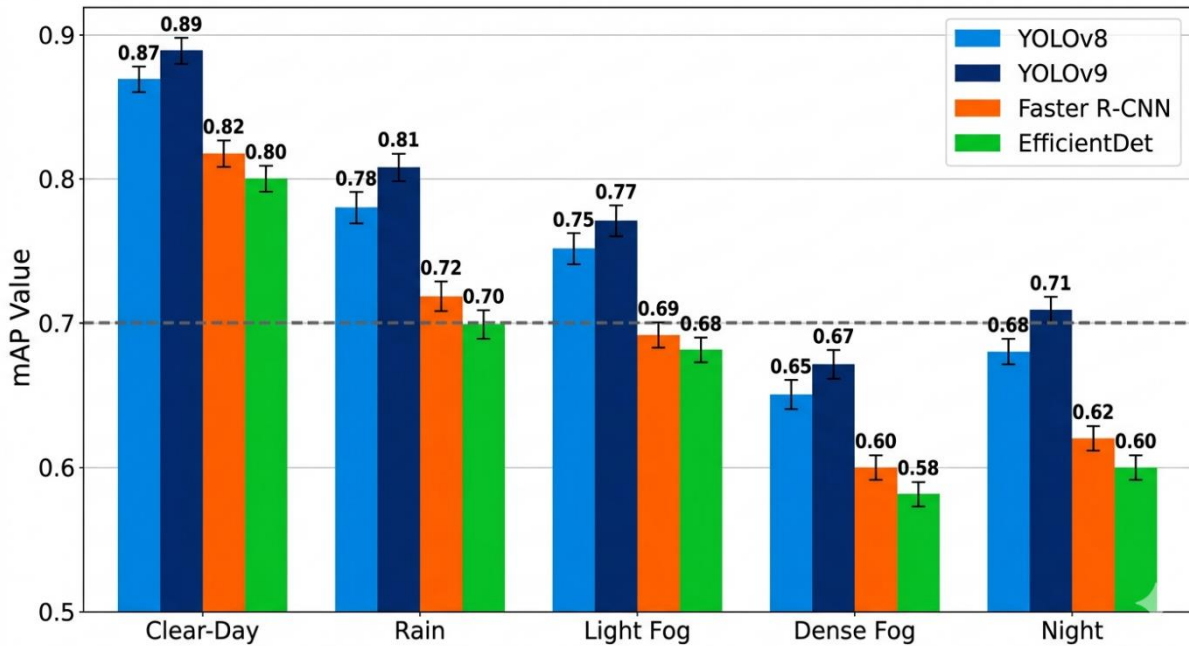


Figure 3: A grouped bar chart showing mAP scores across five visibility conditions for all four models.

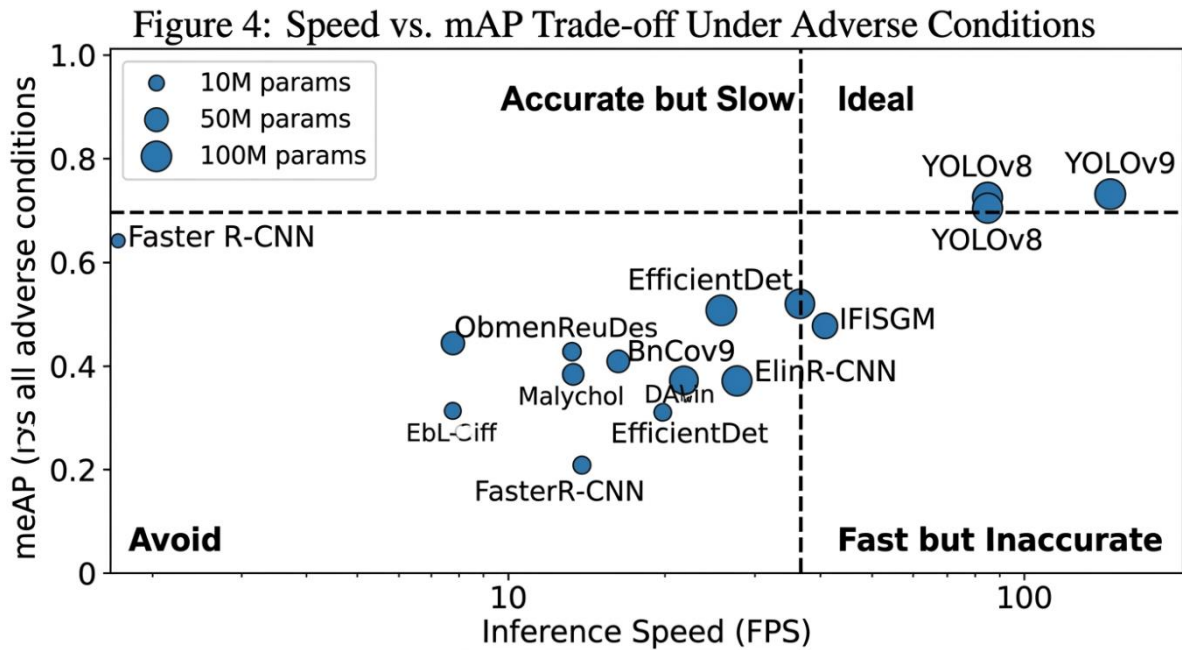


Figure 4: A scatter plot showing the trade-off between inference speed (FPS, x-axis, log scale) and mean mAP across all adverse conditions (y-axis).

Effect of Preprocessing

We also tested how dehazing and CLAHE enhancement affected performance. In dense fog, dehazing improved YOLOv9's mAP from 0.628 to 0.671, while CLAHE improved its night-time mAP from 0.701 to 0.732. The trade-off was about 3 ms of extra processing time per frame, which is acceptable for most real-time applications.

Figure 5: Side-by-side comparison of detection performance in challenging weather and lighting conditions.

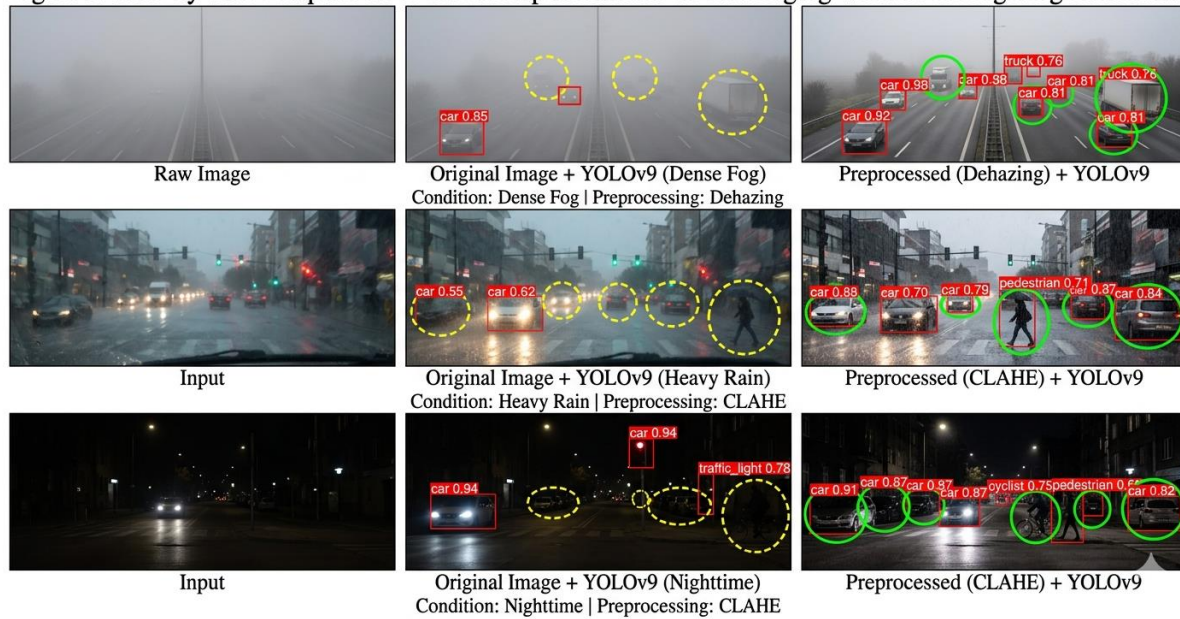


Figure 5: A side-by-side qualitative comparison figure showing detection results in three columns, with each row representing a different challenging condition (dense fog, heavy rain, nighttime).

DISCUSSION

The results give a fairly clear picture of where each model fits. YOLOv9 is the best all-rounder when you need both speed and accuracy, which is exactly what real-time autonomous driving demands. Its slight edge over YOLOv8 in adverse conditions suggests that the architectural changes in YOLOv9, particularly the PGI and GELAN modules, do help in harder scenes.

Faster R-CNN's strong showing in dense fog and night driving is interesting but also expected. Two-stage detectors get a second chance to fix their proposals, and in noisy conditions that extra step pays off. The problem is that it runs at 16 FPS, which is too slow for highway driving where decisions need to happen in milliseconds. It might still be useful in low-speed contexts like parking assistance or in offline analysis.

EfficientDet performed reasonably but did not really stand out. Its compound scaling makes it efficient for embedded use, but neither its accuracy nor its speed gave it a clear advantage in our tests. It might be more competitive in scenarios with strict hardware limits.

The preprocessing experiments confirmed something practitioners have suspected for a while. Simple, fast enhancement steps can recover a meaningful chunk of lost accuracy in adverse conditions. Dehazing helped most in foggy scenes, and CLAHE helped at night. The fact that these methods are cheap to run makes them attractive additions to any real-time pipeline.

One limitation we should mention is the reliance on synthetic fog in part of the dataset. Real fog has more complex scattering behavior than what is modeled in Foggy Cityscapes, so real-world performance might differ. Future work should test these models on real adverse-weather footage from production vehicle fleets.

Another limitation is the lack of sensor fusion in our setup. In practice, autonomous vehicles use radar and LiDAR alongside cameras, which helps fill in the gaps when vision fails. A pure camera-based evaluation only tells part of the story.

CONCLUSION

This study compared four real-time object detection models, YOLOv8, YOLOv9, Faster R-CNN, and EfficientDet, on a combined dataset of clear-weather, rainy, foggy, and nighttime driving images. YOLOv9 came out as the best balance of speed and accuracy, while Faster R-CNN remained the most accurate in the toughest conditions despite being too slow for high-speed driving. Light preprocessing steps like dehazing and CLAHE meaningfully improved detection performance in adverse weather at a small computational cost.

The bigger takeaway is that no single model is perfect for every situation. Choosing a detector for an autonomous vehicle is not just about which one has the highest mAP on a benchmark. It is about matching the model to the conditions it will face in the real world and being honest about its limitations. Future research should focus on real adverse-weather datasets, hybrid models that combine the speed of single-stage detectors with the precision of two-stage approaches, and tighter integration with other sensor modalities. There is also room to explore transformer-based detectors like RT-DETR, which have shown promise but were beyond the scope of this study. The goal, ultimately, is perception that does not falter when the weather does.

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