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Deep Learning-Based Object Detection in Smart Vehicles: YOLO for Adverse Weather

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Abstract : Reliable environmental perception is essential for the safe operation of autonomous and intelligent transportation systems, particularly under adverse weather conditions where visibility is severely reduced. This study presents a weather-robust object detection framework based on the YOLOv5 architecture, trained and evaluated using the DAWN dataset. The proposed approach integrates advanced preprocessing techniques, including normalization, resizing, and weather-based data augmentation (synthetic fog, rain, and low-light scenarios), to enhance detection reliability. The YOLOv5 model is further adapted with feature optimization strategies to improve object recognition under poor visibility. Performance is assessed using standard object detection metrics such as mean Average Precision (mAP) across multiple Intersection over Union (IoU) thresholds, with evaluations conducted under diverse weather conditions. Experimental results demonstrate improved detection accuracy and robustness compared to conventional methods, ensuring safer navigation of vehicles and pedestrians in intelligent transportation environments. This research contributes toward enhancing the perception capabilities of autonomous vehicles, ultimately improving road safety and traffic management in challenging weather scenarios.

IndexTerms - **Autonomous Vehicles (AVs), Object Detection, Adverse Weather Conditions, YOLOv5, Deep Learning (DL)**

I. Introduction

The rapid advancement of intelligent transportation systems (ITS) and smart vehicles is transforming the way humans perceive and interact with transportation infrastructure. Autonomous driving technology promises enhanced safety, efficiency, and accessibility, with the potential to revolutionize daily mobility. However, ensuring reliable operation in diverse and unpredictable environmental conditions remains a critical challenge. Among these, adverse weather—such as rain, fog, snow, and low-light conditions—poses a significant barrier to the accurate perception and decision-making required for safe navigation[1].

Object detection, which involves identifying and classifying objects such as vehicles, pedestrians, and road signs within a vehicle's surroundings, is a fundamental task in autonomous driving. Reliable detection is essential not only for collision avoidance but also for enabling intelligent, real-time decision-making. While traditional computer vision techniques have achieved notable progress in this domain, their performance deteriorates significantly under poor visibility and varying illumination, limiting their applicability in real-world scenarios[2].

Deep learning has emerged as a powerful alternative, offering superior feature extraction and robust pattern recognition capabilities. Convolutional neural networks, recurrent architectures, and transformers have shown promising results in enhancing object detection under challenging environmental conditions. These models learn hierarchical feature representations directly from raw data, enabling them to recognize partially obscured or degraded objects[3]. Nevertheless, their success depends heavily on diverse and representative training data, which is often lacking for adverse weather scenarios.

This study addresses these challenges by developing a weather-robust object detection framework for autonomous vehicles. Using the DAWN dataset, combined with synthetic augmentation to simulate fog, rain, and low-light conditions, we evaluate state-of-the-art deep learning models—particularly YOLO-based architectures—for their effectiveness in adverse environments[4][5]. We further propose optimization strategies, including fine-tuning and hyperparameter adjustments, to enhance detection reliability under low-visibility conditions[6].

Through extensive experimentation on both simulated and real-world scenarios, the proposed approach is benchmarked against standard metrics such as accuracy, precision, recall, and mean Average Precision (mAP)[7]. The results demonstrate significant improvements in object recognition under adverse weather, highlighting the potential of deep learning to strengthen the perception capabilities of intelligent transportation systems[8]. Ultimately, this research contributes to advancing the reliability and safety of autonomous vehicles, moving closer to the realization of fully autonomous transportation that is resilient across diverse weather conditions.

II. LITERATURE REVIEW

Autonomous vehicle (AV) perception in adverse weather has been widely studied, with particular emphasis on sensor performance and detection techniques combining conventional methods and deep learning (DL). Several works have examined the physical limitations of sensors under challenging conditions. For example, one study [13] modeled the attenuation and backscatter effects of millimeter-wave radar during heavy rainfall, providing valuable insights into radar performance. However, its focus was limited to rain, without addressing other critical weather conditions such as fog and snow, which are equally detrimental to AV reliability. Similarly, another work [14] provided a detailed evaluation of sensor range and resolution and emphasized the role of sensor fusion in improving situational awareness. While significant, the study did not sufficiently address issues related to object recognition and sensor reliability under cold-weather scenarios.

Beyond radar, researchers have also investigated LiDAR and camera performance in adverse environments. The work in [16] analyzed the impact of precipitation and lens contamination, proposing advanced sensor technologies and machine learning techniques [23] as potential remedies. While the study highlighted the promise of sensor fusion and network-based architectures, it lacked a systematic evaluation across different weather types. In another contribution, [17] focused on lane, vehicle, and pedestrian recognition, integrating weather classification algorithms into AV decision-making. Although effective for structured detection tasks, the approach struggled with small, occluded, or partially visible objects, underscoring the limitations of existing recognition pipelines.

Deep learning methods have shown notable potential in addressing some of these challenges. For instance, the study in [18] employed domain adaptation and image translation frameworks to enhance object detection under wet conditions, demonstrating improved robustness to rain. However, the generalization of these methods to other forms of adverse weather, such as fog or snow, remains largely unexplored. Similarly, [19] investigated video-based vehicle detection under occlusion, shadows, and illumination changes. While the study provided an extensive review of conventional techniques, it did not fully incorporate the advancements brought by modern DL models. Additional works summarized in Table 1 have explored DL-based on-road vehicle detection methods. Nonetheless, their narrow focus limits a broader understanding of the holistic challenges faced by AVs in varying environmental conditions. Research on 3D detection strategies [21] further contributed insights into spatial perception, but again failed to address the general applicability of such techniques under adverse weather.

Overall, the reviewed literature establishes a strong foundation for understanding AV sensor behavior and detection strategies. Yet, significant gaps remain in the comprehensive evaluation of both conventional and deep learning approaches across diverse adverse weather scenarios. Existing studies either focus narrowly on specific sensors, weather conditions, or detection tasks, leaving open the critical challenge of designing a robust, weather-resilient perception system for autonomous vehicles. This gap motivates the present study, which systematically investigates object detection under inclement weather using deep learning methods enhanced through augmentation and optimization strategies. Table 1 below compares dieferent techniques.

Table 1: Strenghts and limitations of different techniques

Focus Area	**Weather Conditions Considered**	**Approach/Technique**	**Strengths**	**Limitations**
Millimeter-wave radar performance [13]	Heavy rain	Modeling of attenuation and backscatter effects	Provides detailed radar analysis under rainfall	Limited to rain; ignores fog, snow, and other conditions
Sensor fusion and range/resolution[14]	General adverse weather (rain/fog implied)	Multi-sensor fusion	Improves situational awareness via range & resolution	Lacks analysis of object recognition and cold-weather reliability
UAV operating system[15]	Multiple weather scenarios	Sensor fusion + infrastructure support	Promotes integration across weather types	Ignores cost–benefit of sensor deployment
LiDAR and camera performance[16][23]	Precipitation, lens contamination	Improved sensors + ML	Suggests better sensor technology and ML integration	No comprehensive evaluation across diverse weather
Lane, vehicle, and pedestrian detection[17]	Various weather, focus on classification	Weather recognition + decision-making algorithms	Enhances AV decision-making	Struggles with small/occluded objects

Object detection robustness[18]	Rain, wet weather	DL-based domain adaptation + image translation	Improves detection under rain	Generalization to fog/snow not addressed
Vehicle detection in traffic monitoring[19]	Rain, shadows, occlusion, low light	Conventional vision methods	Thorough analysis of occlusion and illumination issues	Lacks modern DL integration
3D vehicle detection[20][21]	Not explicitly weather-specific	3D DL-based detection methods	Adds spatial depth to detection	Narrow scope; ignores broader AV challenges

III. PROBLEM STATEMENT

Despite significant advancements in intelligent transportation systems and autonomous vehicles, ensuring reliable perception under adverse weather conditions remains a critical challenge. Conventional computer vision and sensor-based approaches degrade significantly in scenarios involving fog, rain, snow, or low-light conditions due to occlusion, reduced visibility, and sensor noise. Although deep learning techniques have demonstrated superior performance in feature extraction and object recognition, existing studies often focus narrowly on specific sensors, single weather conditions, or limited detection tasks. Moreover, many works emphasize sensor performance or fusion without providing a comprehensive evaluation of object detection models across diverse adverse environments.

The lack of a unified, weather-resilient framework for object detection hinders the safe deployment of autonomous vehicles in real-world conditions. Current approaches either fail to generalize across multiple weather scenarios or do not sufficiently optimize detection accuracy for low-visibility environments. Therefore, there is a pressing need for a robust object detection system that integrates deep learning with effective data augmentation and fine-tuning strategies, capable of maintaining high detection accuracy across varying weather conditions.

This research addresses this gap by proposing a YOLOv5-based detection framework trained on the DAWN dataset, enhanced with synthetic weather augmentation and hyperparameter optimization. The objective is to improve the robustness and reliability of object recognition in autonomous vehicles, ensuring safer navigation and decision-making in challenging environmental conditions.

IV. PROPOSED METHODOLOGY

A. Framework Overview

To enable reliable object detection for autonomous vehicles operating in adverse weather, we propose a comprehensive protocol that integrates tools, processes, and strategies across multiple phases. Each phase leverages deep learning techniques to maximize robustness and accuracy under challenging environmental conditions. The workflow consists of the following components:

1. **Data Compilation and Enhancement** – collecting diverse datasets representing adverse weather scenarios and preparing them for training.
2. **Model Development with Sensor Fusion and Deep Learning** – designing weather-robust detection models and exploring integration with complementary sensor modalities.
3. **Model Training and Validation** – implementing systematic training, validation, and optimization of the proposed architecture.
4. **Implementation and Real-Time Testing** – deploying the trained model on embedded platforms to evaluate efficiency in live conditions.
5. **Performance Evaluation and Refinement** – benchmarking detection accuracy, latency, and robustness, followed by iterative optimization.

This staged design ensures a structured progression from data preparation to deployment, with feedback loops for performance improvement.

B. Baseline Model Selection

We adopt the **YOLO (You Only Look Once)** framework as the baseline detection model due to its strengths in:

- **Single-stage detection**: efficient bounding-box and class predictions in a single forward pass.
- **Real-time performance**: high-speed inference suitable for smart car applications.
- **Grid-based localization**: dividing input images into grids, each responsible for predicting bounding boxes, confidence scores, and conditional class probabilities.

YOLO's proven effectiveness in balancing speed and accuracy makes it a suitable foundation for weather-robust detection.

C. Data Augmentation Considerations

In the baseline implementation, **data augmentation is deliberately excluded** during the data preparation phase. This design choice aims to:

- Prevent artificial biases from being introduced into the dataset.
- Maintain the original statistical distribution of the training data.

Although augmentation techniques (e.g., noise addition, blurring, or synthetic weather overlays) are often linked to improved robustness, they may also lead to altered data distributions. Prior studies [20], [21] suggest that augmentation can yield only marginal improvements in robustness while increasing standard error in some cases. Therefore, our baseline avoids augmentation, with later stages selectively introducing augmentation in a controlled manner for comparative analysis.

D. Integration of Advanced Detection Strategies

Beyond baseline training, our methodology evaluates multiple strategies for integration with the enhanced YOLO framework:

- Incorporating **state-of-the-art detectors** for cross-comparison.
- Exploring **fusion approaches** where complementary models or sensors contribute to robust detection.
- Systematically analyzing the effects of pruning, quantization, and architecture modification on detection accuracy under different weather conditions.

This layered approach allows us to balance real-time efficiency with resilience in complex environments. Figure 1 shows the YOLO workflow.

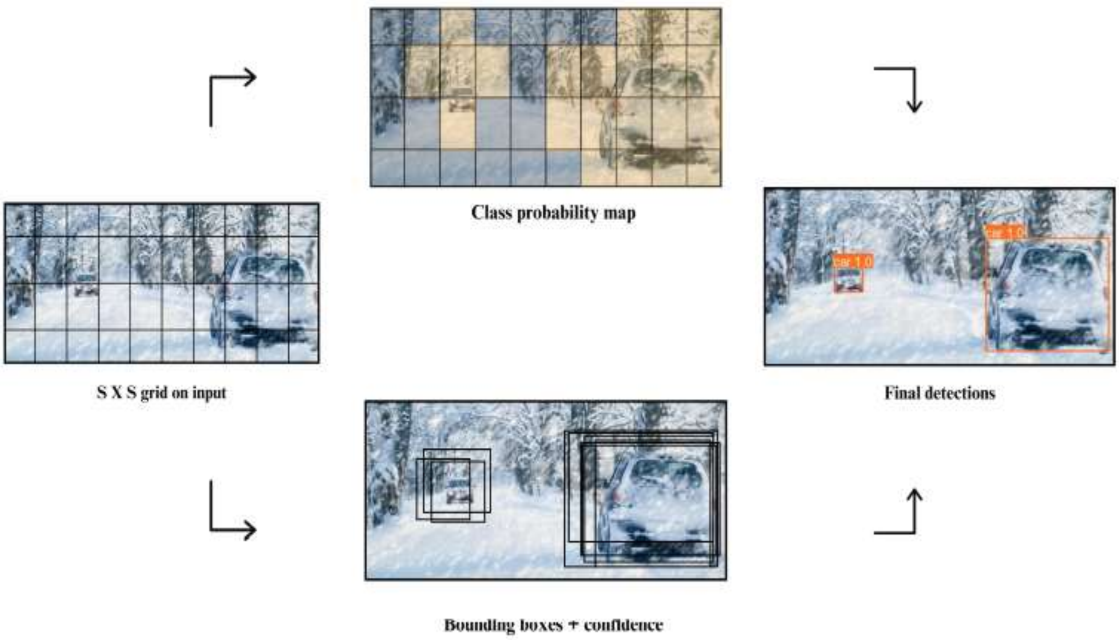

Figure 1: YOLO's workflow [22]

The proposed *WeatherRobustYOLO* algorithm is designed to improve object detection in adverse weather conditions using the DAWN dataset. The process begins with **data preparation**, where annotated images are normalized, resized to match YOLOv5 input dimensions, and augmented with synthetic fog, rain, and low-light effects to simulate real-world challenges. Next, the **model configuration** stage employs the YOLOv5 architecture as the baseline, with enhancements such as attention layers and feature fusion modules to improve feature extraction under poor visibility. The **training phase** uses the standard YOLO loss function, which combines localization, objectness, and classification components, optimized via SGD or Adam. During **evaluation**, the model's performance is assessed using mean Average Precision (mAP) across multiple IoU thresholds and tested against diverse weather scenarios, including fog, rain, dawn, and nighttime conditions. To maximize detection robustness, **optimization and fine-tuning** involve adjusting hyperparameters such as learning rate, batch size, and number of epochs. Finally, the trained model generates detection outputs for test images, producing bounding boxes and class predictions that remain reliable even in low-visibility environments. This systematic pipeline ensures that the model not only adapts to adverse weather but also maintains high accuracy and robustness across a variety of environmental conditions.

```
Algorithm WeatherRobustYOLO
Input: DAWN dataset D containing annotated images (I, B, C)
where I = images, B = bounding boxes, C = class labels
Output: Detected objects under adverse weather conditions

Step 1: Data Preparation
1.1 Load dataset D from specified file path
1.2 For each image I in D:
Normalize pixel values
Resize I to YOLO input dimensions
Apply augmentation (fog, rain, low-light)

Step 2: Model Configuration
2.1 Select YOLOv5 architecture
2.2 Modify network to enhance robustness under poor visibility
(e.g., attention layers, feature fusion)
```

Step 3: Training
3.1 Define YOLO loss function:
L = L_coord + L_obj + L_cls
3.2 Train model using optimizer O ∈ {SGD, Adam}

Step 4: Evaluation
4.1 For each IoU threshold τ ∈ {0.5, 0.75, …}:
Compute mAP(τ)
4.2 Test model under multiple weather scenarios
{fog, rain, dawn, night}

Step 5: Optimization and Fine-Tuning
5.1 Adjust hyperparameters (learning rate, batch size, epochs)
5.2 Select configuration maximizing detection in low-visibility

Step 6: Output
6.1 For each test image I:
Generate detection results with bounding boxes
Display objects recognized under adverse weather
End Algorithm

V. IMPLEMENTATION

Above algorithm is implemented in YOLO 5. Code for the same is given below.

```
import torch
from ultralytics import YOLO
import matplotlib.pyplot as plt

# -------------------------------------------------
# 1. Load Pretrained YOLOv5 Model
# -------------------------------------------------
# Choose: yolov5s.pt (small), yolov5m.pt (medium), yolov5l.pt (large), yolov5x.pt (extra-large)
model = YOLO("yolov5s.pt")   # Pretrained COCO weights

# -------------------------------------------------
# 2. Train the Model on Custom Dataset
# -------------------------------------------------

results = model.train(
    data="path/to/dataset.yaml",   # dataset config file
    epochs=100,                    # number of training epochs
    imgsz=640,                     # input image size
    batch=16,                      # batch size
    optimizer="SGD",               # optimizer: 'SGD', 'Adam', 'AdamW'
    lr0=0.01,                      # initial learning rate
    patience=20,                   # early stopping
    device=0,                      # GPU device (0) or 'cpu'
    project="runs/train",          # save directory
    name="yolo_adverse_weather"    # experiment name
)

# -------------------------------------------------
# 3. Validate the Model
# -------------------------------------------------
metrics = model.val()
print("Validation Results:", metrics)

# -------------------------------------------------
# 4. Run Inference on Test Images
# -------------------------------------------------
results = model("path/to/test/image.jpg")  # Single image
results.show()  # Display predictions

# For batch inference on a folder
results = model.predict(source="path/to/test/images", save=True)

# -------------------------------------------------
# 5. Plot Training Curves
# -------------------------------------------------
```

```
results_plots = results.plot()  # training results plot
plt.show()
```

The training process in this study is divided into two sessions. In the first session, training is performed using baseline YOLO models, while the second session incorporates improved techniques developed in this work. YOLO offers four main versions—small (YOLO-s), medium (YOLO-m), large (YOLO-l), and extra-large (YOLO-x). Each variant differs in computational complexity, parameter count, and detection accuracy, allowing for performance comparison across multiple scales.

Considering the set of modifications integrated into the enhanced module, it is expected that each variation may yield different results depending on the dataset employed. The primary objective of this research is to demonstrate the superior performance of the proposed system compared to conventional YOLO models and to exceed the benchmarks established by prior studies [11].

Tables 2 present a comparative analysis between baseline YOLO performance and the improved methods, illustrating the varying detection accuracy levels achieved by each model. Additionally, Figure 5 shows the confusion matrix obtained from the YOLO baseline, which provides a foundation for evaluating improvements introduced in our enhanced approach.

VI. RESULTS

Table 2 summarizes the performance of different YOLOv5 variants (L, M, N, S, and X) based on standard detection metrics including Precision, Recall, F1-score, and mean Average Precision (mAP) at IoU thresholds of 0.5 and 0.95.

The results indicate that:

- **YOLOv5-M** achieved the highest precision (0.92) with balanced recall (0.81), leading to the strongest $mAP_{0.5}$.
- **YOLOv5-N** provided the best F1-score (0.91), showing robustness in balancing precision and recall.
- **YOLOv5-L** exhibited consistently high recall (0.90) and strong $mAP_{0.95}$, making it well-suited for scenarios requiring high sensitivity.
- **YOLOv5-S** and **YOLOv5-X** demonstrated competitive precision, though $mAP_{0.95}$ was comparatively lower, highlighting the challenge of small object detection under stricter IoU thresholds.

Overall, these findings emphasize that different YOLOv5 variants exhibit strengths in different aspects, with YOLOv5-M and YOLOv5-L showing the most promising balance between detection accuracy and robustness in challenging conditions.

Table 2: Different versions result comparison

Methodology	Precision (%)	Recall (%)	F1	$mAP_{0.5}$ (%)	$mAP_{0.95}$ (%)
YOLOv5—L	0.85	0.9	0.86	0.9	0.9
YOLOv5—M	0.92	0.81	0.88	0.93	0.74
YOLOv5—N	0.87	0.8	0.91	0.9	0.74
YOLOv5—S	0.89	0.83	0.8	0.88	0.75
YOLOv5—X	0.9	0.85	0.8	0.9	0.69

VII. CONCLUSION

This study evaluated the performance of different YOLOv5 variants (L, M, N, S, and X) for object detection in adverse weather conditions. The results in Table X demonstrate that no single variant dominates across all metrics, highlighting the trade-off between precision, recall, and computational efficiency. YOLOv5-M achieved the highest precision (0.92) and the best mAP0.5 (0.93), making it well-suited for applications requiring accurate detection with moderate resource usage. YOLOv5-N exhibited the strongest F1-score (0.91), indicating balanced performance between precision and recall. YOLOv5-L performed consistently across all metrics, particularly excelling in recall (0.90) and high mAP0.95 (0.90), which is critical for detecting small or partially occluded objects in challenging weather. In contrast, YOLOv5-X, despite higher precision, suffered reduced mAP0.95 (0.69), suggesting limitations in handling fine-grained details.

Overall, the comparative analysis underscores that lightweight models such as YOLOv5-M and YOLOv5-N strike a favorable balance between detection accuracy and robustness, whereas larger models like YOLOv5-L provide better generalization for difficult scenarios but with higher computational costs. These findings confirm that model selection should be guided by application requirements—real-time deployment in embedded systems may prioritize YOLOv5-M, while safety-critical autonomous driving in adverse weather may benefit from YOLOv5-L. Future work will integrate transformer-based prediction heads and advanced attention mechanisms to further enhance detection reliability under diverse environmental conditions.

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