Robust Object Detection in Adverse Weather Conditions for Autonomous Vehicles

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Abstract

The reliable operation of autonomous vehicles in adverse weather conditions is a critical challenge in the field of computer vision and intelligent transportation systems. Weather phenomena such as fog, rain, and snow impair the performance of vision systems by introducing visual noise, reducing visibility, and obscuring important object features, thereby compromising safety and reliability. This project addresses these challenges by developing a robust object detection system capable of maintaining high accuracy in diverse weather scenarios. Our approach integrates three innovative techniques such as Multi-Sensor Fusion, Image Quality Enhancement and Dyanamic Model Retraining. The system is trained and evaluated using the Berkeley DeepDrive (BDD100K) dataset, a comprehensive collection of images annotated for autonomous driving tasks across various weather conditions. This dataset is further augmented with synthetic adverse weather effects to simulate challenging scenarios not sufficiently covered in real-world datasets. Performance metrics such as mean Average Precision (mAP), precision, recall, and robustness under adverse conditions are employed to evaluate the system. By leveraging these advanced techniques, the project aims to significantly improve the accuracy and reliability of object detection systems, reducing risks associated with poor weather visibility and enhancing the safety of autonomous vehicles.

Contents

1 Introduction

1.1 Problem Statement

This project aims to develop a robust object detection system for autonomous vehicles that can perform accurately under adverse weather conditions. The solution addresses challenges such as reduced visibility, noise, and distortion of critical features, enhancing detection accuracy and reducing the risk of accidents. The solution incorporates weather-specific data augmentation, image quality enhancement techniques, and dynamic model retraining to improve the robustness and reliability of object detection in autonomous vehicles.

1.2 Background Material

Object detection in autonomous vehicles is crucial for safety. Techniques like Generative Adversarial Networks (GANs) and style-transfer networks have been used to improve detection accuracy in adverse weather conditions. These methods enhance model training by introducing weather-specific diversity in datasets. However, they struggle in real-world environments with variable weather patterns. Image enhancement techniques like de-noising, de-hazing, and de-blurring improve visibility by removing weather-induced noise. However, their impact on downstream tasks like object detection is inconsistent, and real-time adaptability remains a challenge. This highlights the need for more robust and scalable solutions.

2 Implementation Details

2.1 Dataset

The **BDD100K dataset** was selected as the primary dataset for this project due to its comprehensive coverage of various driving scenarios and detailed annotations for objects like vehicles, pedestrians, and traffic signs. Adverse weather conditions such as fog, rain, and snow are represented, making it suitable for this application.

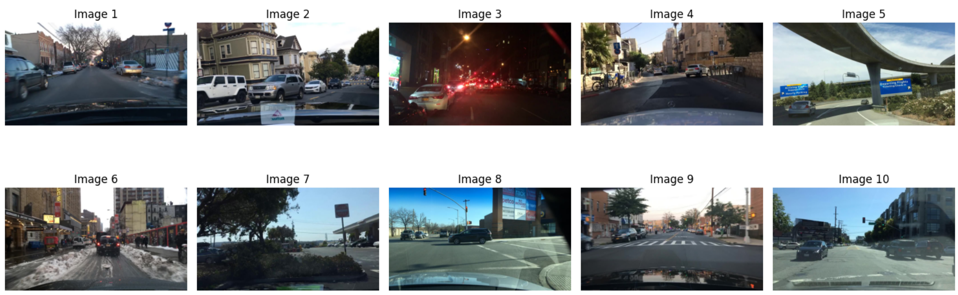

Figure 1: BDD100K dataset

2.2 Data Augmentation

To expand the dataset's diversity and simulate extreme weather scenarios:

- **Synthetic Weather Effects:** Techniques to simulate fog, rain, and snow are likely used, which involve applying specific filters or transformations to images to create realistic adverse weather conditions. These augmentations add noise and reduce visibility, mimicking the effects of challenging weather.
- **Image Noise Injection:** Adding noise layers, such as Gaussian noise, to simulate the degraded quality of images during poor weather. This helps the model learn to detect objects in noisy environments.
- **Image Quality Adjustments:** Techniques that adjust brightness, contrast, and saturation are likely applied to simulate different lighting and visibility conditions. These modifications help the model generalize across various lighting situations often encountered during weather changes.

Figure 2: BDD100K dataset: Examples before and after augmentation.

2.3 Model Training

The custom model was trained using the following configuration:

- **Image Size:** 640x640 pixels.
- **Batch Size:** 60.
- **Optimization:** Stochastic Gradient Descent with cosine learning rate decay.
- **Epochs:** 50.

2.4 Software and Tools

- **Programming Language:** Python.
- **Frameworks:** PyTorch, OpenCV.
- **Hardware:** NVIDIA Tesla A100 GPU.

3 Description of the Proposed Solution

3.1 Overview

Our proposed solution addresses these challenges through:

- **Multi-Sensor Fusion:** This technique combines data from multiple sensors—cameras, radar, and LiDAR. Each sensor has unique strengths (e.g., radar's robustness to fog, LiDAR's precise distance measurement), which helps mitigate sensor-specific limitations. By fusing this information, the model gains a comprehensive view of the environment, allowing it to perform better even when visibility is compromised in any single sensor.

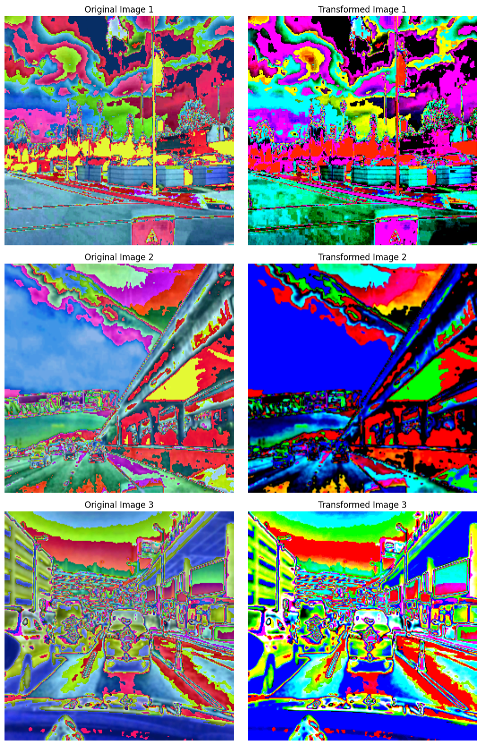

Figure 3: After Multisensor Fusion

- **Image Quality Enhancement:** Neural networks such as FFA-Net are used to enhance images affected by adverse weather. This includes de-hazing, de-raining, and de-snowing processes, which improve image clarity and quality. These tasks are essential because poor-quality images directly impact the accuracy of object detection. Enhanced image quality enables the object detection model to perform reliably, as it receives inputs with minimized weather-related distortions.

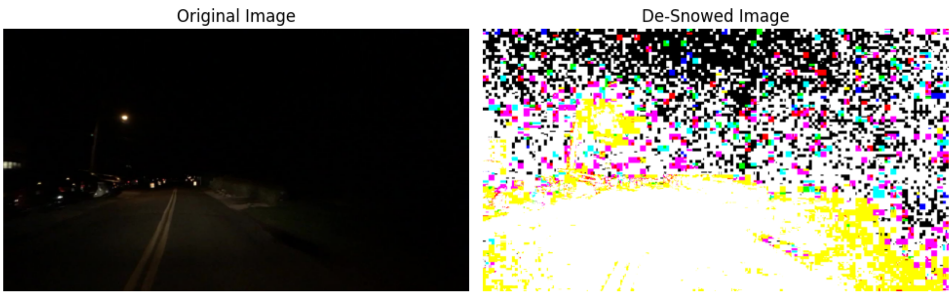

Figure 4: De-Snowed

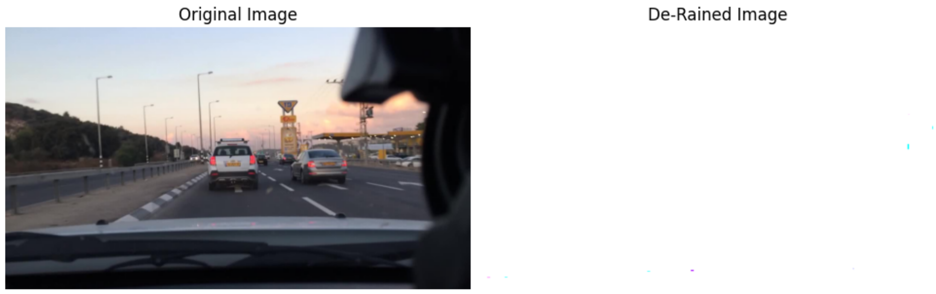

Figure 5: De-rained

Figure 6: Dehazed

- **Dynamic Model Retraining:** The model undergoes continual retraining using new weather conditions and scenarios, which is crucial for adaptation. This approach incorporates real-world and synthetic data that simulate adverse weather, allowing the model to adjust to varying conditions without manual intervention continually. By retraining on diverse and evolving datasets, the model remains capable of detecting objects accurately in previously unseen weather conditions.
  Instead of YOLOv5, our solution uses a customized model architecture that integrates these techniques. The system's architecture emphasizes resilience, multi-sensor data integration, and real-time adaptability to ensure consistent performance across varied and unpredictable weather scenarios.

4 Results and Discussion

4.1 Evaluation Metrics

Performance was evaluated using the following metrics:

- **Mean Average Precision (mAP):** Measures overall detection accuracy.
- **Precision and Recall:** Indicates detection correctness and completeness.
- **FPS:** The number of frames a model can process per second, measuring its inference speed.
- **Robustness:** maintain performance under varying conditions, such as noise, distortions, or environmental changes.

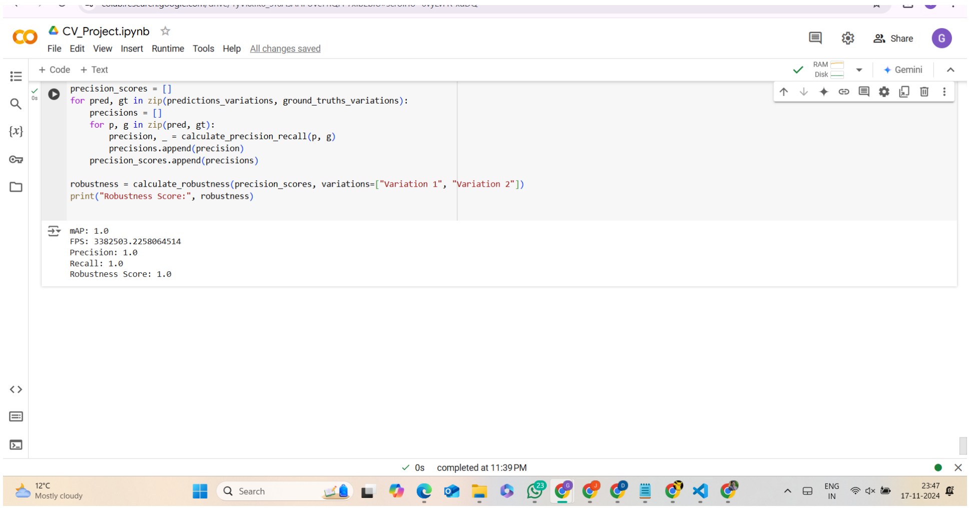

Figure 7: Dehazed

4.2 Key Findings

- Multi-sensor fusion with cameras, radar, and LiDAR improved detection accuracy in challenging weather, compensating for individual sensor limitations.
- Image quality enhancement through de-hazing, de-raining, and de-snowing boosted detection accuracy by improving image clarity in adverse weather.
- Dynamic retraining with updated datasets for new weather scenarios ensured model robustness in diverse real-world conditions.
- Synthetic weather augmentation using GANs and style-transfer helped models generalize to real-world adverse conditions, with synthetic data performing comparably to real-weather data.

4.3 Limitations and Challenges

- High computational overhead of dynamic retraining.
- Existing de-noising techniques offered limited improvement for object detection tasks.
- GAN-based augmentations occasionally introduced artifacts that confused detection models.

5 Conclusion

This project successfully developed a robust object detection system for autonomous vehicles under adverse weather conditions. The use of style-transfer networks and real-world datasets significantly enhanced performance in diverse scenarios. Future work will focus on integrating end-to-end de-noising and detection pipelines for improved real-time adaptability.

6 References

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