Final Project Report: Real-Time Object Detection for Autonomous Vehicles

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1. Introduction

The goal of this project was to develop a real-time object detection system to be integrated into autonomous vehicles. The system aims to detect and classify critical road elements such as pedestrians, vehicles, traffic signs, traffic lights, and potholes under varying environmental conditions. This enhances the safety and decision-making capabilities of autonomous systems in real-world driving scenarios.

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2. Project Overview

Problem Statement: Autonomous vehicles require robust object detection systems that work in real-time across different environments to ensure safety and performance. Challenges include class imbalance, deployment complexity, and robustness under variable lighting and weather conditions.

Solution: Implement a real-time object detection pipeline using the YOLOv8 model, optimized via transfer learning, and supported by an MLOps pipeline for monitoring and scalability.

Key Technologies: YOLOv8, YOLOv11, OpenCV, Streamlit, MLflow

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3. Milestone 1: Data Collection, Exploration, and Preprocessing

Tasks Completed:

Datasets Used:

- KITTI: Primary dataset for vehicle and pedestrian detection
- S2TLD: Primary dataset for traffic light detection
- ITSD: Primary dataset for traffic sign detection
- APID: Primary dataset for pothole detection

Class Coverage: Pedestrians, vehicles, cyclists, road signs, traffic lights, potholes

Exploration Insights:

- Notable class imbalance (e.g., more cars than pedestrians)
- Varying lighting/weather conditions across datasets

Preprocessing Steps:

- Resized images when necessary.
- Normalized pixel values between [0,1]
- Applied augmentation techniques:
  - Random flip, changing brightness, and rotation
  - Exposure and contrast adjustments

Deliverables:

- Dataset Exploration Report with class distribution and quality observations
- Cleaned and Augmented Dataset in YOLO-compatible format

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4. Milestone 2: Object Detection Model Development

Model Selection:

- Chosen Model: YOLOv8 and YOLOv11 for optimal accuracy and low latency

Training & Fine-Tuning:

- Used pre-trained weights from COCO
- Fine-tuned on KITTI, S2TLD, ITSD, and APID datasets

Training Environment:

- NVIDIA GPU (e.g., RTX 3050)

Evaluation Metrics:

- mAP@0.5: ~75%
- Classification Loss: ~1.2
- Box Loss: ~1
- Precision: ~85%

Deliverables:

- Model Evaluation Report from YOLO training
- Final YOLOv8 model exported to MLflow

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5. Milestone 3: Deployment and Real-Time Testing

Deployment Strategy:

- Inference pipeline built using OpenCV and Streamlit
- Real-time video feed processed on-vehicle
- MLflow used for tracking performance

Testing Scenarios:

- Urban roads, highways, night time

Performance Observations:

- Stable detection in most environments
- Minor performance degradation in low light/fog (improved via augmentation)

Deliverables:

- Deployed Model Container (Streamlit + MLflow)
- Real-time testing videos and logs

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6. Milestone 4: MLOps and Monitoring

MLOps Setup:

- MLflow for tracking experiments, parameters, and model versions
- Performance monitoring with detection loss, precision and recall

Deliverables:

- MLOps Report outlining CI/CD and retraining workflow
- Monitoring Dashboard with MLflow integration

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7. Milestone 5: Final Documentation and Presentation

Final Report Summary:

- Developed a robust object detection system with real-time performance
- Achieved strong accuracy and fast inference across various conditions
- End-to-end system includes MLOps for deployment and scalability

Challenges & Solutions:

Challenge	Solution
Low light/fog detection	Augmentation and retraining with synthetic data
Class imbalance	Oversampling and class-weighted loss
Deployment complexity	Multi-model inference and MLOps integration

Future Work:

- Add object tracking (e.g., Deep SORT)
- Sensor fusion (e.g., LiDAR + Camera)
- Detect more object classes (e.g., animals, road conditions)
- Quantize model for edge deployment
- Integration with smart city infrastructure

Deliverables:

- Final Project Report (this document)
- Final Presentation (slide summary with demo videos)

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8. Conclusion

This project delivers a high-performance, real-time object detection system tailored for autonomous vehicles. Using cutting-edge deep learning models and MLOps best practices, the system is built for scalability, maintainability, and real-world reliability, supporting the evolution of safe autonomous mobility.