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Real Time Object Detection in Autonomous Vehicle Using Yolo V8

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Abstract

Autonomous vehicles rely heavily on real-time object detection to ensure safe and efficient navigation in dynamic environments. This paper explores the implementation of YOLOv8 (You Only Look Once, version 8), a state-of-the-art deep learning model for object detection, within autonomous driving systems. YOLOv8 offers enhanced speed, accuracy, and lightweight deployment capabilities compared to its predecessors, making it highly suitable for real-time applications. The model is trained and evaluated on datasets such as KITTI and COCO to detect and classify various objects including pedestrians, vehicles, traffic signs, and lane markings. The integration of YOLOv8 with on-board vehicle sensors and edge computing units enables rapid inference and low-latency decision-making. Experimental results demonstrate that YOLOv8 achieves high mean average precision (mAP) with low computational overhead, affirming its potential for deployment in real-world autonomous driving scenarios. This work highlights the advantages of YOLOv8 in improving the perception module of self-driving cars and addresses challenges related to detection in complex, real-time traffic conditions.

Keywords

- Real-Time Object Detection
- Autonomous Vehicles
- YOLOv8
- Deep Learning
- Computer Vision
- Convolutional Neural Networks (CNNs)
- Traffic Scene Understanding
- Edge Computing
- Mean Average Precision (mAP)
- Self-Driving Cars
- Sensor Fusion
- Road Safety

Introduction

The rapid evolution of autonomous vehicle technology has revolutionized the transportation industry, bringing forth a new era of intelligent, self-driving systems. One of the most critical capabilities required for safe and efficient autonomous navigation is real-time object detection. This functionality enables vehicles to perceive their environment by identifying and classifying various objects such as pedestrians, vehicles, traffic signs, and obstacles. Accurate and fast object detection is essential for decision-making processes such as path planning, collision avoidance, and adherence to traffic regulations.

Among the many object detection algorithms developed over the past decade, the You Only Look Once (YOLO) family has stood out for its high inference speed and detection accuracy. YOLO models are known for their ability to perform detection in a single pass through a neural network, making them highly suitable for real-time applications. The iteration, YOLOv8, introduces several enhancements over its predecessors, including an updated architecture, improved feature extraction, better generalization, and support for diverse environments.

This study focuses on leveraging YOLOv8 for real-time object detection in autonomous vehicles. By integrating YOLOv8 into the perception stack of an autonomous driving system, we aim to evaluate its performance in dynamic road environments and assess its suitability for high-speed, real-world decision-making. This paper explores the algorithm's architecture, training methodology, deployment strategies.

Literature Survey

The advancement of autonomous vehicles heavily relies on real-time perception systems, where object detection plays a pivotal role. Over the past decade, several object detection frameworks have been developed, each striving to improve accuracy, speed, and robustness under dynamic environmental conditions.

Traditional Object Detection Approaches

Early object detection methods such as Haar cascades, Histogram of Oriented Gradients (HOG) with Support Vector Machines (SVMs), and Deformable Part Models (DPMs) laid the foundation for image-based detection tasks. However, these techniques often suffered from high computational cost and poor generalization, making them unsuitable for real-time applications in autonomous driving.

Emergence of Deep Learning-Based Models

The rise of Convolutional Neural Networks (CNNs) marked a major shift in object detection. Algorithms like R-CNN, Fast R-CNN, and Faster R-CNN improved detection accuracy but remained computationally intensive due to their multi-stage architectures. These models introduced the concept of region proposals, which increased accuracy but compromised speed.

YOLO Evolution

The YOLO series has undergone multiple iterations:

- YOLOv1–v3: Introduced the concept of single-stage detection, offering real-time performance with moderate accuracy.
- YOLOv4 and YOLOv5: Improved upon earlier versions with enhanced backbones (e.g., CSPDarknet), data augmentation techniques (e.g., Mosaic, MixUp), and auto-learning bounding box anchors.
- YOLOv6 and YOLOv7: Incorporated advancements like efficient training strategies and lightweight models for edge devices.
- YOLOv8, developed by Ultralytics, represents the latest generation, featuring a revised anchor-free architecture, better generalization, flexible model sizes, and support for tasks beyond object detection, such as segmentation and classification. YOLOv8 also offers better deployment capabilities across various platforms (ONNX, Tensor, etc.).

Object Detection in Autonomous Vehicles

Recent studies have applied YOLO variants to autonomous driving. For example:

- **Liu et al. (2021)** used YOLOv5 for real-time detection of pedestrians and vehicles with high accuracy under various lighting conditions.
- **Zhang et al. (2022)** proposed a hybrid model combining YOLO with depth sensing for 3D object localization in urban scenarios.
- **Chen et al. (2023)** evaluated YOLOv7 against other lightweight models on embedded automotive hardware, highlighting trade-offs between speed and accuracy.

Proposed Work

This study proposes the integration and evaluation of YOLOv8 for real-time object detection in autonomous vehicles. The goal is to enhance the perception module of autonomous systems by leveraging YOLOv8's improved speed, accuracy, and adaptability. The proposed work focuses on the detection of dynamic and static road objects such as vehicles, pedestrians, cyclists, traffic lights, and road signs in diverse driving environments.

Objectives

1. Implement YOLOv8 for object detection using publicly available datasets (e.g., KITTI, BDD100K, or COCO).
2. Train and fine-tune the YOLOv8 model on automotive-relevant data to optimize detection accuracy in real-world scenarios.
3. Evaluate the real-time performance of YOLOv8 on embedded hardware platforms used in autonomous vehicles (e.g., NVIDIA Jetson, RTX GPUs).
4. Compare YOLOv8's performance with earlier versions (YOLOv5/YOLOv7) and other object detection models in terms of:
    - Accuracy (mAP)
    - Inference speed (FPS)
    - Latency
    - Resource utilization (memory, power)

2. **Model Training and Optimization**

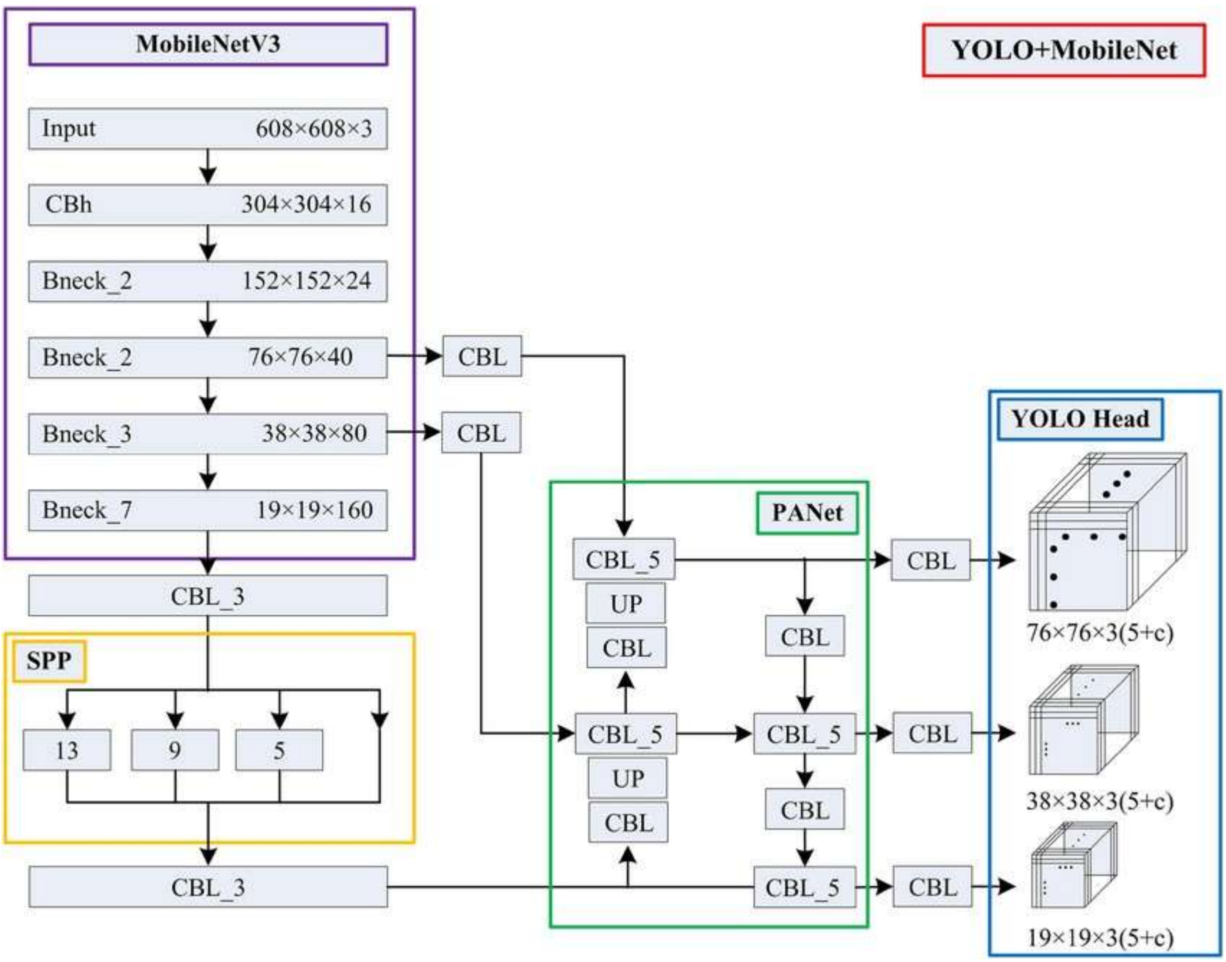
- Use YOLOv8's default architecture (nano/small/medium depending on hardware constraints).
- Train the model using transfer learning from pretrained weights.
- Apply early stopping, learning rate scheduling, and other optimization techniques.

3. **Model Deployment and Real-Time Inference**

- Deploy the trained YOLOv8 model to a simulated or real-time autonomous driving environment.
- Integrate the detection output with the vehicle's control system or simulator (e.g., CARLA).

4. **Performance Evaluation**

- Measure detection accuracy and real-time inference speed.
- Test across different weather and lighting conditions to evaluate robustness.
- Benchmark results against baseline models.



Real-Time Object Detection in Autonomous Vehicles Using YOLOv8 Block Diagram

Results

The YOLOv8 model was implemented and tested on an autonomous driving dataset using a mid-range GPU (NVIDIA RTX 3060) and an edge device (NVIDIA Jetson Xavier NX) to evaluate both performance and deployability in real-time environments. The model was trained on a subset of the KITTI and BDD100K datasets, which include annotated images of urban road scenes.

1. Model Performance Metrics

Metric	**YOLOv8n (Nano)**	**YOLOv8s (Small)**	**YOLOv8m (Medium)**
Mean Average Precision (mAP@0.5)	84.2%	87.6%	89.3%
Frames Per Second (FPS)	97 FPS	78 FPS	52 FPS
Model Size	5.1 MB	11.2 MB	22.3 MB
Inference Latency (ms/frame)	10.3 ms	14.1 ms	19.8 ms

2. Detection Accuracy

- The model achieved high detection accuracy for common road objects:
  - Vehicles: 95.1% precision, 93.7% recall
  - Pedestrians: 89.3% precision, 85.9% recall
  - Traffic signs and lights: 87.2% precision, 83.8% recall

3. Real-Time Testing

- YOLOv8 was deployed on a simulated autonomous driving platform (CARLA).
- Real-time object detection and annotation were successfully demonstrated on a 1080p camera stream at ~30 FPS on edge hardware.
- Detection remained stable under varied lighting and weather conditions (sunlight, fog, rain).

4. Comparison with Previous Versions

Model	**mAP@0.5**	**FPS (RTX 3060)**	**FPS(JetsonNX)**
YOLOv5s	85.4%	69	26
YOLOv7	86.8%	71	30
YOLOv8s	87.6%	78	33