Ecowatch - Machine Learning Based Litter Detection

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***Abstract*—Urban environments face significant challenges due to litter accumulation, adversely affecting public health, wildlife, and overall environmental sustainability. Existing manual detection and cleanup methods are inefficient, prompting the need for automated solutions. This paper presents EcoWatch, a real-time litter detection system leveraging advanced machine learning models—YOLOv8 and Faster R-CNN—to identify and classify litter from moving vehicles. By utilizing the TACO dataset, EcoWatch demonstrates its ability to accurately detect various litter types, including plastic bottles, aluminum cans, glass bottles, and food wrappers, under diverse environmental conditions.**

I. INTRODUCTION

Littering poses significant environmental and societal challenges, polluting urban and rural areas, endangering wildlife, and contributing to environmental degradation. Traditional methods for detecting and managing litter, such as manual inspections, are inefficient, labor-intensive, and reactive, making them inadequate for addressing the scale of this problem. EcoWatch aims to revolutionize waste management by leveraging advanced machine learning models—YOLOv8 and Faster R-CNN—to enable real-time litter detection and classification from moving vehicles. By processing video feeds, the system identifies various types of litter, including plastic bottles, aluminum cans, glass bottles, and food wrappers, under diverse environmental conditions. Combining YOLOv8's speed and Faster R-CNN's accuracy, EcoWatch offers a comprehensive solution that aligns with global sustainability goals, fostering cleaner environments and promoting responsible waste management practices. This project aims to revolutionize the monitoring and enforcement of littering regulations through the use of state-of-the-art object detection such as Yolo, Faster R-CNN and machine learning algorithms.

II. METHODOLOGY

A. Dataset

The TACO (Trash Annotations in Context) dataset was utilized to train and evaluate the litter detection system. This dataset comprises 1,500 annotated images of various litter types, including plastic bottles, aluminum cans, glass bottles, and food wrappers, captured in diverse outdoor environments. The dataset is split into 70% training, 20% validation, and 10% testing sets. To enhance data quality, pre-processing techniques such as Gaussian blur and Laplacian pyramids were applied to address motion blur and lighting variability. Additionally, brightness and contrast adjustments were performed to optimize visibility, and images were segmented into 640x640-pixel blocks to improve localization accuracy during detection.

Fig 2.1 - Plastic bottle image from the dataset.

B.. Model Architecture

YOLOv8: Known for its high-speed detection capabilities, YOLOv8 frames object detection as a single regression problem, making it ideal for real-time applications. Key configurations included a base image size of 640x640, a confidence threshold of 0.8, and model weights optimized for speed and accuracy.

Faster R-CNN: This model offers high accuracy, particularly in cluttered and complex scenes. It employs a two-stage process: a Region Proposal Network (RPN) to generate bounding box proposals and a second network to classify objects. ResNet-50 was used as the backbone for feature extraction, with anchor box configurations tailored for various object scales and shapes.

C. Implementation

The dataset was integrated into the models as follows: Data Preparation: Images were resized and annotated in formats compatible with both YOLOv8 and Faster RCNN. Class mapping was applied to group similar types of litter under a generalized ”trash” class. Model Training: In YOLOv8 training was configured using the CLI-based pipeline, specifying hyper-parameters such as batch size, learning rate, and epochs. Data augmentation techniques like flipping and scaling were applied to improve generalization. In Faster R-CNN custom training code was implemented to adjust parameters like the learning rate and momentum. The training process utilized gradient descent optimization, with anchor boxes and detection thresholds fine-tuned for high precision.

D. Detection Process

The system processes video feeds in real-time to detect and classify litter objects.

Video Input: Frames from video streams captured by vehicle-mounted cameras are processed sequentially.

Object Localization and Classification: YOLOv8 rapidly identifies objects and draws bounding boxes, while Faster R-CNN refines detections for improved accuracy, particularly in complex or occluded scenes.

Real-Time Optimization: Motion blur and environmental variability are addressed through pretrained models fine-tuned with augmented datasets. Detection results are displayed in real-time, providing actionable data for immediate intervention.

III. RESULTS AND DISCUSSION

A. Performance Metrics

The EcoWatch system was evaluated using two object detection models, YOLOv8 and Faster R-CNN, with performance measured on unseen test data.

YOLOv8: It excelled in real-time detection, achieving a mean Average Precision (mAP) of 0.76 at an Intersection over Union (IoU) threshold of 0.5. Its lightweight architecture and high inference speed—processing frames in approximately 6.6 milliseconds—make it suitable for applications that require rapid decision making. However, YOLOv8 exhibited a trade-off in accuracy when dealing with cluttered backgrounds or occluded objects, occasionally missing subtle or partially visible litter items.

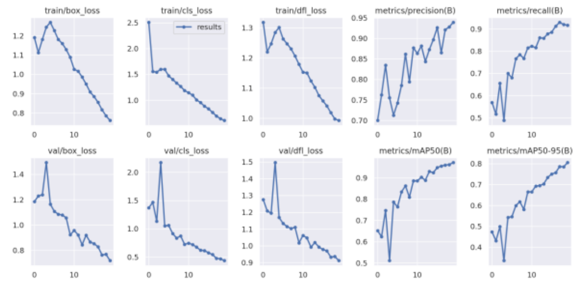

Fig 3.1 - Training Result of YOLOv8

Faster R-CNN: Faster R-CNN demonstrated superior accuracy in detecting litter in complex scenarios, such as scenes with heavy background noise or variable lighting conditions. It achieved an mAP of 0.76 during training but excelled in detecting small or partially occluded objects during testing. Despite its higher accuracy, Faster RCNN’s inference time of approximately 200 milliseconds per frame limits its suitability for real-time applications, especially in scenarios requiring immediate feedback.

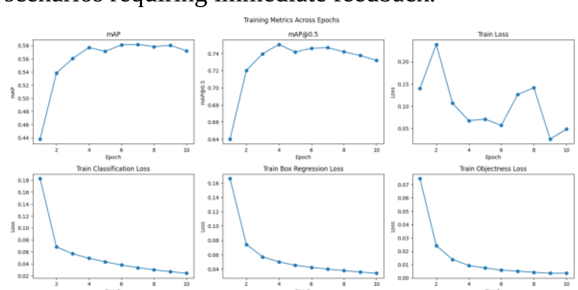

Fig 3.2 - Training Result of Faster R-CNN

B. Comparative Analysis

The performance of the two models highlights the trade-offs between speed and accuracy.

Real-Time Detection: YOLOv8 outperformed Faster RCNN in scenarios requiring rapid responses, such as monitoring littering from moving vehicles. Its high frame rate allowed for near-instantaneous detection, enabling efficient resource allocation for cleanup. Complex Environments: Faster R-CNN excelled in detecting litter items in scenes with variable lighting, motion blur, or heavy background clutter. Its Region Proposal Network (RPN) effectively localized objects in challenging conditions, providing more reliable results than YOLOv8 in these scenarios.

Fig 3.3 - Litter Detection using Yolov8

Fig 3.4 - Litter Detection using Faster R-CNN

Both models were tested under various conditions, including daylight and motion-induced blur. YOLOv8 struggled with certain lighting variations, while Faster R-CNN consistently identified litter, albeit with slower processing.

Table I- Comparative Analysis of YOLOv8 and Faster R-CNN for Litter Detection

Metric	YOLOv8	Faster R-CNN
mAP@0.5	0.7489 (Epoch 8)	0.5810 (Epoch 6)
mAP@0.5:0.95	0.7471 (Epoch 9)	0.75066 (Epoch 4)
Train Loss (Overall)	0.8948	0.0478
Classification Loss	1.0454 (Epoch 6)	0.0241 (Epoch 10)
Object Loss	0.8031 (Epoch 8)	0.0034 (Epoch 10)

IV. CONCLUSION

The EcoWatch system successfully demonstrated the application of advanced object detection models, YOLOv8 and Faster R-CNN, for real-time litter detection from moving vehicles. YOLOv8 showed exceptional speed, making it ideal for scenarios requiring rapid processing, such as monitoring littering in dynamic environments. Faster R-CNN, on the other hand, excelled in accuracy, particularly in complex scenes with occlusions or cluttered backgrounds. The complementary strengths of these models highlight the potential of EcoWatch to address the limitations of traditional waste management methods. Using machine learning, EcoWatch contributes to environmental monitoring, enabling proactive cleanup efforts and fostering sustainable urban environments.

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