Solution Document: Traffic Light Detection Using Faster R-CNN and YOLOv8

Introduction

This document outlines a solution for detecting traffic lights in images using two advanced object detection models: Faster R-CNN and YOLOv8. These models are designed to handle the complexities of detecting traffic lights in varying sizes, shapes, and orientations amidst complex backgrounds and lighting conditions.

Objectives

- Accurate Detection: Identify and localize traffic lights in images.
- **Robustness:** Handle different traffic light sizes, shapes, orientations, and lighting conditions.

Approach

Part 1: Traffic Light Detection Using Faster R-CNN

Faster R-CNN is a two-stage object detection model renowned for its accuracy. It consists of a Region Proposal Network (RPN) that generates potential object locations, followed by a second stage that classifies these proposals and refines their bounding boxes.

Key Steps

1. Environment Setup:

o Install necessary libraries like PyTorch, OpenCV, and torchvision.

2. Model Preparation:

Load a pre-trained Faster R-CNN model,, which includes a class for traffic lights.

3. Image Preprocessing:

 Convert images to a format suitable for model input using transformations that ensure consistency in data handling.

4. Object Detection:

- Perform inference on images to obtain bounding box predictions, labels, and confidence scores.
- Filter predictions to isolate traffic light detections using class labels and confidence thresholds.

5. Visualization:

 Display detected traffic lights with bounding boxes and confidence scores annotated on the image.

Expected Outcomes

- **High Detection Accuracy:** Ability to accurately detect traffic lights in diverse conditions.
- Precision in Bounding Boxes: Accurate localization of traffic lights, minimizing false positives and negatives.
- **Visualization Clarity:** Bounding boxes clearly indicate detected traffic lights with associated confidence levels.

Part 2: Traffic Light Detection Using YOLOv8

YOLOv8 is an efficient real-time object detection model. It uses a single-stage approach to predict bounding boxes and class probabilities simultaneously, making it suitable for applications requiring fast inference.

Key Steps

1. Environment Setup:

Install necessary packages, including the ultralytics library for YOLOv8.

2. Model Loading:

 Load a pre-trained YOLOv8 model capable of detecting traffic lights among other classes.

3. Image Inference:

 Use the model to perform inference on input images, generating predictions for various objects including traffic lights.

4. Post-Processing:

 Extract relevant bounding boxes for traffic lights by filtering predictions based on class.

5. Result Visualization:

 Annotate detected traffic lights on the image with bounding boxes and class labels.

Expected Outcomes

- Real-time Detection: Fast inference speeds suitable for real-time applications.
- **High Detection Accuracy:** Reliable detection performance across diverse traffic light conditions.
- **Ease of Deployment:** Suitable for applications requiring quick setup and deployment with efficient model performance.