# Road Object Detection using Deep Learning and YOLOv8

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## Introduction:

The rapid advancements in deep learning and computer vision techniques have revolutionized the field of road object detection. Autonomous vehicles heavily rely on accurate and efficient object detection systems to ensure safe navigation. In this project, we aim to explore the combination of deep learning, YOLOv8, and the PyCharm development environment to develop a robust road object detection system.

## Prior Work:

Previous research in road object detection has focused on various approaches, including traditional computer vision methods and early versions of the YOLO (You Only Look Once) algorithm. However, these methods often faced challenges in accurately detecting and classifying objects in complex road scenarios.

With the introduction of YOLOv8, an upgraded version of the YOLO algorithm, researchers have achieved significant improvements in object detection accuracy and speed. YOLOv8 utilizes a deep convolutional neural network architecture and incorporates advanced features like skip connections and multi-scale prediction to handle different object sizes and capture fine details.

## Our Approach:

Our approach involves implementing the YOLOv8 algorithm using the PyCharm development environment. PyCharm provides a powerful integrated development environment (IDE) for Python programming, allowing us to efficiently write, debug, and test our road object detection system.

To implement YOLOv8, we will use various deep learning libraries and packages such hydra, cvzone etc which provides the necessary tools for creating and training deep neural networks, while Keras simplifies the process of building and configuring the network layers. OpenCV, on the other hand, enables us to process and analyze the images and videos captured by the road cameras.

We will train our YOLOv8 model on a large annotated dataset containing road images with labeled objects. The training process will involve both the training and validation stages, allowing us to fine-tune the model for optimal performance. Additionally, we will augment the dataset by applying transformations to the images, such as rotation and scaling, to increase the model's ability to handle various road scenarios.

## Results:

We will evaluate the performance of our road object detection system on a separate test dataset containing real-world road images. Metrics like precision, recall, and mean average precision (mAP) will be used to assess the accuracy and reliability of our approach. Additionally, we will compare our results with those achieved by previous approaches to demonstrate the effectiveness of YOLOv8 in road object detection.