

Automated Vehicle-Level Feature Annotation Tool

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Project Outline

- 1. Introduction
- 2. My Problem Formulation
- 3. Literature Review
- 4. Research Gap
- 5. Thesis Objective
- 6. Methodology Design & Implementation
 - Explore 2D automatic annotation using YOLOv3, YOLOv11 (combined with Depth Anything v2) and 3D manual annotation using OpenCV, CVAT, and Mindkosh.
 - 2. Demos
- 7. Results and Discussion: Present samples from YOLOv3, CVAT/Mindkosh, and annotated video frames and outputs of the models.
- 8. Conclusion
- 9. Future Recommendations
- 10. Questions



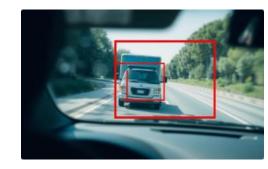
Introduction



In the field of Autonomous driving and intelligent transportation systems ,high-quality annotated datasets are crucial for training and evaluating perception models



These datasets typically include detailed information about vehicles—such as position, speed, orientation, and dimensions—extracted from sensor data or visual input.



While 2D annotations are widely used, they offer limited spatial understanding.



This project focuses on developing a tool for automated vehicle-level feature annotation

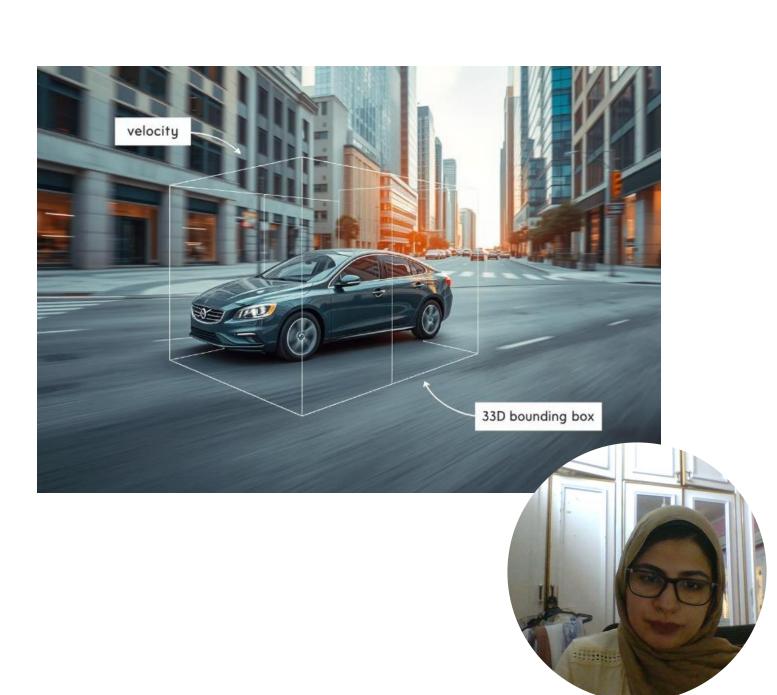


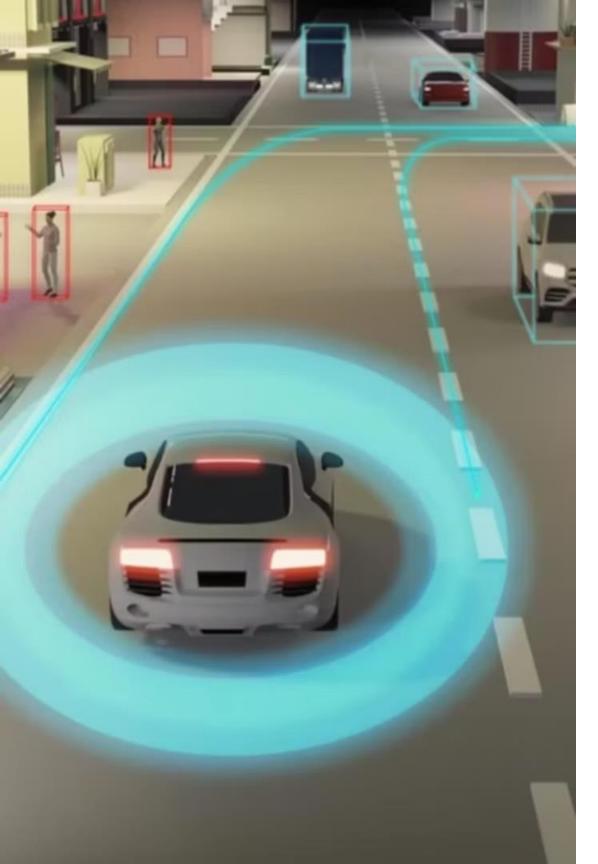
Using monocular camera data, with the goal of enhancing scene understanding in a low-cost, sensor-free environment.



problem formulation

- Current vehicle-level annotation tools often rely on 2D bounding boxes or sensor fusion (e.g., LiDAR, radar) to capture features like speed, orientation, and dimensions.
- However, these approaches either lack spatial depth or require expensive hardware.
- Moreover, manual annotation—especially for 3D bounding boxes—is time-consuming and error-prone, leading to inconsistencies in training data.
- This project addresses the dual challenge of (1) achieving accurate, sensor-free vehicle feature extraction using only monocular camera input and 3D bounding box annotations, and (2) improving the efficiency and consistency of the annotation process for rich feature labeling (e.g., velocity, orientation, inter-vehicle distance, time-to-collision).





Literature Review Summary

Most Commonly Detected Vehicle Features

- Vehicle Type
- Trajectory & Speed
- 3D Bounding Box (Position, Orientation, Dimensions)
- License Plate / ID
- Object Motion Status (Moving / Stationary)

Popular Detection Methods

- YOLO / CNN-based Object
 Detection
- LiDAR Point Cloud
 Segmentation
- Sensor Fusion (Camera + LiDAR + Radar)
- 3D Object De (PointNet, V
- Manual And Labelimg

Extended Literature Review: Monocular 3D Object Detection

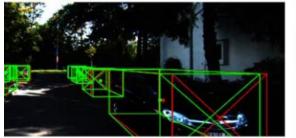
In the last two weeks, I expanded my literature review by exploring recent monocular 3D object detection models using Papers with Code and Google Scholar. I studied papers indexed from 21 to 27 in my spreadsheet:, which provided a variety of models suitable for automatic annotation tasks.

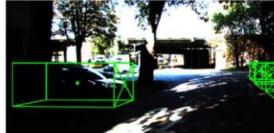
Key insights from these papers:

- Rapid advancements in monocular 3D detection without the need for expensive LiDAR sensors.
- Diverse model architectures focusing on depth estimation, 3D localization, and bounding box refinement.
- Available models offer different trade-offs between accuracy, speed, and computational efficiency.
- Several models showed strong potential for vehicle feature extraction directly from monocular images, enabling efficient dataset annotation.

This exploration helped me select potential candidates for automatic annotation, including YOLOv8+Depth, YOLOv11+Depth Anything v2, and MonoLSS.

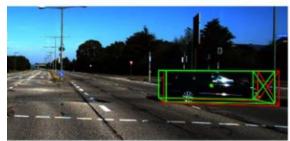
Spreadsheetlink:https://1drv.ms/x/c/5962268546b6d7e5/ETV2CZ7LUBNNt_BeV_03efQB4 MlPjgUBlb6lZJhG02lyxg?e=gk3DVA&nav=MTVfezNEREFEODZDLTkwRUUtNDU3RC05MUYyL TZCOEY5QzQwMkMyMH0



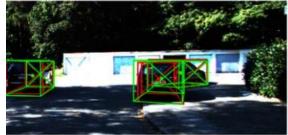




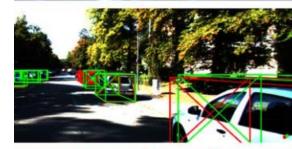
















Research Gap



Most existing datasets and annotation tools either rely heavily on LiDAR/radar or offer only 2D bounding box annotations.



Monocular 3D detection models are improving, but their integration into annotation tools for vehicle-level feature extraction is still limited.



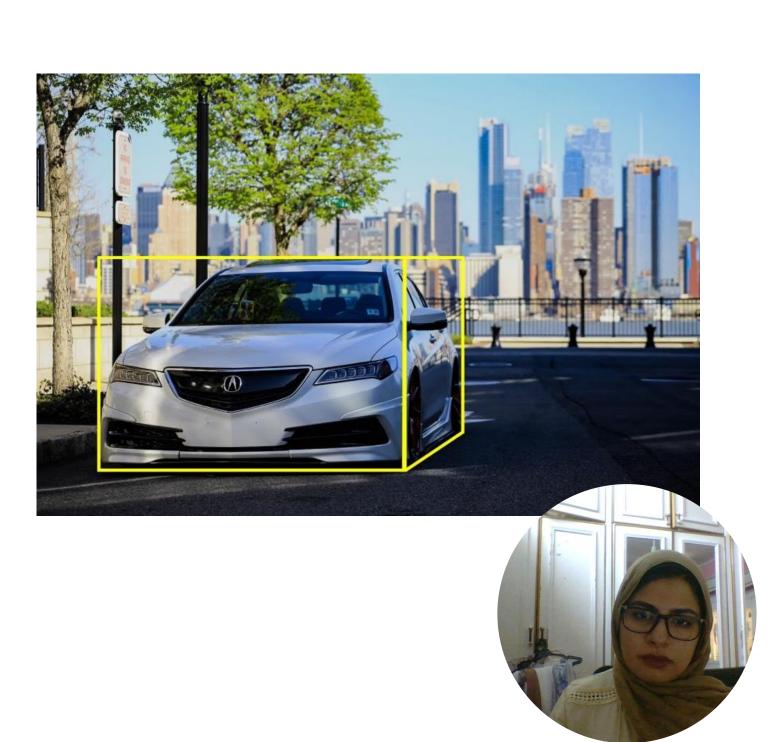
Limited work is available on extracting detailed dynamic features (velocity, acceleration, inter-vehicle distance) from monocular 3D outputs without sensor fusion.



Lack of accessible and standardized pipelines for fully automatic 3D annotation from a monocular catraining an purposes.

My topic Objectives

- Develop a 3D annotation tool for vehicles using only monocular camera data.
- Extract detailed vehicle-level features such as velocity, acceleration, dimensions, and orientation.
- Compare different monocular 3D detection models for annotation efficiency and accuracy.
- Reduce reliance on expensive sensors while maintaining rich scene understanding.
 - Propose a pipeline for efficient vehicle feature annotation and validate it on real-world datasets.



Methodology & Implementation

1. Early Stage:

- Automated 2D vehicle detection using YOLOv3.
- Manual 3D annotation using OpenCV, CVAT, and Mindkosh platforms.

2. Mid Stage:

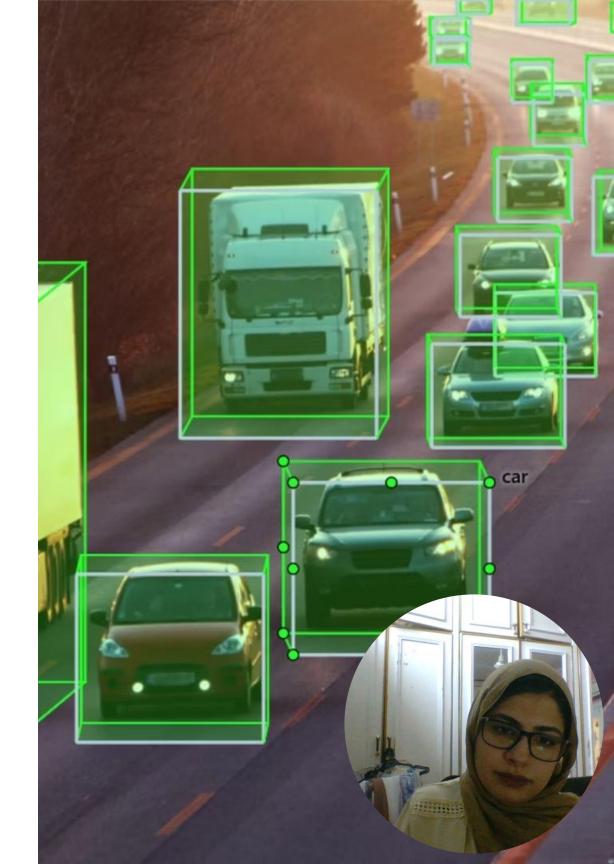
- Semi-automated annotation using YOLOv11 with Depth Anything v2.
- Extracted vehicle-level features: 3D bounding box dimensions, centroids, velocities, accelerations, inter-vehicle distances.

3. Current Stage:

- Training and evaluating MonoLSS on KITTI dataset.
- Comparing performance with YOLOv11 + Depth Anything v2 outputs.
- Feature extraction improvements: occlusion handling, time-to-collision estimation.

4. Challenges:

- Code unavailability for some models (e.g., YOLOBU).
- Selection of best monocular 3D model based on practical considerations.



Why You Chose MonoLSS over Others

Why MonoLSS?

- Compared to MoGDE:
- MonoLSS better models geometric depth explicitly rather than only depth prediction.
- Compared to MonoCAN:
- MonoCAN uses uncertainty-aware attention but underperforms in spatial accuracy compared to MonoLSS.
- Compared to Implicit3DUnderstanding:
- MonoLSS directly supervises depth and geometry, making it easier to train and generalize without complex implicit learning techniques.
- Compared to SMOKE:
- SMOKE predicts 3D boxes from 2D heatmaps but struggles with depth ambiguity.

 MonoLSS addresses depth supervision better, leading to more reliable 3D positions.
- Overall:
- MonoLSS strikes a strong balance between detection performance, training stability, and implementation simplicity—making it ideal for an annotation tool.



Results

Here are some sample outputs showcasing both our automatic and manual annotation methods.

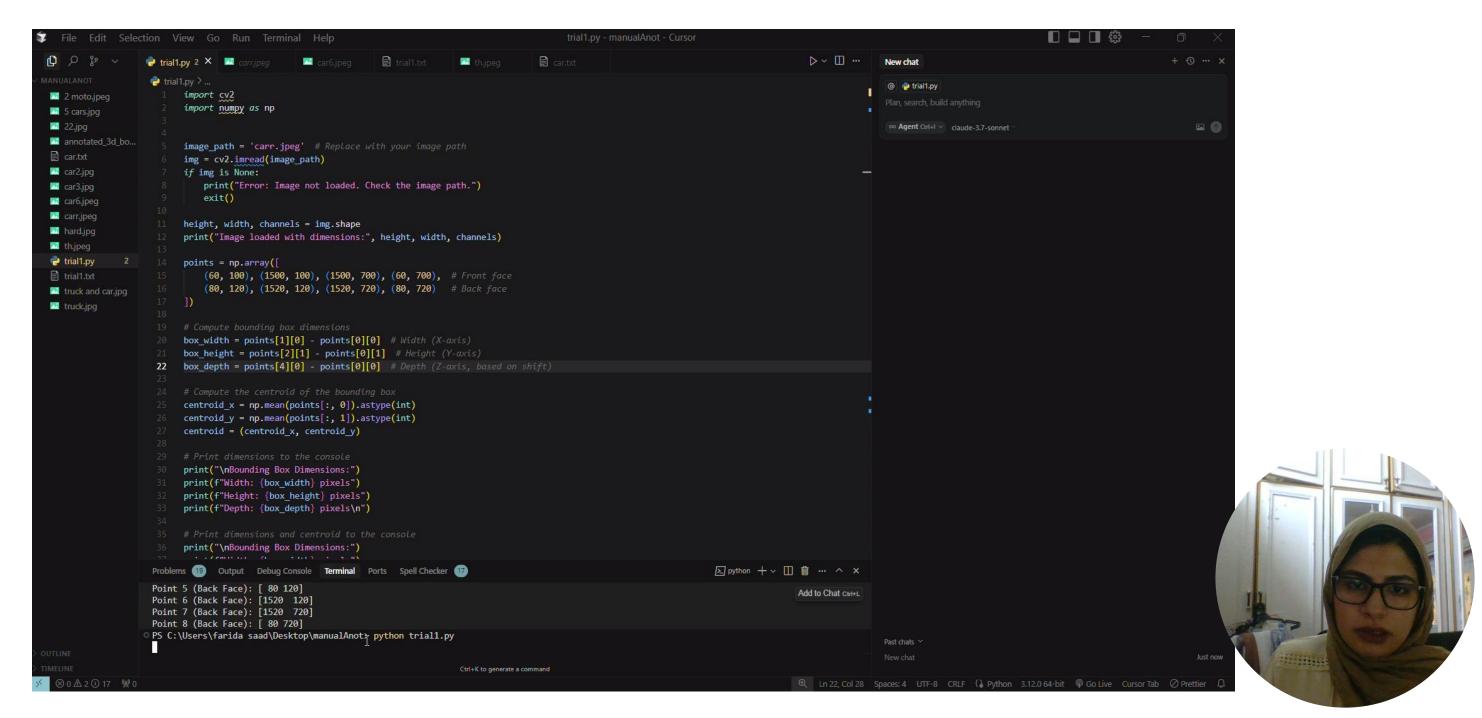
Yolo Detection (2D bounding boxes)

```
D ~ III ...
                   vehicle_detection_yolo.py 2 X  volo3D.py 9+
                   vehicle_detection_yolo.py >
                          import cv2
                          import numpy as np
                         net = cv2.dnn.readNet('yolov3.weights', 'yolov3.cfg')
                         layer_names = net.getLayerNames()
                         output_layers = [layer_names[i - 1] for i in net.getUnconnectedOutLayers()]
                         with open('coco.names', 'r'
                         ) as f:
                             classes = [line.strip() for line in f.readlines()]
output.jpg
                             print("Classes loaded:", classes)
vehicle detec... 2
                         image_path = '2ostrYarab.jpg' # Replace with your image path
                          img = cv2.imread(image_path)
                          if img is None:
                             print("Error: Image not loaded. Check the image path.")
                             exit()
yolov3.weights
                         height, width, channels = img.shape
                         print("Image loaded with dimensions:", height, width, channels)
                         blob = cv2.dnn.blobFromImage(img, 0.00392, (416, 416), (0, 0, 0), True, crop=False)
                         net.setInput(blob)
                         outs = net.forward(output layers)
                         class_ids = []
                         confidences = []
                         boxes = []
                                                                                                                                 Problems (78) Output Debug Console Terminal Ports Spell Checker (61)
                   PS C:\Users\farida saad\Desktop\demo1> python vehicle_detection_yolo.py
```





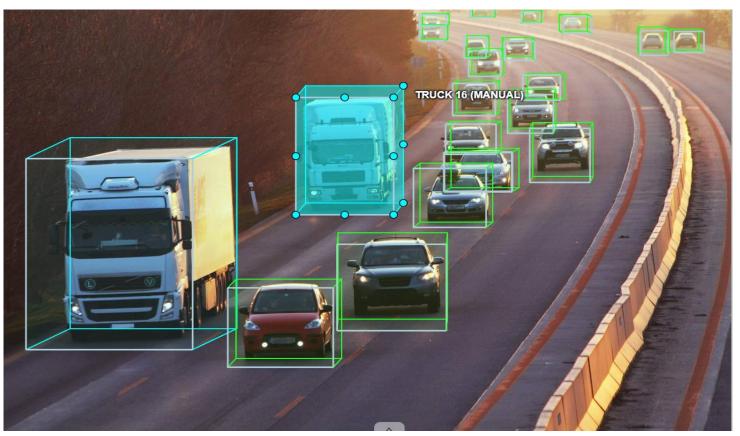
3D bounding boxes manual annotation using OpenCV



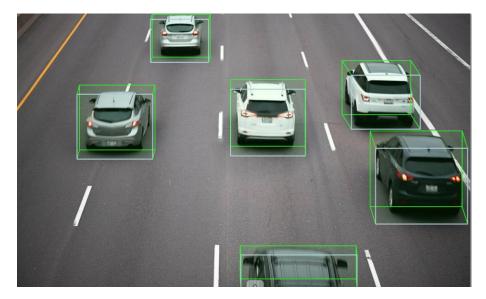
Annotated CVAT/Mindkosh Outputs

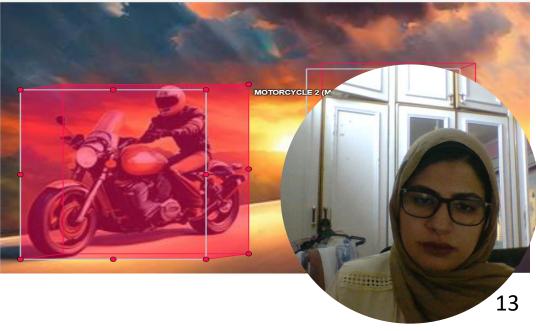






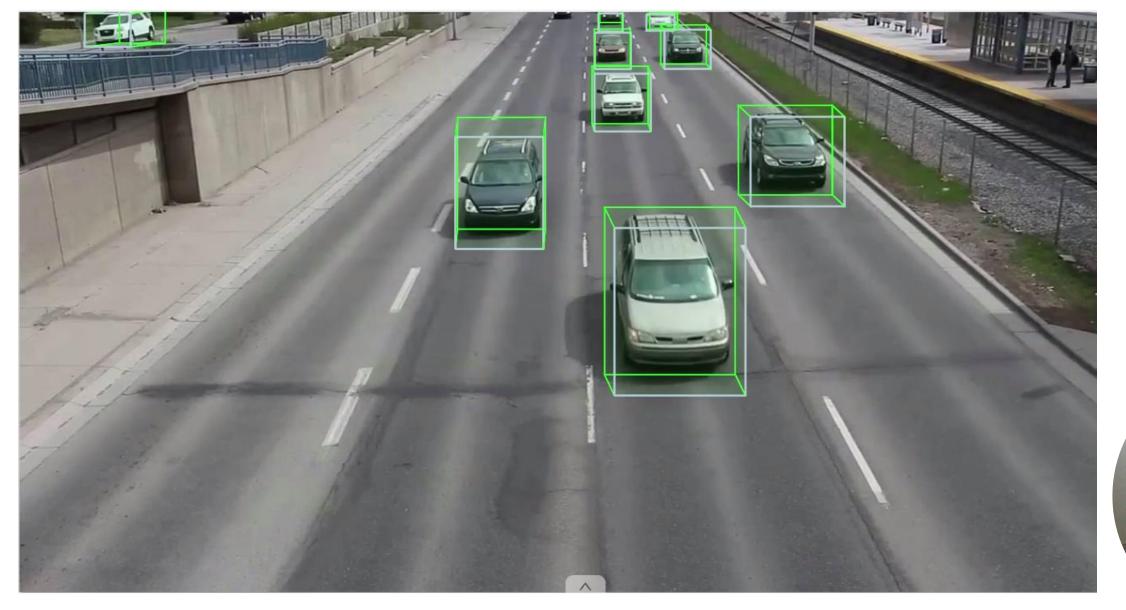






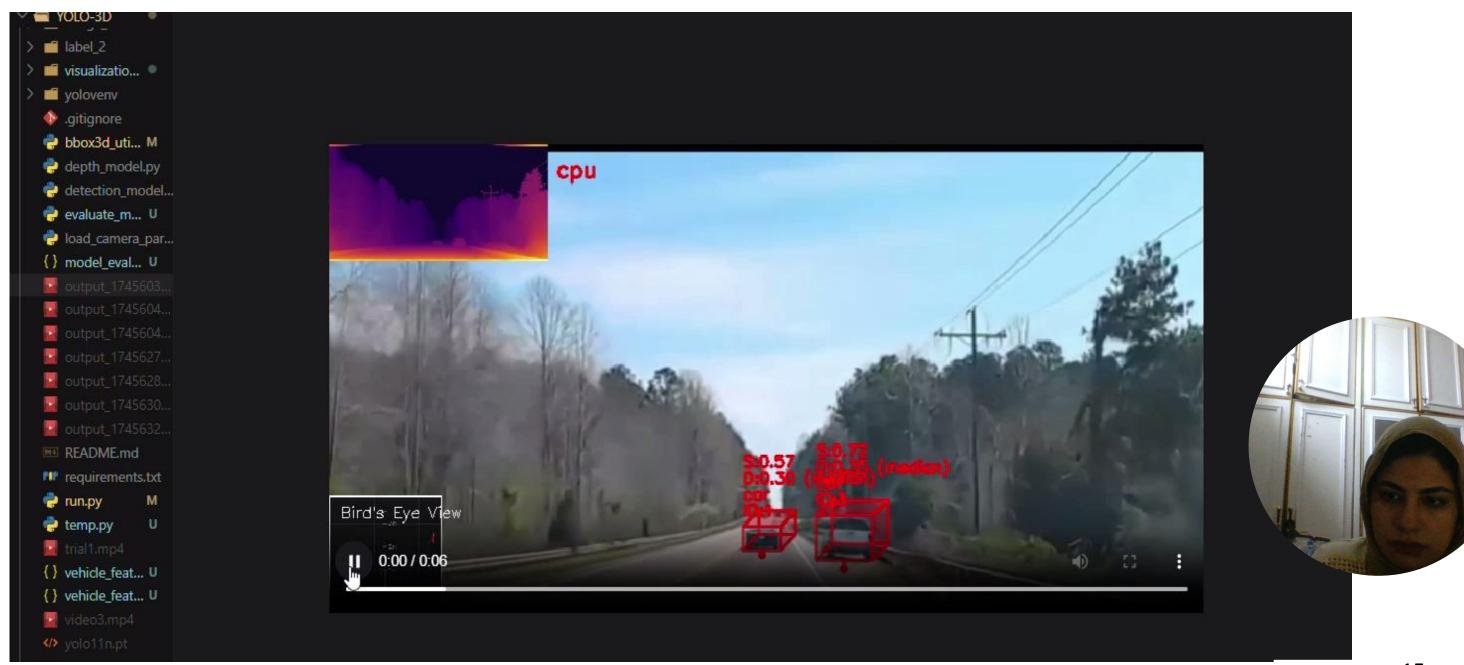
Annotated Video Results

Here is the **60-frame video** I annotated. It shows the progress of labeling over 60 frames. Doing this frame-by-frame using the track features helps create high-quality training data for vehicle detection models.

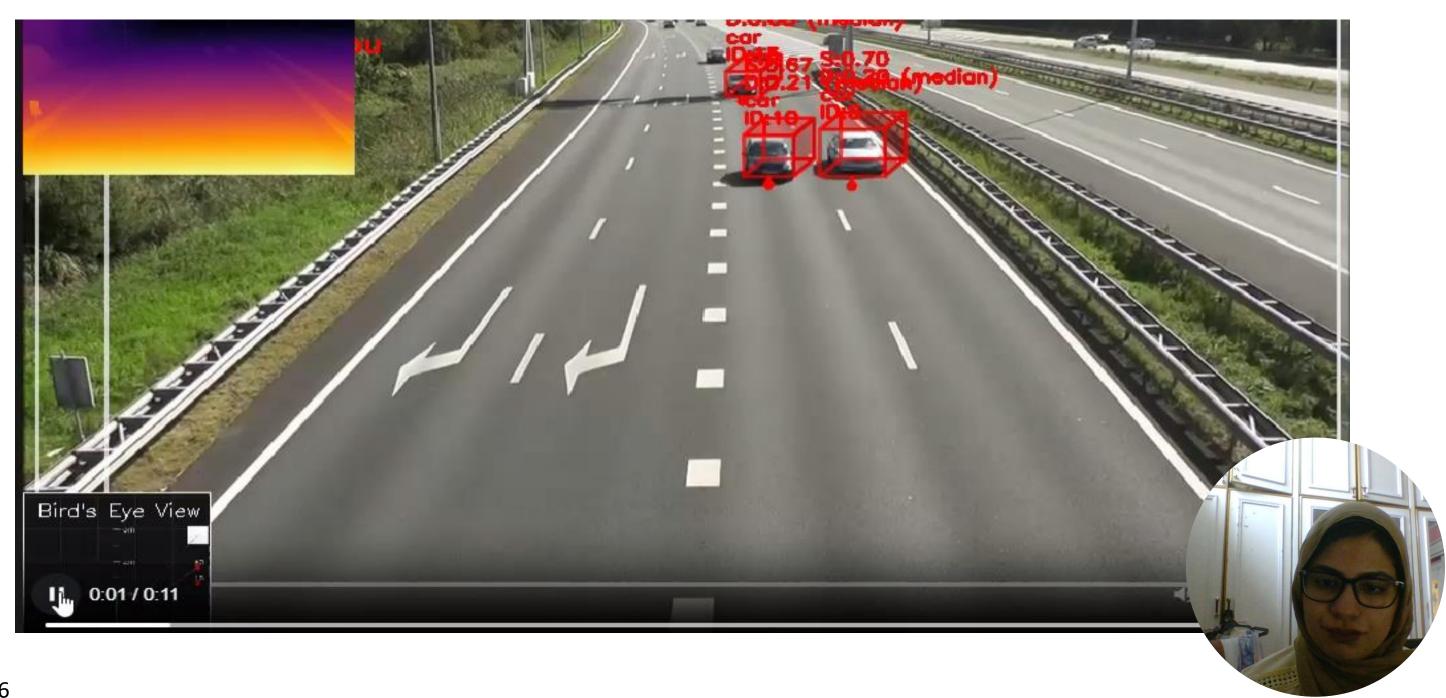




YOLOv11 and Depth Anything v2



YOLOv11 and Depth Anything v2



YOLOv11 and Depth Anything v2 with annotations

```
~ & Q (f)
                                                                                                                                                                      detection_model.py 4, M 🗡 🥏 depth_model.py 8, M
                                                                        utput 1745604635.mp4
                      YOLO-3D > e detection_model.py > ...
                             import os
> iii temp_evaluation
                             import torch
 YOLO-3D
                             import numpy as np
                             import cv2
 > 📠 calib
                             from ultralytics import YOLO
 > image_2
                             from collections import deque
  label 2
  visualizations
                            os.environ['TORCH WEIGHTS ONLY'] = '0'
 yoloveny 🔍
   .gitignore
                             class ObjectDetector:
   bbox3d_uti... M
   e depth_m... 8, M
                                 Object detection using YOLOv8 from Ultralytics
   detectio... 4, M
                                 def __init__(self, model_size='small', conf_thres=0.25, iou_thres=0.45, classes=None, device=None):
   evaluate_m... U
   load camera par...
                                     Initialize the object detector
   output_1745603.
   output_1745604.
                                     Args:
   output 1745604.
                                         model_size (str): Model size ('nano', 'small', 'medium', 'large', 'extra')
   output_1745627.
                                         conf thres (float): Confidence threshold for detections
                                         iou thres (float): IoU threshold for NMS
   output 1745628
                                         classes (list): List of classes to detect (None for all classes)
      output_1745 C:\Users\farida saad\Desktop\automatic_annot\YOLO-3D\output_1745630983.mp4 ce on ('cuda', 'cpu', 'mps')
   README.md
   requirements.txt
                                     if device is None:
                                         if torch.cuda.is_available():
   run.py
                                             device = 'cuda'
   temp.py
                                         elif hasattr(torch, 'backends') and hasattr(torch.backends, 'mps') and torch.backends.mps.is_available():
   trial1.mp4
   {} vehicle feat... U
  {} vehicle feat... U
                                             device = 'cpu'
   video3.mp4
   video 10.mp4
                                     self.device = device
                                     if self.device == 'mps':
                                         print("Using MPS device with CPU fallback for unsupported operations")
  evaluate 3d.py
                                         os.environ['PYTORCH_ENABLE_MPS_FALLBACK'] = '1'
 () evaluation_results...
 extract vehicle fe...
                                     print(f"Using device: {self.device} for object detection")
 kitti_evaluation.py
                                                                                                                                                > pwsh - YOLO
                                   Output Debug Console Terminal Ports Spell Checker (27)
                      PS C:\Users\farida saad\Desktop\automatic annot\YOLO-3D>
```

Features extracted

```
YOLO-3D > {} vehicle_features_1745628665.json > [ ] frames > {} 9 > {} vehicles > {} 6 > # closest_vehicle
        "metadata": {
          "source": "trial1.mp4",
          "processed frames": 335,
          "fps": 29,
          "resolution": "960x540",
          "processing time": 835.4210057258606,
         "timestamp": 1745628665,
          "velocity_scale": 2.5,
          "smoothing factor": 0.7
        "frames": [
            "frame": 0,
            "timestamp": 4.836977481842041,
            "vehicles": {}
            "frame": 1,
            "timestamp": 7.927078723907471,
            "vehicles": {}
            "frame": 2,
            "timestamp": 10.037362098693848,
            "vehicles": {}
            "frame": 3,
            "timestamp": 12.4356849193573,
            "vehicles": {}
            "frame": 4,
            "timestamp": 14.732065677642822,
            "vehicles": {}
             "frame": 5,
            "timestamp": 16.602839946746826,
            "vehicles": {}
```

```
detection_model.py 4, M () vehicle_features_1745632167.json U X () vehicle_features_1745628665.json U 0 🕴 run.py 3, M () model_evaluation.json U 🗣 depth_modi 🖏 🗓
                    YOLO-3D > {} vehicle_features_1745632167.json > ...
                               "frames": [
visualizatio...
 goloveny 🔍
                                   "frame": 9,
 .gitignore
                                   "timestamp": 24.495667934417725,
 e bbox3d_uti... M
                                    "vehicles": {
 depth m... 8, M
 detectio... 4, M
                                      "class": "car",
 evaluate_m... U
                                       "velocity": {
                                         "lateral": 0.0,
 e load_camera_par..
                                         "longitudinal": 0.0
   model eval... U
                                        "acceleration": {
                                         "lateral": 0,
                                         "longitudinal": 0
                                        "orientation": 1.569000005722046,
                                        "position": [
                                         0.009384678676724434,
                                         0.11372549019607843
  requirements.txt
 <equation-block> run.py 3, M
                                        "closest vehicle": 7,
                                        "closest distance": 0.075,
 👘 temp.py U
                                        "dimensions": {
                                         "width_px": 29.413000106811523,
   vehicle_feat... U
                                         "height px": 25.815000534057617,
   vehicle feat... U
                                         "width m": 0.032999999821186066,
   vehicle feat... U
                                         "height m": 0.028999999165534973
                                        "centroid": {
                                         "x": 562.52001953125,
                                         "y": 72.93399810791016
                                        "centroid 3d": [
evaluate_3d.py
                                         0.008999999612569809,
extract vehicle fe.
                                         0.114
                                                                                              Review next file
                                        "depth": 0.114
```

Evaluation of YOLOv11 + Depth Anything v2

Evaluation Setup:

- Tested on a sampled subset of the KITTI dataset.
- Metrics used: Precision, Recall, Average Precision (AP).
- Focused classes: Cars, Trucks, Buses, and Other Road Users.

Detection Performance:

• Overall mAP: **6.8%**

Car class:

• **Precision:** 50.5%

• **Recall:** 50.5%

• AP (car): 25.5% (better performance achieved compared to Cursor baseline)



```
import os
YOLO-3D
                          import torch
📹 visualizatio...
                          import numpy as np
 VIS3d UUU... U
                          import cv2
 N vis3d 000... U
                          from ultralytics import YOLO
 vis3d 000... U
                          from collections import deque
 ™ vis3d 000... U
 vis3d_000... U
                     8 # Force disable weights only mode
 vis3d_000... U
                          os.environ['TORCH WEIGHTS ONLY'] = '0'
 vis3d 000... U
                         class ObjectDetector:
 vis3d 000... U
 N vis3d 000... U
                              Object detection using YOLOv8 from Ultralytics
 vis3d 000... U
 vis3d_000... U
                              def __init__(self, model_size='small', conf_thres=0.25, iou_thres=0.45, classes=None, device=None):
 vis3d 000... U
                                  Initialize the object detector
 vis3d 000... U
voloveny
                                  Args:
.gitignore
                                      model_size (str): Model size ('nano', 'small', 'medium', 'large', 'extra')
🐡 bbox3d_uti... M
                                      conf thres (float): Confidence threshold for detections
depth_m... 8, M
                                      iou thres (float): IoU threshold for NMS
🗬 detectio... 4, M
                                      classes (list): List of classes to detect (None for all classes)
evaluate m... U
                                      device (str): Device to run inference on ('cuda', 'cpu', 'mps')
load_camera_par...
                                  # Determine device
utput 1745603...
                                  if device is None:
output_1745604...
                                      if torch.cuda.is_available():
output_1745604...
                                          device = 'cuda'
output_1745627...
                                      elif hasattr(torch, 'backends') and hasattr(torch.backends, 'mps') and torch.backends.mps.is_available():
output 1745628...
                                          device = 'mps'
utput 1745630...
                                      else:
                                          device = 'cpu'
output_1745632.
README.md
                                  self.device = device
requirements.txt
run.py
                                  # Set MPS fallback for operations not supported on Apple Silicon
temp.py
                                  if self.device == 'mps':
trial1.mp4
                                      print("Using MPS device with CPU fallback for unsupported operations")
                                      os.environ['PYTORCH ENABLE MPS FALLBACK'] = '1'
{} vehicle feat... U
{} vehicle feat... U
                                  print(f"Using device: {self.device} for object detection")
video3.mp4
                                                                                                                                             Dwsh - YOLO-3D
                                 Output Debug Console Terminal Ports Spell Checker 27
video 10 mn4
                   PS C:\Users\farida saad\Desktop\automatic annot\YOLO-3D>
```

Current Pipeline Status

Automatic Annotation:

• Using YOLOv11 combined with Depth Anything v2 for real-time pseudo-3D bounding box generation.

Vehicle Feature Extraction:

- 3D bounding box dimensions and centroids
- Orientation (yaw angle)
- Lateral and longitudinal velocity and acceleration
- Inter-vehicle distances
- Occlusion levels (still working on it)
- Time to Collision (TTC) (still working on it)

• Automatic Annotation : (I'm Here)

- Training MonoLSS on the KITTI dataset for monocular 3D object detection.
- Evaluating model performance using Average Precision 3D (AP3D) and Bird's Eye View Average Precision (APBEV).

Next Steps:

• Compare YOLOv11 + Depth Anything v2 with MonoLSS to select the best model for automatic annotation.



Conclusion



Developed an efficient vehiclelevel feature annotation tool using monocular camera input.



Extracted critical vehicle features including velocity, acceleration, dimensions, and time-to-collision without using LiDAR or radar.



Demonstrated the feasibility of using real-time monocular models for detailed 3D object defined.

Future Recommendations

Enhance Feature Extraction:

Refine extraction of occlusion and collision risk metrics.

Expand Dataset Size:

• Annotate longer video sequences and diverse traffic scenes to strengthen training data.

• Explore Advanced Models:

Investigate emerging monocular 3D detection models like YOLOBU or MonoFlex once accessible.

• Automation Improvements:

• Develop a fully automatic pipeline minimizing manual intervention.

• Generalization Testing:

Test the trained pipeline across different datasets to ensure model robustness.



Any Questions?

Thank you for your time. I welcome any questions you may have.



