1. End-to-End Self-driving Perception with YOLO (Detection), ResNet (Classification), and U-Net (Segmentation)

September 1, 2025

Step 1: Import Libraries & Check Versions

Before starting the project, we first import the core libraries and verify their versions.
This helps ensure our environment is correctly set up and avoids compatibility issues later.

- **fastai** → high-level deep learning framework (we'll use it for classification & segmentation).
- **torch** → PyTorch backend (fastai is built on top of this).
- **opencv (cv2)** → computer vision utilities for image processing and visualization.
- **numpy** → numerical operations and data handling.
- **YOLO (Ultralytics)** → modern object detection framework (used to detect traffic lights).

[7]:
```
import fastai, torch, cv2, numpy as np
from fastai.vision.all import *
from ultralytics import YOLO

print("fastai:", fastai.__version__)
print("torch:", torch.__version__)
print("opencv:", cv2.__version__)
print("numpy:", np.__version__)
```

```
fastai: 2.7.17
torch: 2.4.1+cu121
opencv: 4.8.1
numpy: 1.26.4
```

Why this step
Before running any model, it's important to check:
- the image file is in the notebook folder
- the library can read the format (.webp / .jpg / .png)
- the preview looks correct (orientation, size, visible traffic lights/roadway)

What the code does
- `PILImage.create("road.webp")` → loads the image into memory
- `img.to_thumb(640)` → shows a smaller preview (640px wide)

---

[8]:
```
from fastai.vision.all import PILImage
img = PILImage.create("road.webp")
img.to_thumb(640)
```

[8]:

Why this step
- YOLO is designed for *object detection* (find & draw boxes around things).
- Starting with `yolov8n.pt` (nano) lets us test quickly before moving to larger models (s / m).

What the code does
- Loads YOLOv8n model from Ultralytics.
- Runs inference (prediction) on our road image.
- Displays the detected objects with bounding boxes.

---

[9]:
```
from ultralytics import YOLO

# load a pre-trained YOLOv8n (nano) model
```

```python
yolo_model = YOLO("yolov8n.pt")

# run detection on our road image
results = yolo_model("road.webp", save=True, show=True)

# display results summary
for r in results:
    print(r.boxes.cls, r.boxes.conf)  # class IDs + confidence scores
```

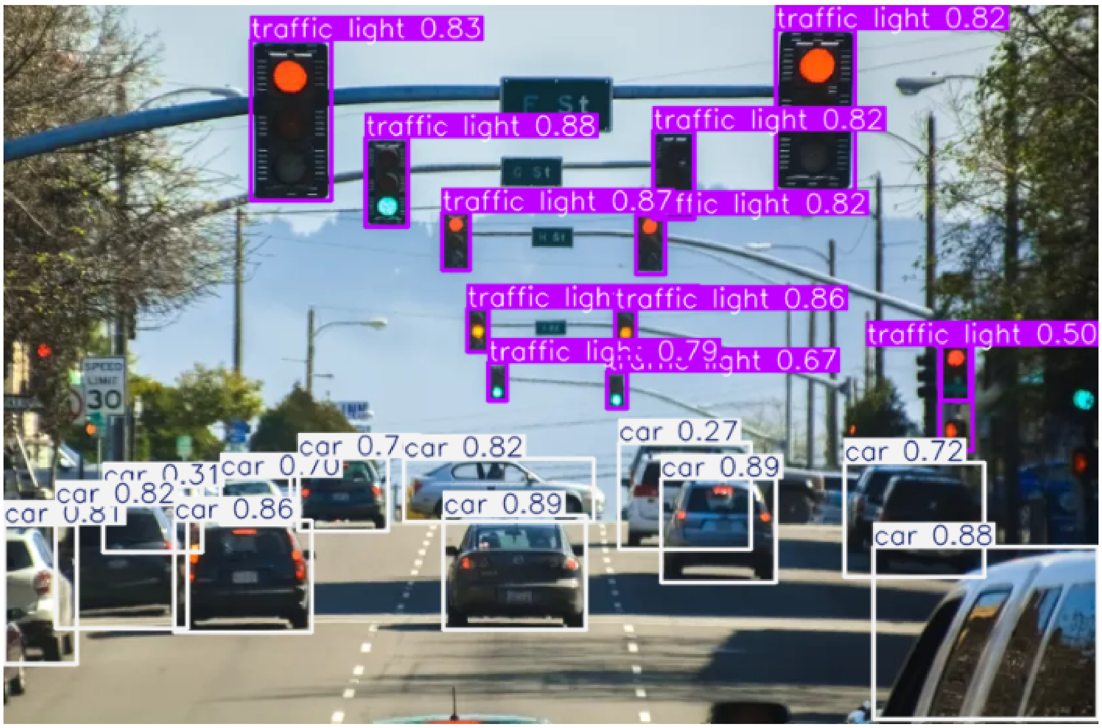
```
Downloading
https://github.com/ultralytics/assets/releases/download/v8.2.0/yolov8n.pt to
'yolov8n.pt'…
```

```
100%|      | 6.25M/6.25M [00:00<00:00, 369MB/s]
/opt/conda/lib/python3.11/site-packages/ultralytics/nn/tasks.py:781:
FutureWarning: You are using `torch.load` with `weights_only=False` (the current
default value), which uses the default pickle module implicitly. It is possible
to construct malicious pickle data which will execute arbitrary code during
unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-models for
more details). In a future release, the default value for `weights_only` will be
flipped to `True`. This limits the functions that could be executed during
unpickling. Arbitrary objects will no longer be allowed to be loaded via this
mode unless they are explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control of the
loaded file. Please open an issue on GitHub for any issues related to this
experimental feature.
  ckpt = torch.load(file, map_location="cpu")
```

```
WARNING  Environment does not support cv2.imshow() or PIL Image.show()
The DISPLAY environment variable isn't set.

image 1/1 /home/jovyan/ML Projects /road.webp: 448x640 12 cars, 12 traffic
lights, 47.4ms
Speed: 5.9ms preprocess, 47.4ms inference, 132.6ms postprocess per image at
shape (1, 3, 448, 640)
Results saved to runs/detect/predict2
tensor([2., 2., 9., 2., 9., 2., 9., 9., 2., 2., 9., 9., 9., 2., 9., 9., 2., 2.,
2., 9., 9., 9., 2., 2.], device='cuda:0') tensor([0.8948, 0.8941, 0.8819,
0.8808, 0.8711, 0.8616, 0.8572, 0.8297, 0.8241, 0.8202, 0.8189, 0.8167, 0.8167,
0.8056, 0.7887, 0.7867, 0.7574, 0.7184, 0.6975, 0.6665, 0.5011, 0.4418, 0.3121,
0.2740], device='cuda:0')
```

Why this matters:
This forms the foundation for later steps (classification + segmentation), since we first need to *locate* the traffic lights before checking their state.

```
[10]: import matplotlib.pyplot as plt
import cv2
img_annot = results[0].plot() # Takes YOLO detection results from first image and draws bounding boxes and confidence labels
plt.figure(figsize=(10,6))
plt.imshow(cv2.cvtColor(img_annot, cv2.COLOR_BGR2RGB)) # Fixes colours
plt.axis('off')
plt.show()
```

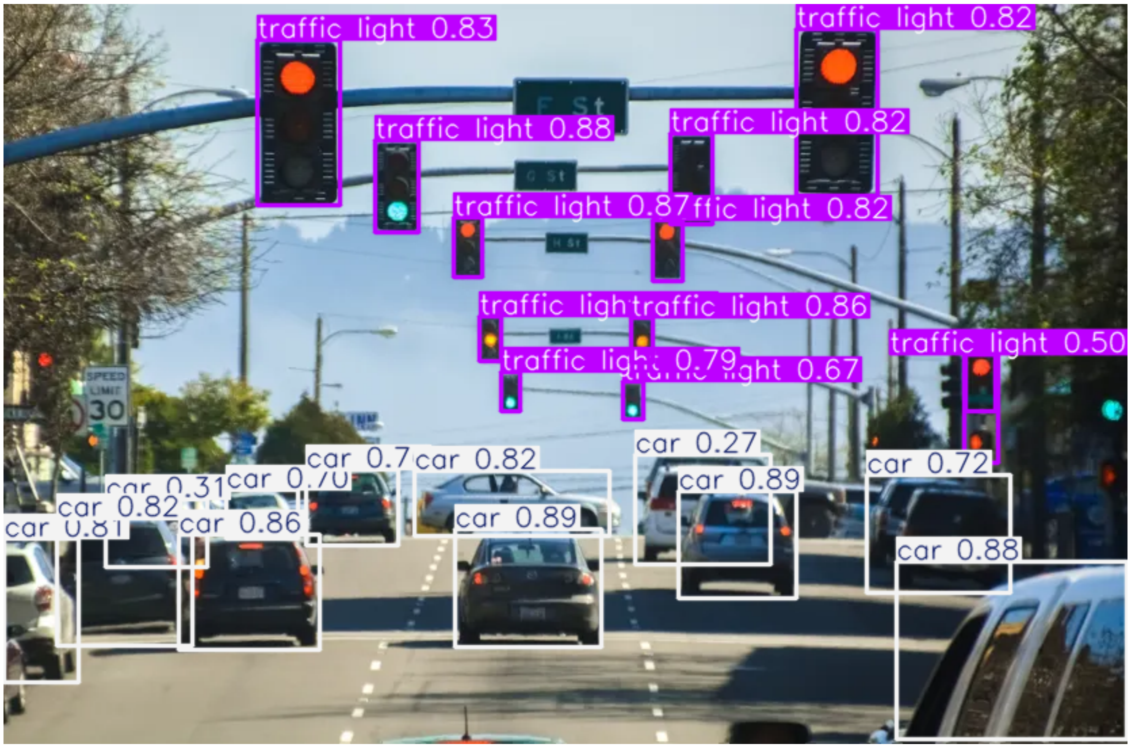


Why this step matters:
- Confirms that YOLO actually saved the detection results.
- Lets us visually inspect the bounding boxes (cars, traffic lights, etc.) at any time.
- Makes it easier to reuse the annotated results later without re-running the model.

What the code does:
- Uses `Path(results[0].save_dir)` → finds the folder where YOLO saved outputs.
- Finds the first `.webp` image in that folder.
- Opens it with PIL (`Image.open`) and displays the annotated result.

```
[11]: from PIL import Image
from pathlib import Path
```

```
save_dir = Path(results[0].save_dir) #
display(Image.open(next(save_dir.glob("*.webp"))))
```



What the code does:
1. `r = results[0]` → get YOLO's first (and only) result object.
2. `cls = boxes.cls.cpu().numpy()` → get predicted class IDs for each detection.
3. `xyxy = boxes.xyxy.cpu().numpy()` → get bounding box coordinates (x1, y1, x2, y2).
4. `keep = cls == 9` → select only detections with class ID = 9 (traffic lights).
5. `tl_boxes = xyxy[keep]` → extract their bounding boxes.
6. For each traffic light box:
- `orig.crop(...)` → crop the region of interest from the original road image.
- Save the crops in a list for later analysis.
7. `len(crops)` → confirms how many traffic lights were extracted.

[12]:
```
import numpy as np
from PIL import Image

r = results[0]
names = r.names                # dict id->name
boxes = r.boxes                # Boxes object
cls   = boxes.cls.cpu().numpy().astype(int)
xyxy  = boxes.xyxy.cpu().numpy()   # (N,4)

# keep traffic lights only (class id 9 in COCO)
```

```python
keep = cls == 9
tl_boxes = xyxy[keep]

# crop from the original image
orig = Image.open("road.webp").convert("RGB")
crops = []
for i,(x1,y1,x2,y2) in enumerate(tl_boxes.astype(int)):
    crop = orig.crop((x1,y1,x2,y2))
    crops.append(crop)

len(crops)
```

[12]: 12

What the code does:
1. `cols = 6` → sets the number of columns in the grid display.
2. `rows = int(np.ceil(len(crops)/cols))` → calculates rows automatically based on number of crops.
3. `plt.figure(figsize=(cols*2, rows*2))` → scales the figure so crops aren't too small.
4. `for i, c in enumerate(crops, 1)` → loop through each cropped traffic light.
- `plt.subplot(rows, cols, i)` → place each crop in the grid.
- `plt.imshow(c)` → display the traffic light crop.
- `plt.axis('off')` → remove axis lines for a cleaner view.
5. `plt.tight_layout()` → adjusts spacing to avoid overlap.

[13]:
```python
import matplotlib.pyplot as plt
cols = 6
rows = int(np.ceil(len(crops)/cols))
plt.figure(figsize=(cols*2, rows*2))
for i,c in enumerate(crops,1):
    plt.subplot(rows, cols, i)
    plt.imshow(c)
    plt.axis('off')
plt.tight_layout()
```

Why this step matters - Detecting *where* traffic lights are is not enough — we also need to know *what color they are*.
- HSV makes it easier to apply thresholds for specific colors.
- This step turns cropped traffic lights into meaningful labels: **red, yellow, green**.

What the code does 1. Define a function `light_color_hsv`: - Crops the **center** of each light to reduce background influence.
- Converts the cropped image to **HSV color space**.
- Creates binary masks for **red, yellow, green** using HSV thresholds.

2. Apply **color thresholds** (approximate HSV ranges):
   - Red → Hue near 0° or >170°

   - Yellow → Hue 20–35°

   - Green → Hue 40–85°
3. Score the pixels:
   - Counts how many pixels fall into each color mask.

   - The color with the highest score is chosen as the prediction.
4. Loop through all cropped lights:
   - Runs the classifier on each cropped traffic light.

   - Appends the predicted label into a `labels` list.

[14]:
```python
import cv2
import numpy as np

def light_color_hsv(pil_img):
    # center crop to reduce background influence
    w,h = pil_img.size
    cx, cy = w//2, h//2
    r = int(min(w,h)*0.35)
    crop = pil_img.crop((cx-r, cy-r, cx+r, cy+r))

    img = cv2.cvtColor(np.array(crop), cv2.COLOR_RGB2HSV)
    H,S,V = cv2.split(img)

    # masks (HSV ranges)
    red1   = ((H < 10) & (S>100) & (V>80))
    red2   = ((H >170) & (S>100) & (V>80))
    yellow = ((H>20) & (H<35) & (S>80) & (V>80))
    green  = ((H>40) & (H<85) & (S>60) & (V>60))
```

```python
    score_red    = red1.sum() + red2.sum()
    score_yellow = yellow.sum()
    score_green  = green.sum()

    scores = {"red":score_red, "yellow":score_yellow, "green":score_green}
    label  = max(scores, key=scores.get)
    return label, scores

labels = []
for c in crops:
    label, _ = light_color_hsv(c)
    labels.append(label)
```

Step 9: Overlay Color Labels on the Detections

We've detected traffic lights (YOLO) and classified each one's state (HSV).
Now we'll **draw those labels back on the road image** so the result is easy to read.

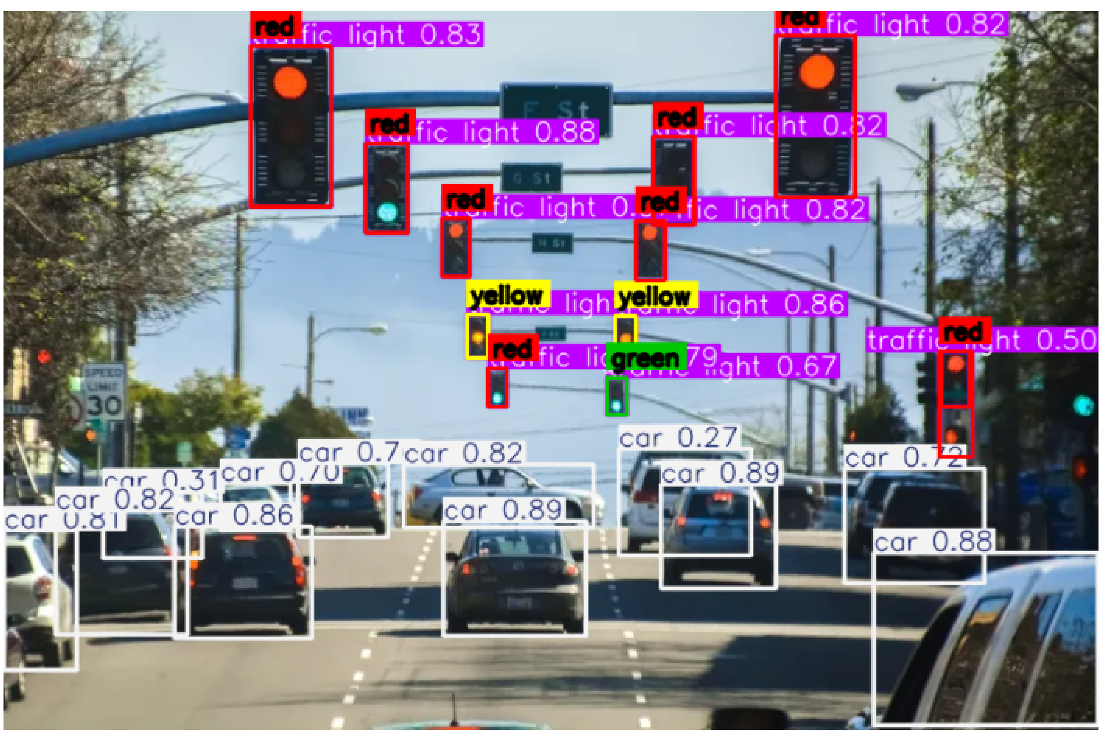
Why this step matters - It ties everything together into one view: *detection + classification*. - Colored labels (**red / yellow / green**) make it obvious which lights are active. - We also handle color-channel order (OpenCV uses **BGR**; Matplotlib expects **RGB**).

What the code does 1. Start from YOLO's annotated image (`results[0].plot()`), then copy it so we can draw on it. 2. For each traffic-light box + predicted label: - Pick a drawing color based on the label (`red`, `yellow`, `green`). - Draw a small **filled box** above the detection and put the text on top. 3. Convert the image from **BGR → RGB** for correct display in `matplotlib`.

> Note: `tl_boxes` (N×4) are the XYXY boxes for just the traffic lights,
> and `labels` is the list of predicted colors for each crop (same order).

[15]:
```python
import cv2
import numpy as np
import matplotlib.pyplot as plt

# Start from YOLO's annotated image (BGR) and copy so we can draw more
img = results[0].plot().copy()

# Color map for labels (OpenCV uses BGR)
color_map = {
    'red':    (0, 0, 255),
    'yellow': (0, 255, 255),
    'green':  (0, 200, 0),
}

font  = cv2.FONT_HERSHEY_SIMPLEX
scale = 0.6
thick = 2
```

```python
# Draw a colored label for each traffic-light box
for (x1, y1, x2, y2), lbl in zip(tl_boxes.astype(int), labels):
    color = color_map.get(lbl, (255, 255, 255))  # white fallback

    # Put a small filled rectangle as label background (for readability)
    text = lbl
    (tw, th), _ = cv2.getTextSize(text, font, scale, thick)
    y_text = max(0, y1 - 6)
    cv2.rectangle(img, (x1, y_text - th - 6), (x1 + tw + 6, y_text), color, -1)

    # Draw the text in black on top of the colored background
    cv2.putText(img, text, (x1 + 3, y_text - 3), font, scale, (0, 0, 0), thick, cv2.LINE_AA)

    # (Optional) draw a box outline in the same color
    cv2.rectangle(img, (x1, y1), (x2, y2), color, 2)

# Convert BGR -> RGB for correct display in matplotlib
img_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

plt.figure(figsize=(10, 6))
plt.imshow(img_rgb)
plt.axis('off')
plt.show()
```



Step 10: Road Segmentation with SegFormer

Now we bring in a segmentation model (SegFormer) to identify the drivable road area in the image. This gives us a binary mask where each pixel is either *drivable* (road, parking) or *not drivable*. We'll then overlay this mask in teal on top of the original road image.

##Why this step matters - Adds **scene understanding**: beyond objects, we now know which pixels are road.
- Provides a **navigation space** for vehicles, complementing detection results.
- Overlaying the mask visually confirms what the model considers drivable.

What the code does 1. Load the SegFormer model (pre-trained on Cityscapes).
2. Define drivable classes (`road`, `parking`) from the model's label map.
3. Create a helper function `make_drivable_mask` that returns a 0/1 mask for drivable pixels.
4. Create an `overlay_mask` function to color the drivable pixels teal and blend them with the RGB image.
5. Load your input image (`road.webp`), run the model, and generate the overlay visualization.
6. Optionally save the result (e.g., `road_with_drivable.png`).

Notes - The overlay mask uses teal `(0,255,200)` with transparency for clarity.
- The printout of `drivable mean` shows the fraction of pixels classified as drivable.

[16]:
```
# --- Road segmentation (SegFormer) + overlay on road.webp ---

# 1) imports (install transformers/accelerate first if missing)
import numpy as np, cv2, torch
from PIL import Image
import matplotlib.pyplot as plt
from transformers import SegformerImageProcessor,␣
↪SegformerForSemanticSegmentation

# 2) load SegFormer once
SEG_NAME  = "nvidia/segformer-b0-finetuned-cityscapes-1024-1024"
seg_proc  = SegformerImageProcessor.from_pretrained(SEG_NAME)
seg_model = SegformerForSemanticSegmentation.from_pretrained(SEG_NAME).eval()

# Cityscapes labels we consider "drivable"
id2label = seg_model.config.id2label
DRIVABLE_IDS = [i for i,lbl in id2label.items() if lbl in {"road","parking"}]

def make_drivable_mask(pil_img):
    """Return (H,W) uint8 mask: 1=drivable, 0=other."""
    inputs = seg_proc(images=pil_img, return_tensors="pt")
    with torch.no_grad():
        logits = seg_model(**inputs).logits              # [1,C,h/4,w/4]
    up = torch.nn.functional.interpolate(
```

```python
        logits, size=pil_img.size[::-1], mode="bilinear", align_corners=False
    )                                                    # -> [1,C,H,W]
    pred = up.argmax(dim=1)[0].cpu().numpy()            # (H,W) class ids
    return np.isin(pred, DRIVABLE_IDS).astype(np.uint8) # (H,W) 0/1

def overlay_mask(rgb, mask01, color=(0,255,200), a_base=0.4, a_ov=0.6):
    """Blend teal where mask==1 onto an RGB uint8 image."""
    layer = np.zeros_like(rgb)
    layer[mask01==1] = color
    return cv2.addWeighted(rgb, a_base, layer, a_ov, 0)

# 3) run on your file road.webp
pil = Image.open("road.webp").convert("RGB")
rgb = np.array(pil)

mask01 = make_drivable_mask(pil)
out    = overlay_mask(rgb, mask01)  # <--- overlay result

plt.figure(figsize=(12,7)); plt.imshow(out); plt.axis('off'); plt.
 ↪title('Drivable Road Area'); plt.show()
print("drivable mean (0..1):", mask01.mean())

# Optionally save
# Image.fromarray(out).save("road_with_drivable.png")
```

```
preprocessor_config.json:   0%|          | 0.00/272 [00:00<?, ?B/s]
```

```
/opt/conda/lib/python3.11/site-packages/transformers/utils/deprecation.py:165:
UserWarning: The following named arguments are not valid for
`SegformerImageProcessor.__init__` and were ignored: 'feature_extractor_type'
  return func(*args, **kwargs)
```

```
config.json: 0.00B [00:00, ?B/s]
```

```
pytorch_model.bin:   0%|          | 0.00/15.0M [00:00<?, ?B/s]
```

```
model.safetensors:   0%|          | 0.00/14.9M [00:00<?, ?B/s]
```

Drivable Road Area


```
drivable mean (0..1): 0.16244538593936184
```

Why this step matters - Turns YOLO’s raw detections into an **annotated image**.
- Each box shows the **class label + confidence score**.
- Helps visually confirm which detections YOLO made and with what certainty.

Notes - Uses OpenCV (`cv2`) to handle drawing.
- Labels include the class name from YOLO (`r.names[cls]`).
- Confidence values are shown with 2 decimal places (e.g., 0.83).

[25]:
```
import cv2

def draw_yolo(rgb, results, score_thresh=0.25, classes_keep=None):
    """
    Draw YOLO bounding boxes + labels on an image.
    - rgb: numpy array (HxWx3)
    - results: YOLO predictions
    - score_thresh: minimum confidence to draw
    - classes_keep: list of class ids to keep (optional)
    """
    img = rgb.copy()
    r = results[0]
    if r.boxes is None:
        return img
```

```python
    for box, cls, conf in zip(
        r.boxes.xyxy.cpu().numpy(),
        r.boxes.cls.cpu().numpy().astype(int),
        r.boxes.conf.cpu().numpy()
    ):
        if conf < score_thresh:
            continue
        if classes_keep is not None and cls not in classes_keep:
            continue

        x1, y1, x2, y2 = box.astype(int)
        label = f"{r.names[cls]} {conf:.2f}"

        # draw rectangle + label
        cv2.rectangle(img, (x1, y1), (x2, y2), (255, 255, 255), 2)
        (tw, th), _ = cv2.getTextSize(label, cv2.FONT_HERSHEY_SIMPLEX, 0.6, 2)
        cv2.rectangle(img, (x1, y1 - th - 6), (x1 + tw + 2, y1), (0, 0, 0), -1)
        cv2.putText(img, label, (x1, y1 - 4), cv2.FONT_HERSHEY_SIMPLEX,
                    0.6, (255, 255, 255), 2, cv2.LINE_AA)

    return img
```

Why this step matters - It overlays **detection** (cars, lights) with **segmentation** (road mask).
- The teal overlay clearly highlights safe driving areas.
- Bounding boxes + labels ensure awareness of other traffic agents.

Notes - `YOLO_CLASSES = [2, 9]` restricts detection to cars (class 2) and traffic lights (class 9).
- The drivable road mask uses teal `(0,255,200)` with transparency for clarity.
- The confidence threshold ensures only strong detections are kept.

[26]:
```python
from ultralytics import YOLO

# Load YOLOv8 model (cars + traffic lights etc.)
detector = YOLO("yolov8n.pt")
# 1. Load your image
pil = Image.open("road.webp").convert("RGB")
rgb = np.array(pil)

# 2. Add drivable road mask
mask01 = make_drivable_mask(pil)
rgb    = overlay_mask(rgb, mask01)

BOX_THRES = 0.25         # confidence threshold
YOLO_CLASSES = [2, 9]

# 3. Run YOLO detections + your TL classifier on this rgb
results = detector.predict(rgb, verbose=False)
```

```python
final    = draw_yolo(rgb, results, score_thresh=BOX_THRES, classes_keep=YOLO_CLASSES)

# 4. Show combined output
plt.figure(figsize=(12,7))
plt.imshow(final); plt.axis('off')
plt.title("Cars + Traffic Lights + Drivable Road Area")
plt.show()
```

Cars + Traffic Lights + Drivable Road Area