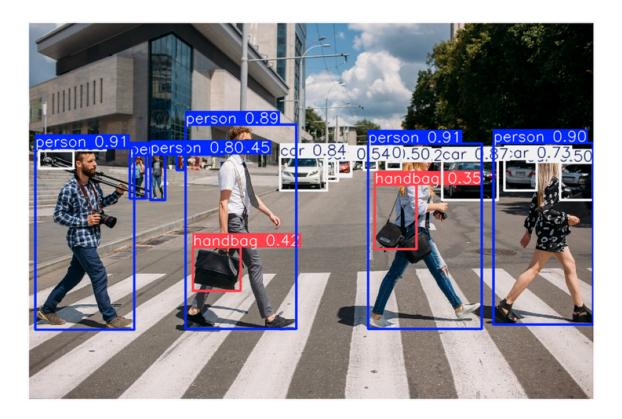
YOLO

★ Summary of Key Points

Topic	Explanation
What is YOLO?	A fast and real-time object detection algorithm.
What does it do?	Detects what objects are in an image and where they are.
Why is it important?	It's extremely fast (real-time capable) and accurate .
Where is it used?	Self-driving cars, surveillance, robotics, etc.
Main idea?	Treats detection as a single regression problem .



What is Object Detection?

Imagine you have a photo, and you want to:

- Classify the objects in it (e.g., "dog", "car", "person")
- Locate them (i.e., draw a box around each one)

That's object detection. You want:

- Class label
- Bounding box coordinates (x, y, width, height)

What is YOLO?

YOLO = You Only Look Once

That means:

The algorithm looks at the image one time and simultaneously finds all objects and their locations.

! Traditional methods (like R-CNN) work in two steps:

- 1. Propose possible object regions
- 2. Classify each region

This is slow.

YOLO does it in one step, making it:

- Very fast
- Suitable for real-time tasks



Real-Time Performance: It's extremely fast — models like **YOLOv4**, **v5**, **v8**, and **YOLO-NAS** can run at real-time FPS on modern GPUs.

How YOLO Works (Step-by-Step)

Step 1: Divide Image into Grid

YOLO divides the input image into an $\mathbf{S} \times \mathbf{S}$ grid (say 7×7 for YOLOv1).

Each grid cell:

- Is responsible for detecting objects whose center falls inside it
- Predicts:
 - Bounding boxes
 - Confidence score for each box
 - Class probabilities

Step 2: Predict Bounding Boxes

Each grid cell predicts **B bounding boxes**:

• Each box = 5 values:

x, y, w, h, confidence

- x, y: center of box (relative to grid cell)
- w, h: width and height (relative to the whole image)
- confidence: how sure the model is that the box contains an object

Step 3: Predict Class Probabilities

Each grid cell also predicts:

• C class probabilities (e.g., dog, person, car...)

Then combine class probabilities × confidence score to find:

final score = class probability × confidence

Step 4: Output Final Detections

- YOLO takes the most confident predictions
- Uses Non-Maximum Suppression (NMS) to remove duplicate boxes

Loss Function (How YOLO learns)

The model minimizes a **custom loss** that includes:

• Localization loss: For bounding box position

• Confidence loss: How certain the model is about object presence

Classification loss: Accuracy of predicted object class

YOLO uses **Mean Squared Error** + tweaks for better box prediction.

Versions of YOLO (Very Important)

Version	What Changed?
YOLOv1	Original paper (2015), fast but less accurate
YOLOv2	Improved accuracy, used anchors, batch norm
YOLOv3	Introduced multi-scale detection, better architecture (Darknet-53)
YOLOv4	Used bag-of-freebies (training tricks) and bag-of-specials (modules)
YOLOv5*	Not official by original authors, but very popular , fast, and flexible
YOLOv6/7/8	Further speed and accuracy improvements; YOLOv8 adds segmentation too

Real-World Applications

Use Case	Why YOLO?	
Self-driving cars	Real-time object detection	
Surveillance	Detect people, threats instantly	
Retail analytics	Track customer movement, products	
Medical imaging	Detect tumors in scans	
Robotics	Detect and interact with objects	

YOLO Python Code

```
pip install ultralytics
```

```
from ultralytics import YOLO
# Load pretrained model
model = YOLO('yolov5s.pt') # 's' means small, also try yolov5m/l/x
# Run on image
results = model('image.jpg')
results
```

```
results[0].show()
```



Another Model

```
from ultralytics import YOLO

# Load pre-trained model (YOLOv8s = small version)
model2 = YOLO("yolov8s.pt")

# Detect objects
results = model("image.jpg")

# Show results
results[0].show()
```





Model	Speed	Accuracy
YOLO	Fastest	High
SSD	Medium	High
Faster-RCNN	Slow	Highest

Train Custom YOLO Model

from ultralytics import YOLO

Load a base model
model = YOLO("yolov8n.pt") # nano version

Train on your dataset (replace with your data.yaml) model.train(data="coco128.yaml", epochs=50)