



# Object Detection using the YOLOs model

Unified Real-Time object Detection  
B-Tech Project

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# Objective

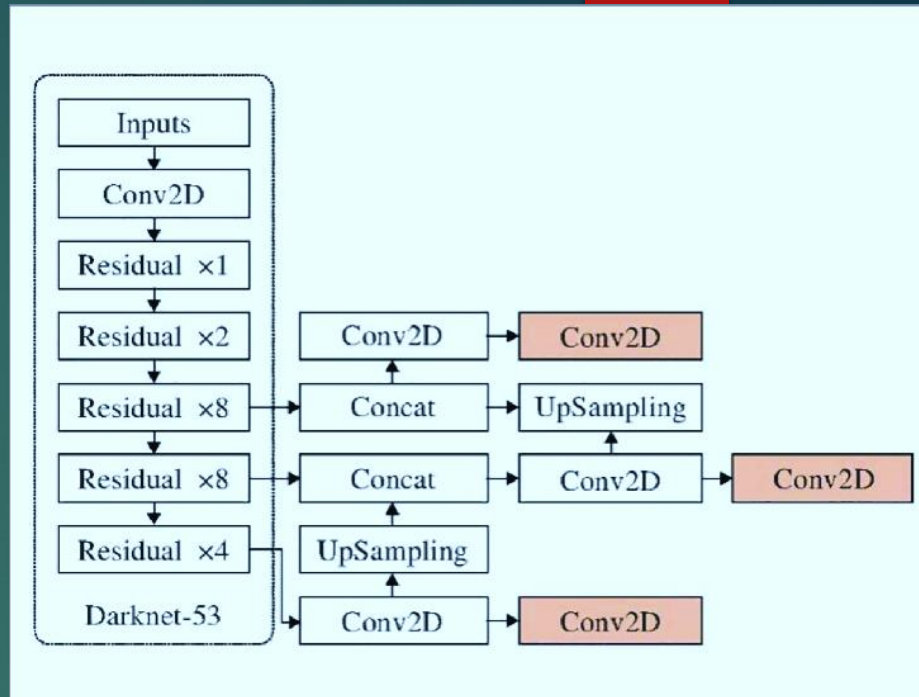
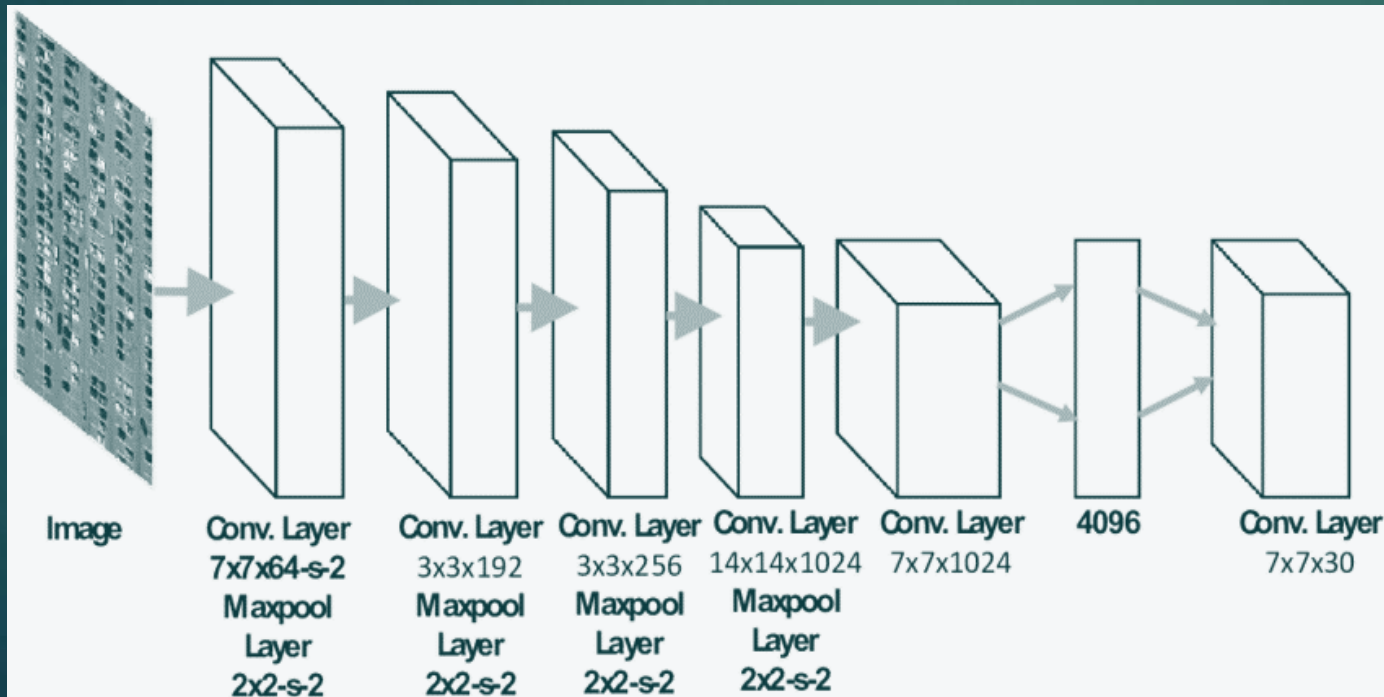
The objective of the provided code is to demonstrate object detection using the YOLOs (You Only Look Once) model. Object detection is a computer vision task that involves identifying and locating objects of interest within an image. The YOLOs model, implemented here through the Ultralytics library, is a popular algorithm for real-time object detection.



We'll cover image preprocessing, the selection and fine-tuning of the YOLOs model, as well as post-processing steps for visualization and result interpretation.

# Network Architecture:

- YOLOv3, one of the popular versions, uses a deep neural network with a Darknet-53 backbone.
- The Darknet-53 architecture is a convolutional neural network (CNN) that extracts features from the input image.



# How Does It Work?

►  $S*S*(C+5)+AB$

## 1. Grid Division:

- The input image is divided into a grid, typically, a fixed-size grid like 19x19 or 45x45.

## 2. Bounding Box Prediction

## 3. Object Confidence

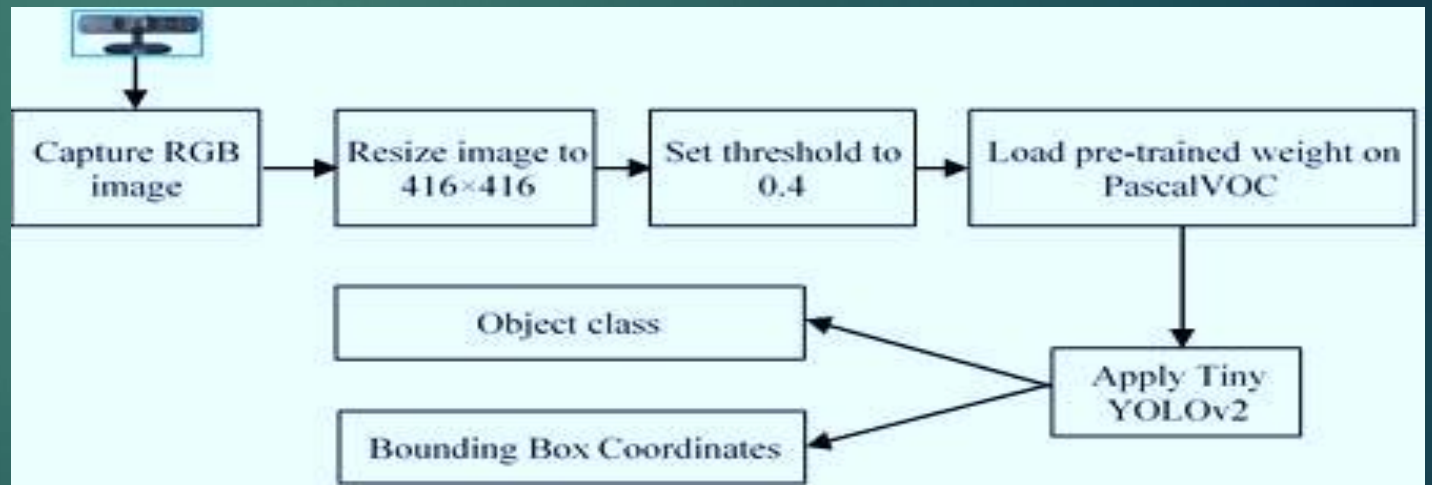
## 4. Class Prediction

## 5. Anchor Boxes

## 6. Single Forward Pass

## 7. Non-Maximum Suppression (NMS)

## 8. Output:



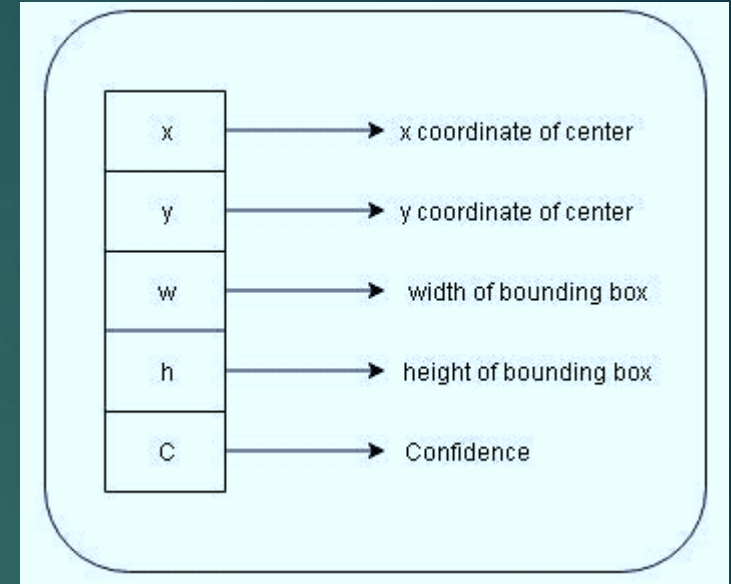


- ▶  $C = Pr(object) * IoU$
- ▶ IoU: Intersection over Union between the predicted box and the ground truth.
- ▶ If no object exists in a cell, its confidence score should be zero.

The loss function defined in YOLO as follows

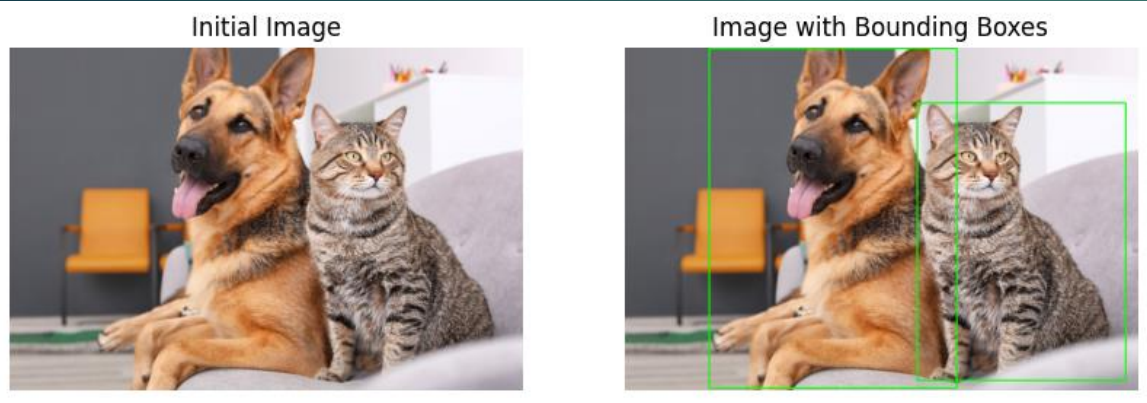
$$\begin{aligned}
 & \lambda_{\text{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^B \mathbb{1}_{ij}^{\text{obj}} \left[ (x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \right] \\
 & + \lambda_{\text{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^B \mathbb{1}_{ij}^{\text{obj}} \left[ \left( \sqrt{w_i} - \sqrt{\hat{w}_i} \right)^2 + \left( \sqrt{h_i} - \sqrt{\hat{h}_i} \right)^2 \right] \\
 & + \sum_{i=0}^{S^2} \sum_{j=0}^B \mathbb{1}_{ij}^{\text{obj}} (C_i - \hat{C}_i)^2 \\
 & + \lambda_{\text{noobj}} \sum_{i=0}^{S^2} \sum_{j=0}^B \mathbb{1}_{ij}^{\text{noobj}} (C_i - \hat{C}_i)^2 \\
 & + \sum_{i=0}^{S^2} \mathbb{1}_i^{\text{obj}} \sum_{c \in \text{classes}} (p_i(c) - \hat{p}_i(c))^2
 \end{aligned}$$

In this model, we taken 5 lambda coord. and 0.5 lambda noobj

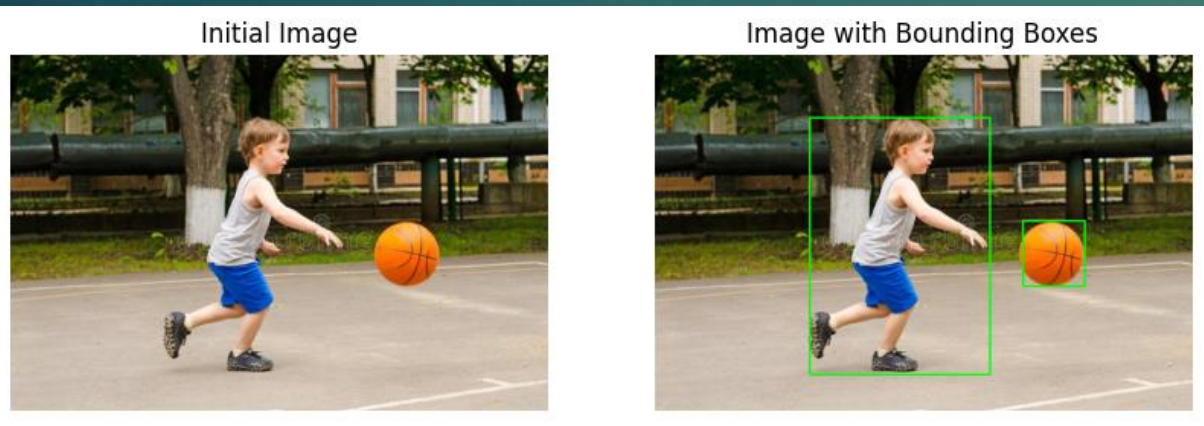


# Results and discussion

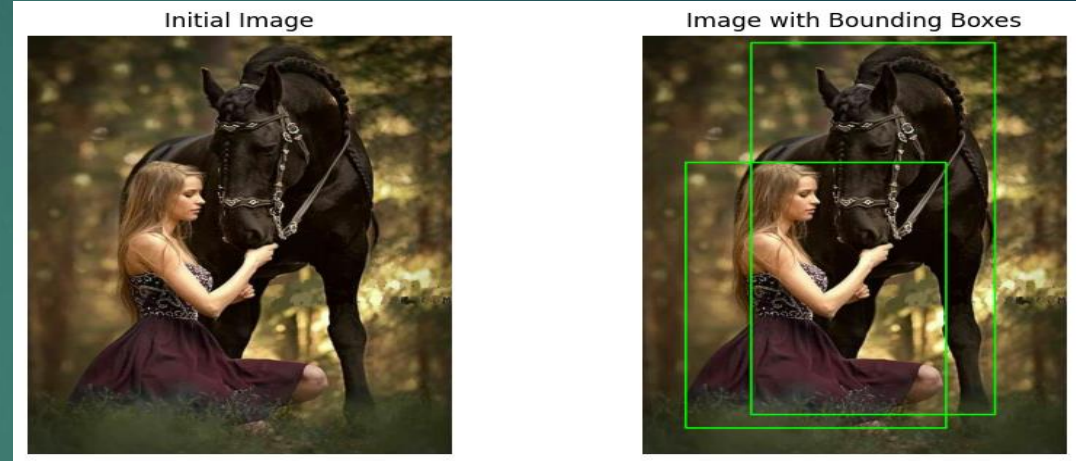
Detected dog with confidence 0.989 at location [164.05, 1.45, 646.14, 662.74]  
Detected cat with confidence 0.996 at location [569.34, 107.56, 975.35, 647.13]



Detected person with confidence 0.993 at location [230.81, 95.43, 498.0, 476.48]  
Detected sports ball with confidence 0.989 at location [547.14, 248.66, 639.59, 345.28]



Detected horse with confidence 0.965 at location [144.58, 12.68, 468.57, 674.67]  
Detected person with confidence 0.995 at location [57.55, 225.47, 403.14, 698.4]

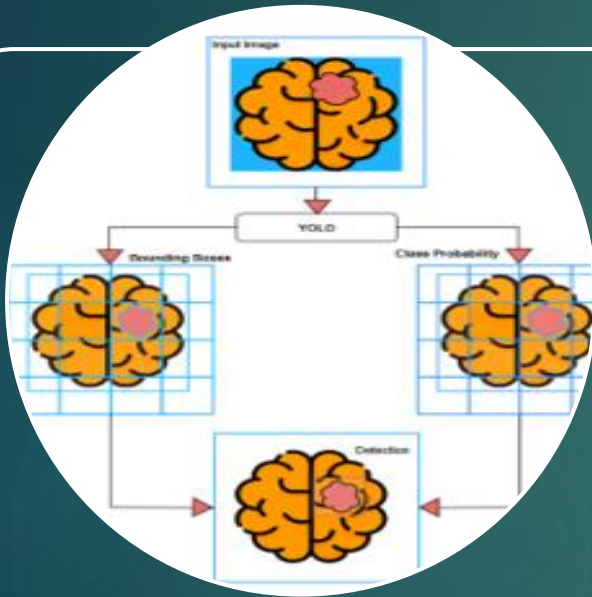


Detected person with confidence 0.987 at location [2.47, 38.71, 163.55, 227.68]  
Detected person with confidence 0.994 at location [143.87, 53.64, 309.17, 211.93]  
Detected person with confidence 0.972 at location [300.14, 56.8, 447.88, 221.98]



# YOLO Applications

- Object detection in images and videos
- Industrial automation



Medical image analysis



Autonomous vehicles

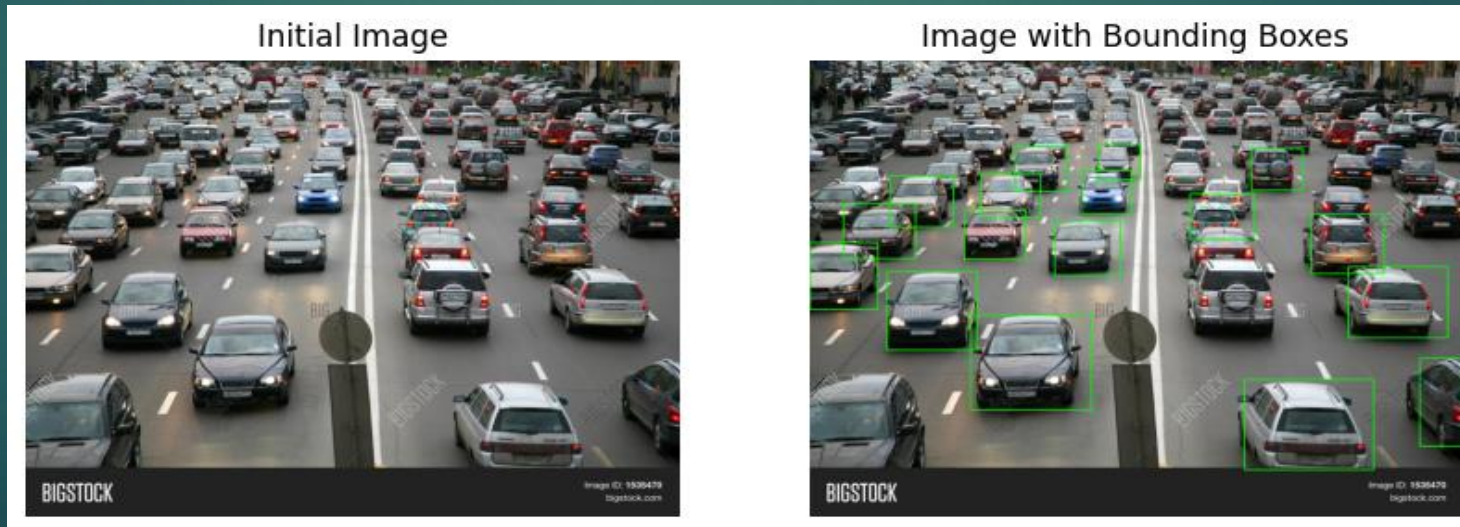


Surveillance systems



# Limitations Of YOLO

- Spatial constraints on bounding box predictions as each grid cell only predicts two boxes and can have only one class.
- It is difficult to detect small objects that appear in groups.
- It struggles to generalize objects in new or unusual aspect ratios as the model learns to predict bounding boxes from data itself.



# Conclusion

- ▶ In conclusion, this project has allowed us to explore the fascinating world of object detection using the YOLO model. We've seen how preprocessing, model selection, fine-tuning, and post-processing come together to create an effective object detection pipeline.

# Future direction



Opportunities for improvement in YOLO models



Integration with other technologies (e.g., deep reinforcement learning)



Emerging trends in object detection



Thank You