SVKM'S NMIMS Deemed to be UNIVERSITY

AUTOMATED WASTE DETECTION & CLASSIFICATION

USING YOLO V8 FOR ENHANCED SORTING EFFICIENCY

GROUP 5

Presented By

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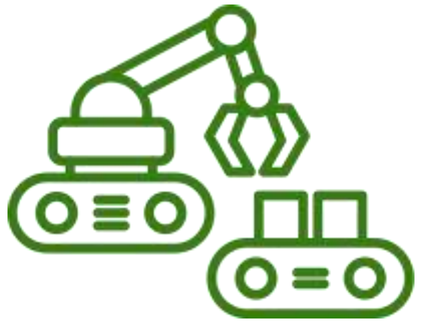
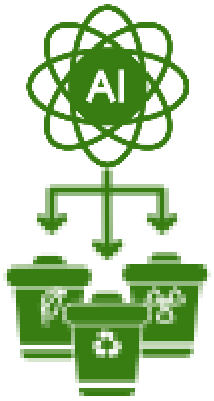
INTRODUCTION

- Dry waste has major role to environmental pollution.
- Improper sorting reduces recycling efficiency.
- Manual sorting of waste is labor-intensive, prone to inaccuracies, and hampers the extraction of clean raw materials for the recycling.
- An automated, scalable solution using computer vision and deep learning can overcome inefficiencies in the dry waste sorting and classification .
- Improved sorting increases the purity of recyclables and support environmental sustainability efforts.





OBJECTIVES

Develop Object Detection Model

Fine-tune YOLOv8 to detect and classify waste materials with high precision and recall.

Boost Sorting Efficiency

Automate waste classification to improve accuracy, reduce contamination, and enhance recycling throughput.

Support Sustainable Practices

Reduce manual sorting, improve waste quality, and drive data-based recycling efforts.

LITERATURE REVIEW

Research Paper Title	Source	Year of Publication	Citation
Solid Waste Detection Using Enhanced YOLOv8 Lightweight Convolutional Neural Networks	MDPI Journal of Mathematics	2024	Li, Pan, Jiayin Xu, and Shenbo Liu. 2024. “Solid Waste Detection Using Enhanced YOLOv8 Lightweight Convolutional Neural Networks.” Mathematics
Hierarchical waste detection with weakly supervised segmentation in images from recycling plants	Journal of Engineering Applications of Artificial Intelligence	2023	Yudin, Dmitry, N Zakharenko, A Smetanin, R Filonov, M Kichik, V Kuznetsov, D Larichev, E Gudov, S Budennyy, A Panov. 2023. “Hierarchical Waste Detection with Weakly Supervised Segmentation in Images from Recycling Plants.” Engineering Applications of Artificial Intelligence
Skip-YOLO: Domestic Garbage Detection Using Deep Learning Method in Complex Multi-scenes	International Journal of Computational Intelligence Systems	2023	Lun, Zhao, Yunlong Pan, Sen Wang, Zeshan Abbas, Md Shafiqul Islam, and Sufeng Yin. 2023. “Skip-YOLO: Domestic Garbage Detection Using Deep Learning Method in Complex Multi-Scenes.” International Journal of Computational Intelligence Systems

OVERVIEW OF IMAGE ANALYSIS

- **Object Detection** :

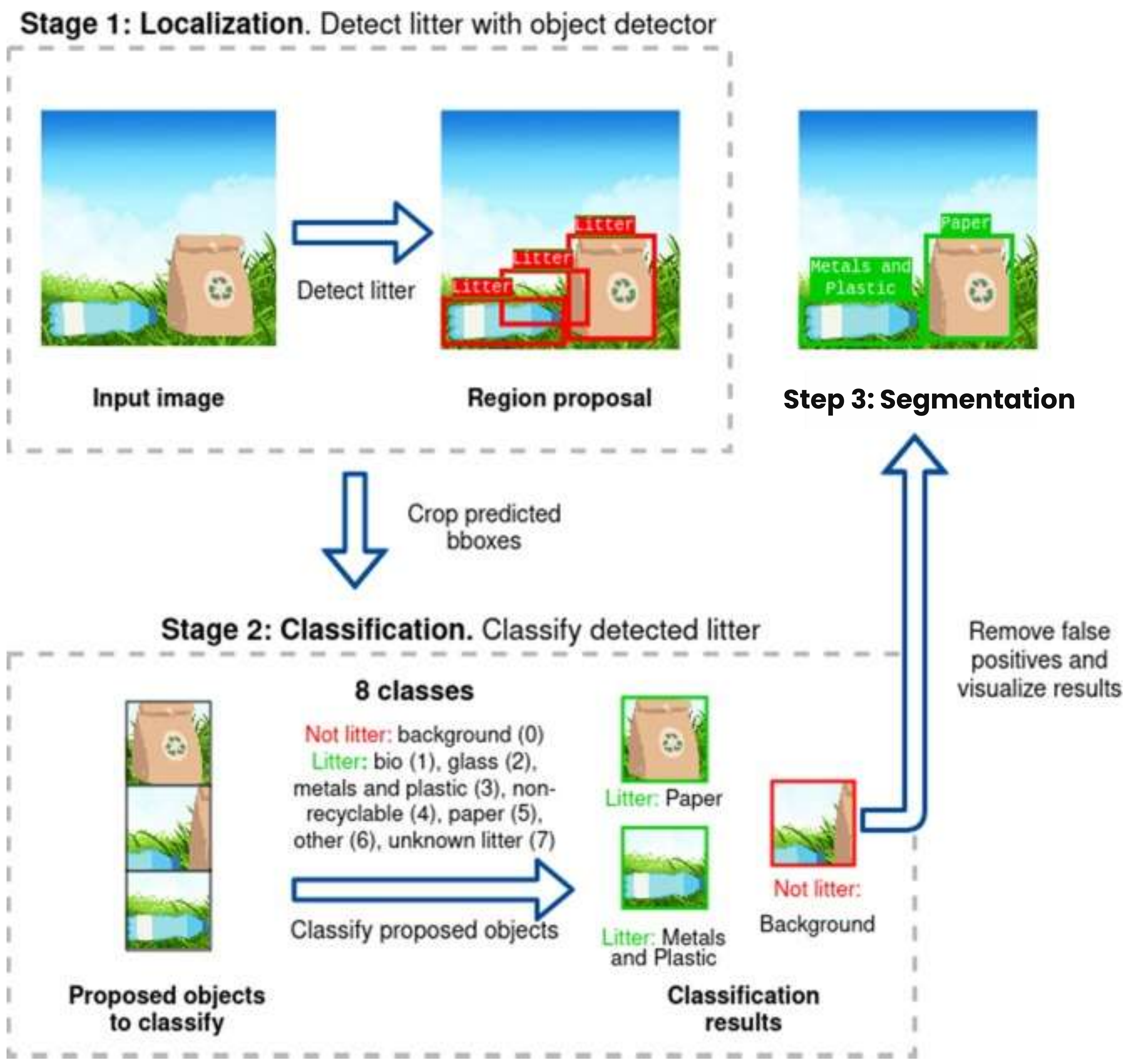
Identifies and localizes the objects in the images.

- **Image Classification** :

Assigns a single label to an entire image.

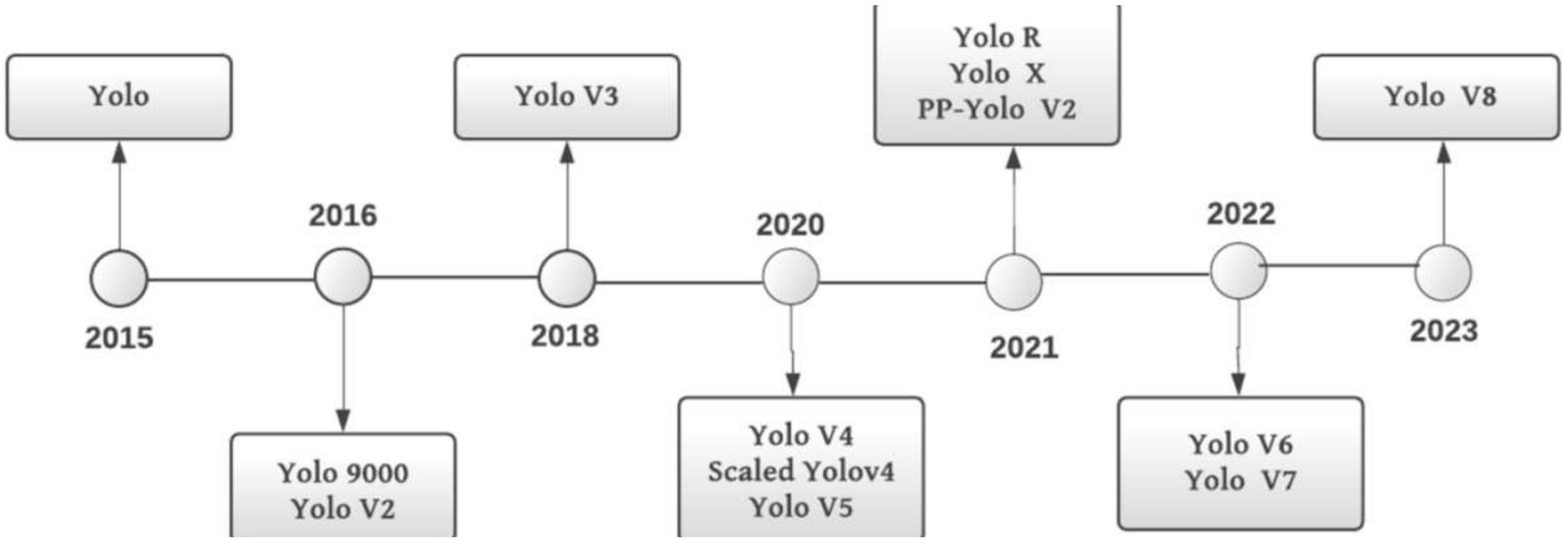
- **Instance Segmentation** :

Classifies each pixel in image, or semantic categories or object instances



YOU ONLY LOOK ONCE (YOLO)

- A type of Convolutional Neural Network.
- A real-time object detection algorithm processes images in single pass.
- YOLO frames object detection as a single regression problem.
- YOLO divides images into flexible grids, predicting the bounding boxes and class probabilities from labels provided.
- Commonly used in tasks like autonomous driving, video surveillance, and robotic vision due to its rapid response time.

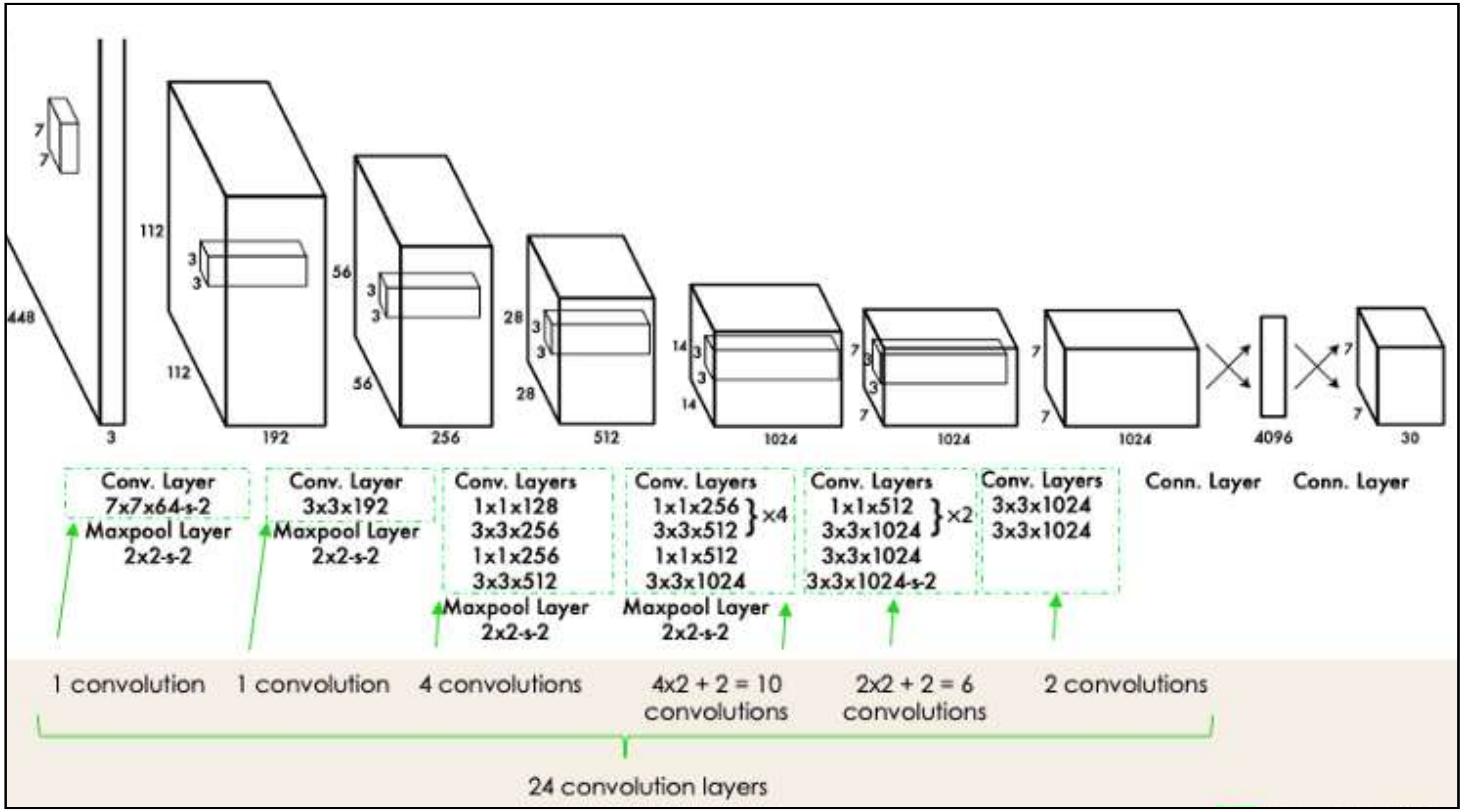


Improved Accuracy

Anchor-Free Design

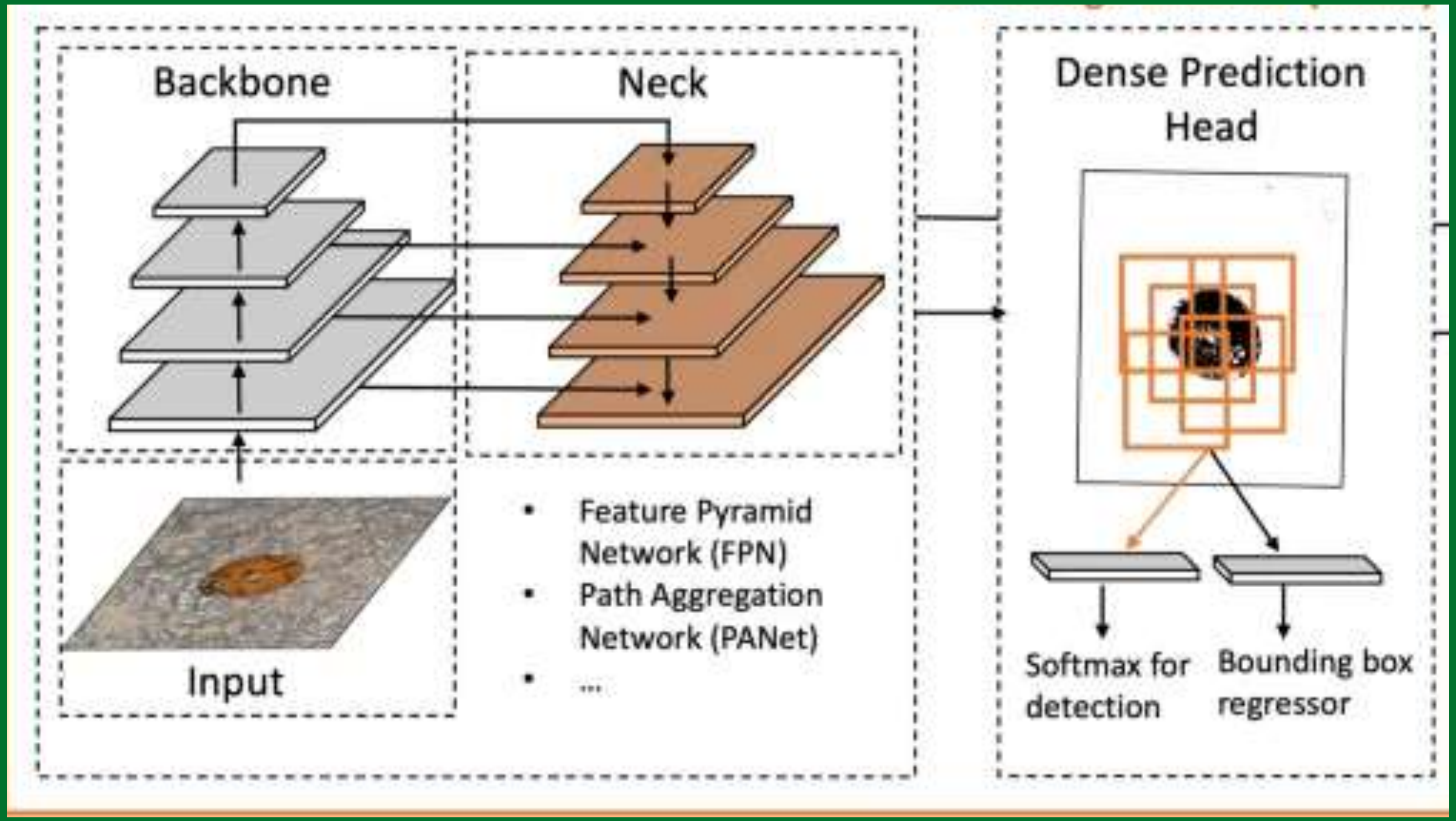
Speed & Efficiency

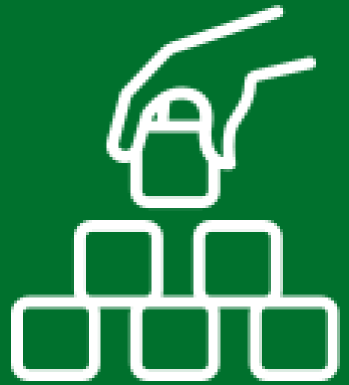
YOLO ARCHITECTURE

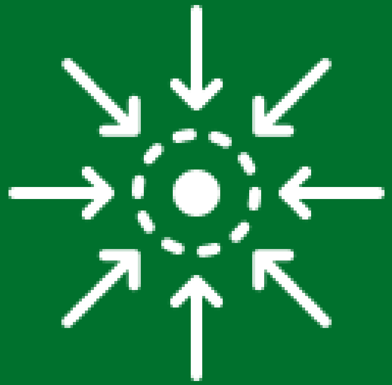


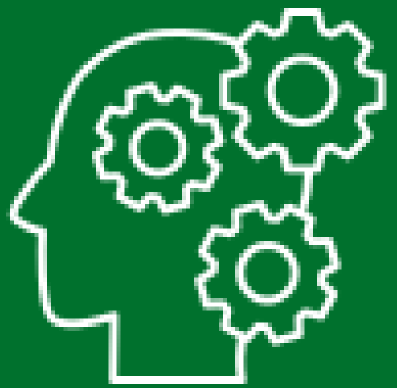
- 24 Convolutional Layers
- 4 Max-Pooling Layers
- 2 Fully Connected Layers

Main Components









Backbone

- Comprised of 24 convolutional layers
- Used to extract visual features from an image.

Neck

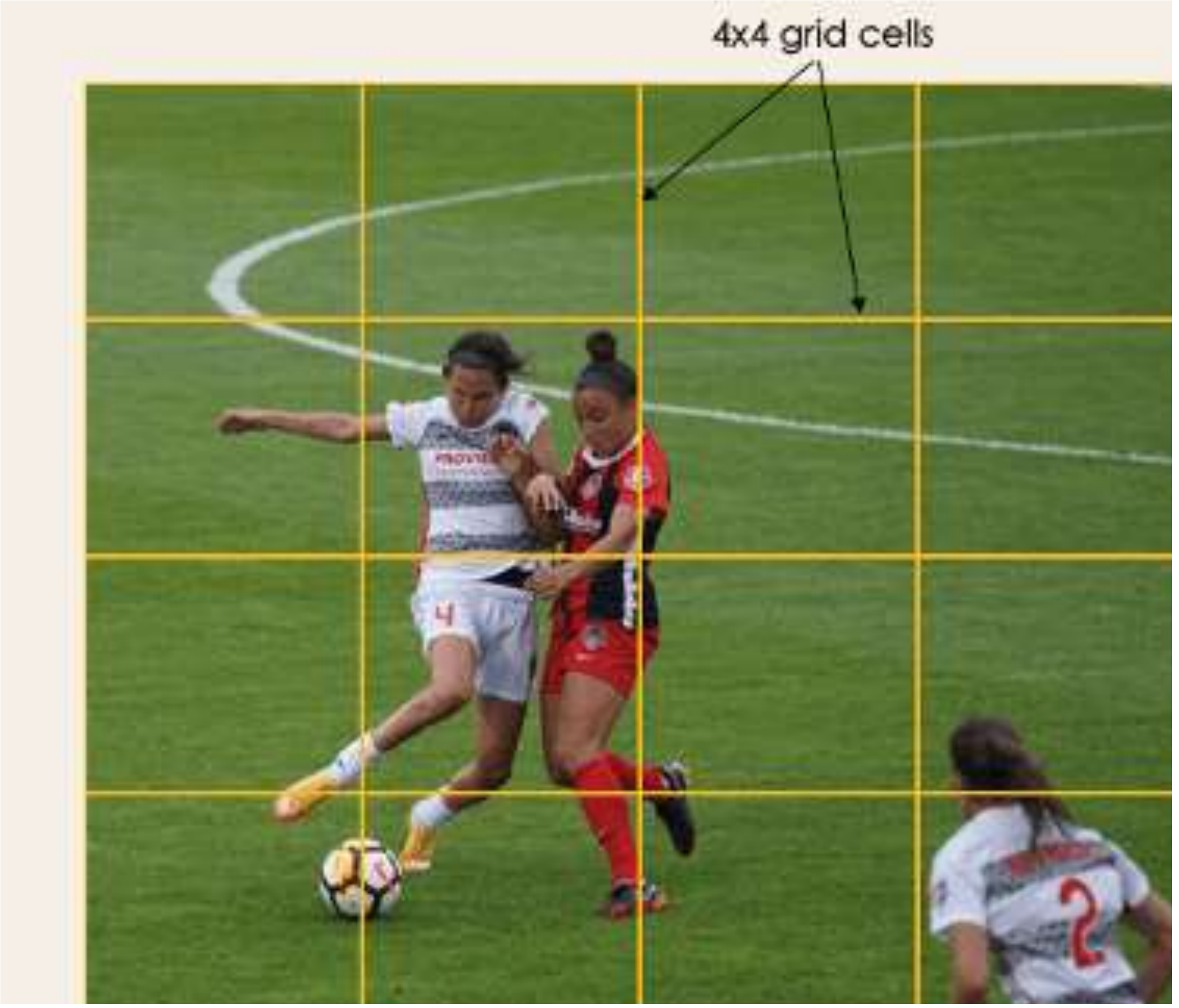
- It combines and refines the features extracted by the Backbone, preparing them for the final detection stage

Head

- It is responsible for predicting classes and bounding box regions of the detected objects, producing the final output.

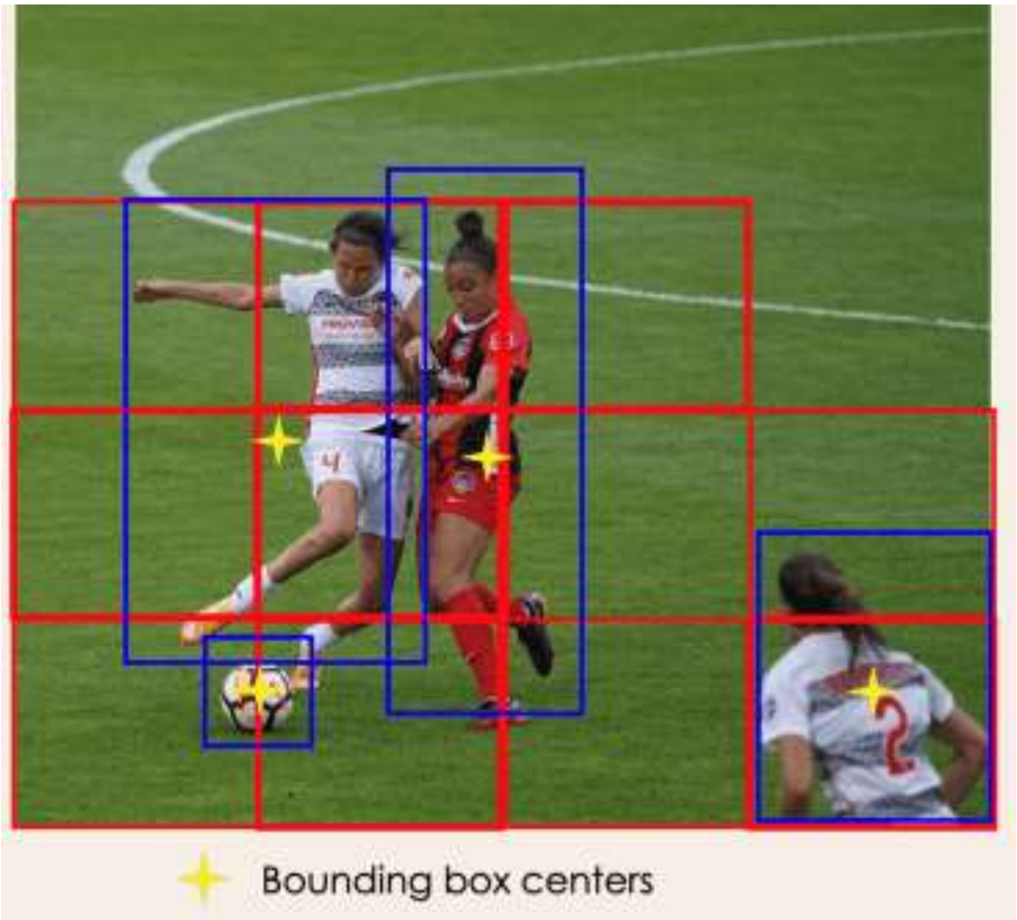
1. RESIDUAL BLOCKS

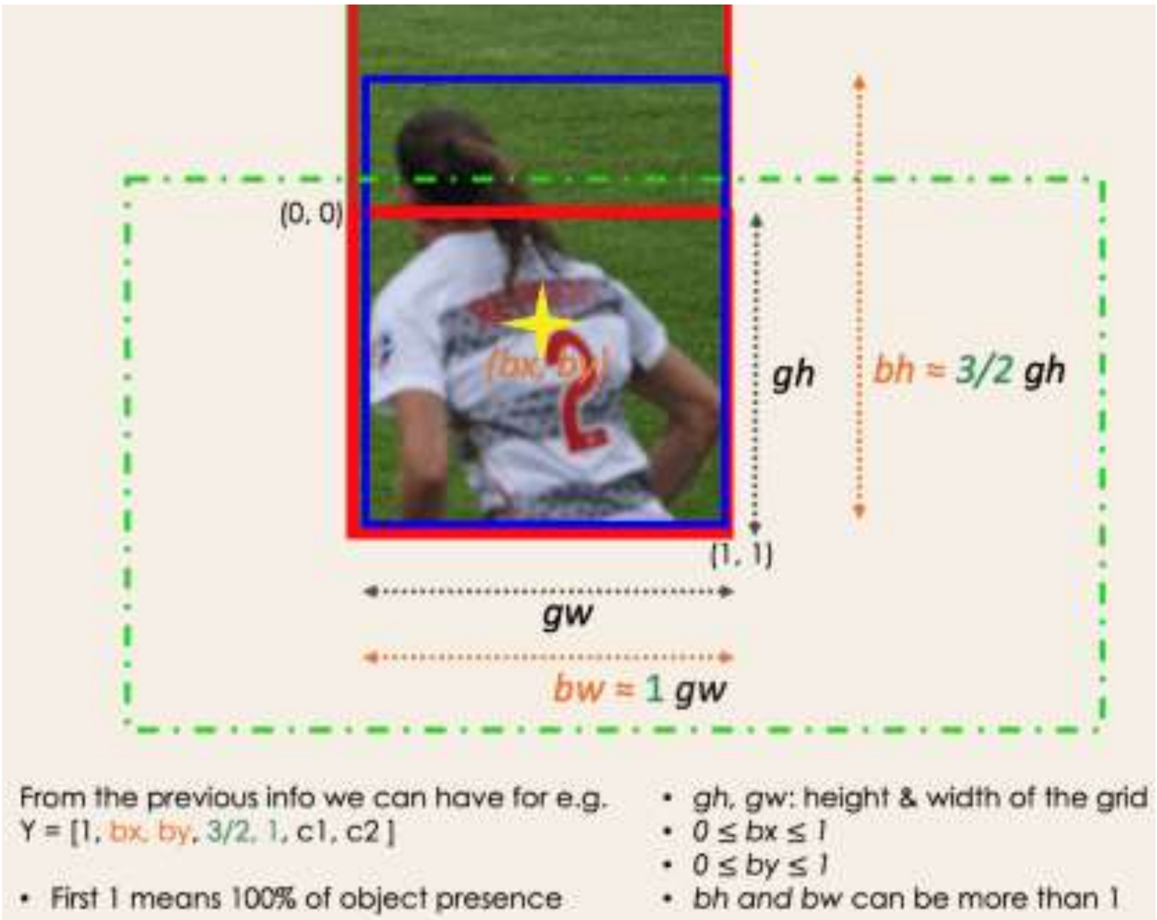
- Dividing the original image into NxN grid cells of equal size
- Each cell in the grid is responsible for predicting the class of the object that it covers, along with the probability
- Here model focuses on smaller regions instead of focusing on entire image



2. BOUNDING BOX REGRESSION

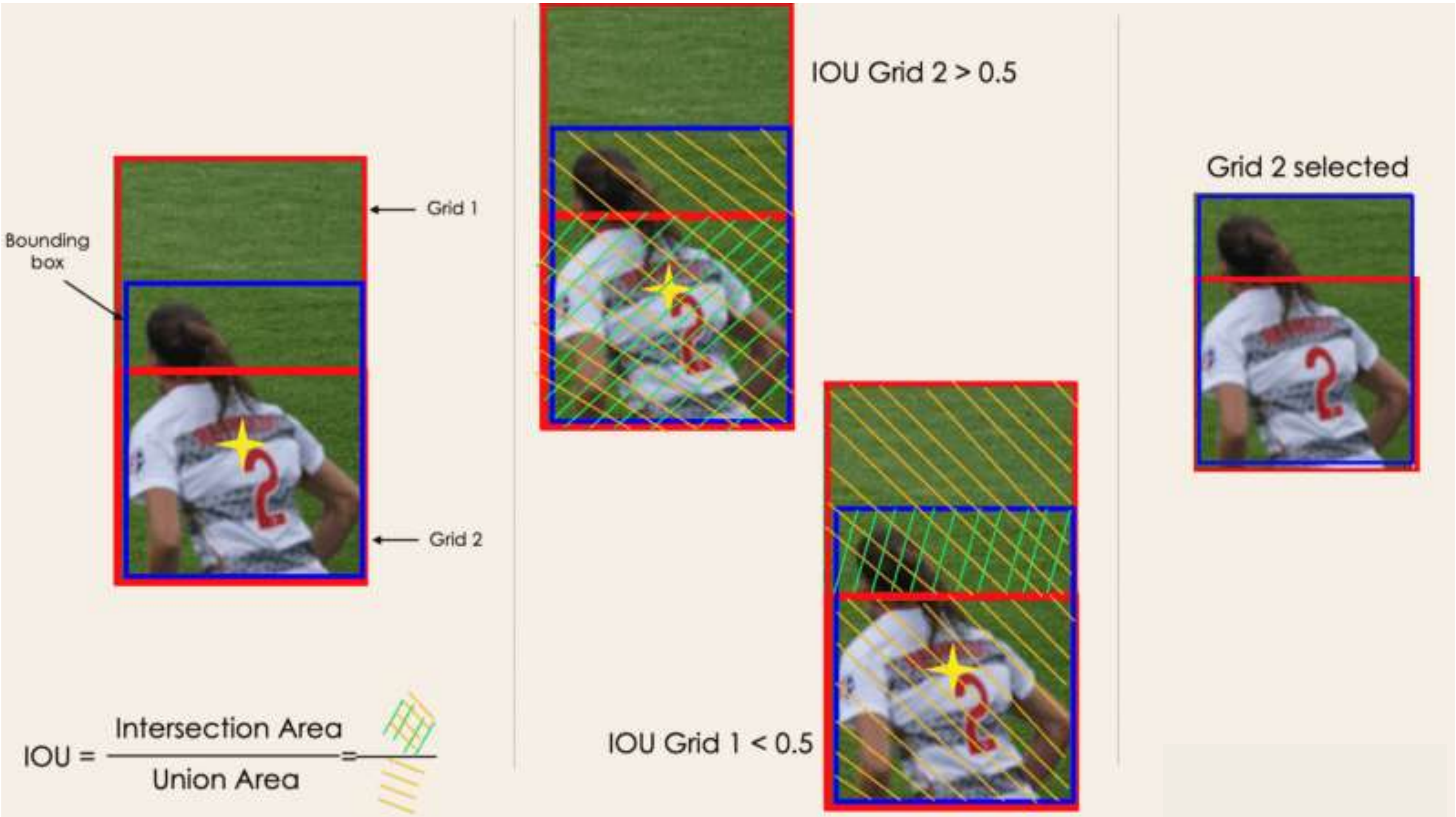
- Determine the bounding boxes corresponding to rectangles, highlighting all the objects in the images.
- Y = [pc, bx, by, gh, gw, c1, c2]
- pc : probability score of the grid containing an object
- bx, by : x and y coordinates of the center of bounding box
- gh, gw : height and the width of the bounding box
- c1, c2 : two classes, Player and Ball

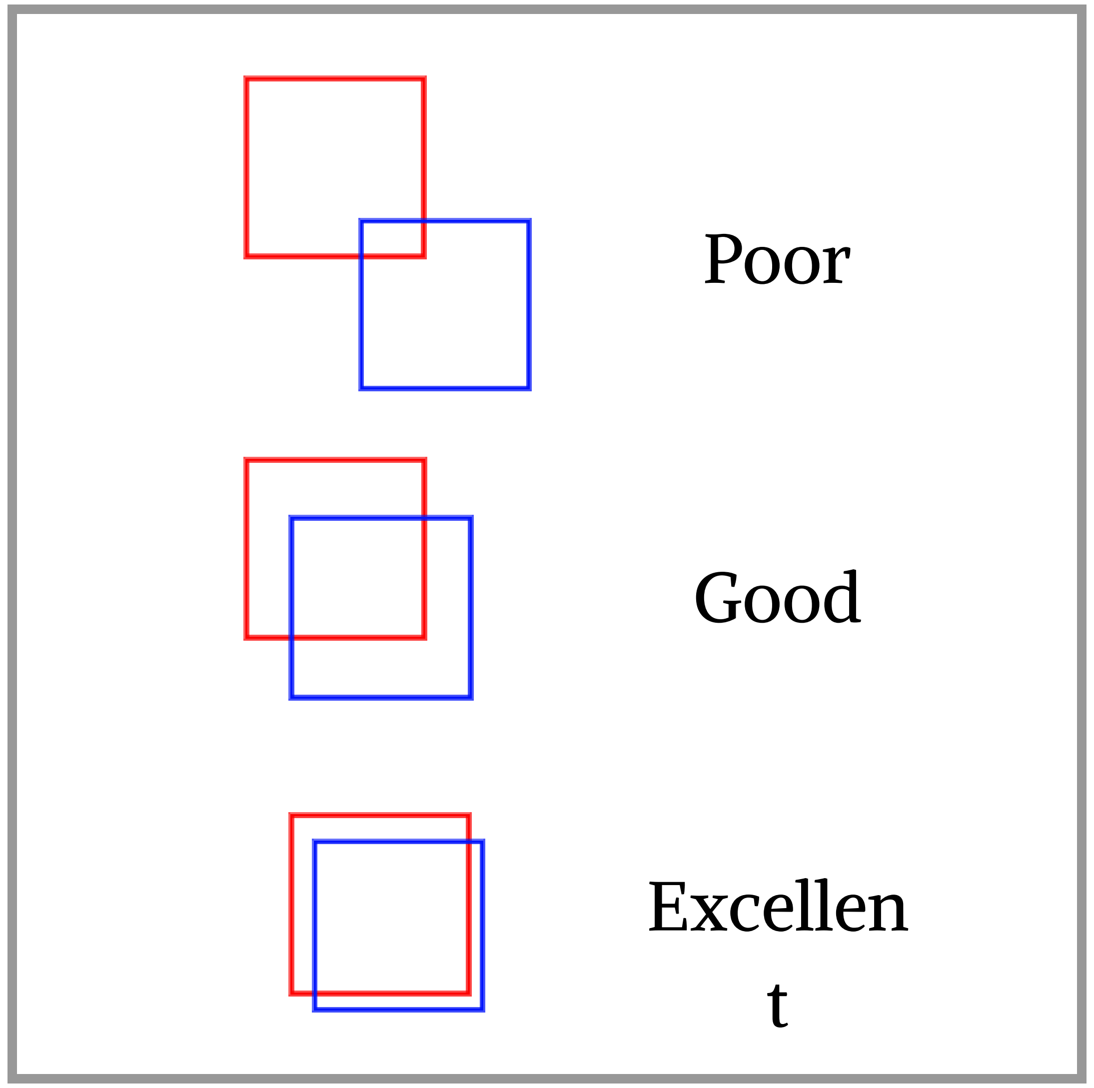




3. INTERSECTION OVER UNION (IOU)

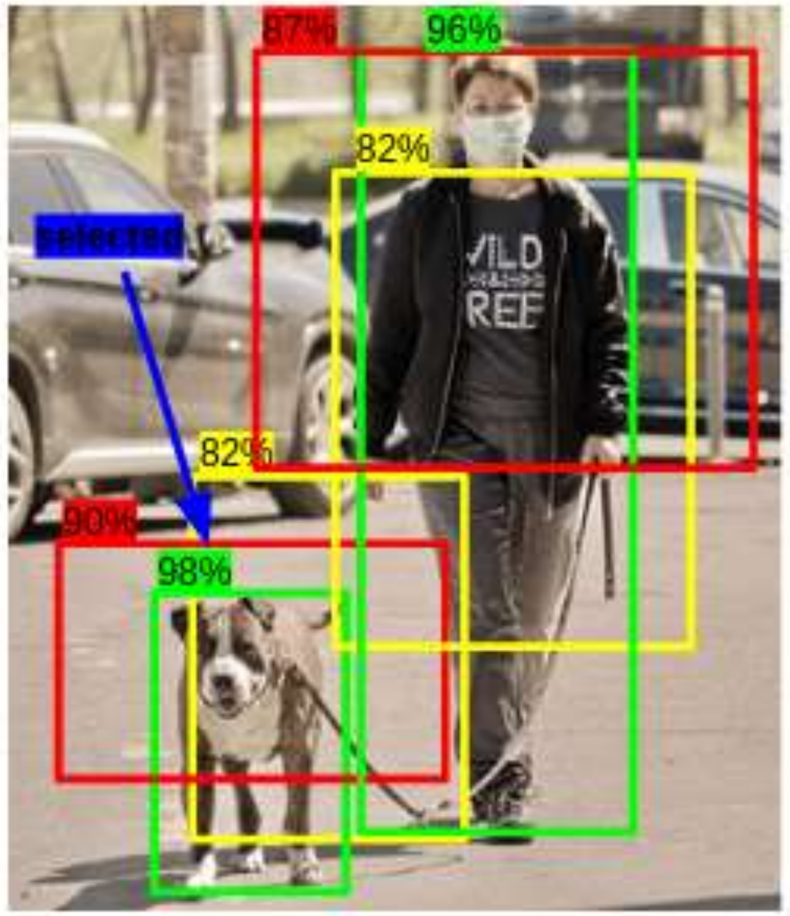
- IOU measures the overlap between two bounding boxes.
- The greater the region of overlap, the greater the IOU.
- The aim of this model would be to keep improving its prediction, until the blue box and the red box perfectly overlap, i.e the IOU between the two boxes becomes equal to 1.



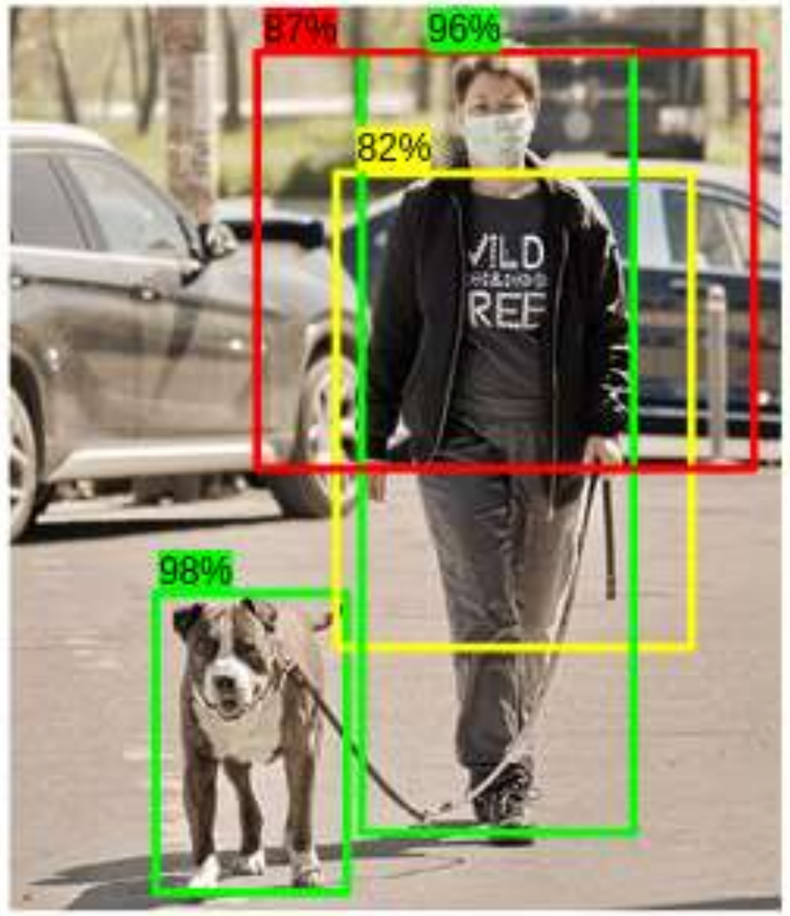


4. NON MAX SUPPRESSION (NMS)

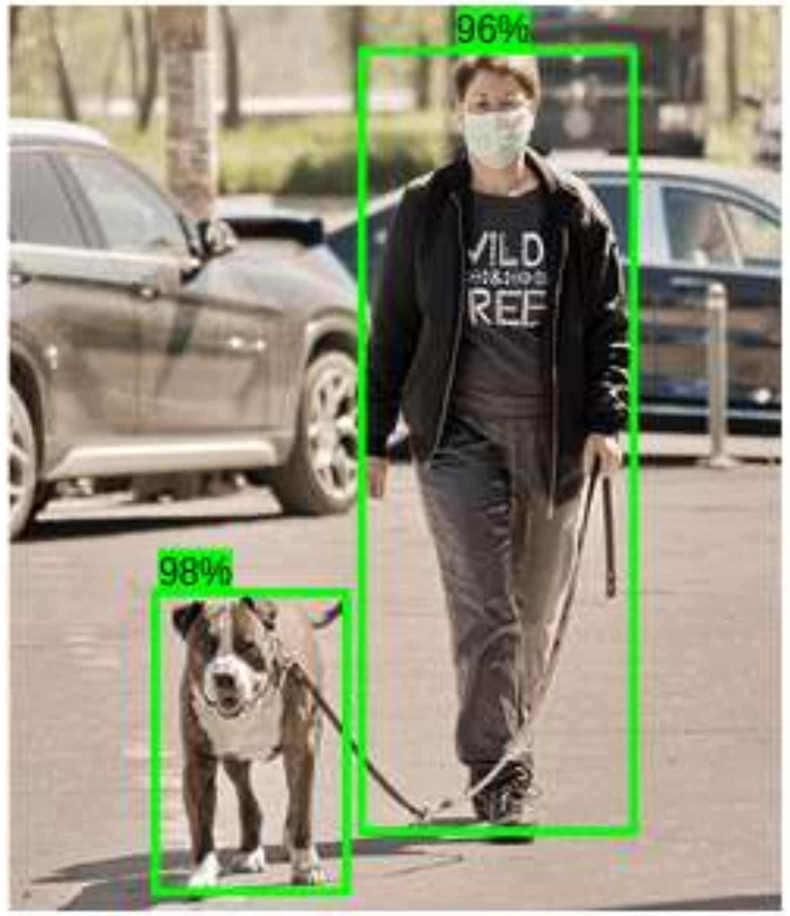
- Used to select the most appropriate bounding box out of a set of the overlapping boxes.
- This process ensures that for each of the object, only one bounding box is selected.



1: Selecting Bounding box with highest score



Delete Bounding box with high overlap



Ste Final Output

DATASET OVERVIEW

The Warp Waste Recycling Plant Dataset from Kaggle

bottle_blue

detergent_white

can

juice_cardboard

detergent_box

bottle_milk

canister

bottle_oil

juice_cardboard

detergent_colour

bottle_glass

canister

can

milk_cardboard

detergent_transp

DATASET CLASS DISTRIBUTION

Bottles

7636 images

- bottle_blue
- bottle_green
- bottle_white
- bottle_colour
- glass_transp
- glass_green
- glass_dark

Cardboard

817 images

- juice_cardboard
- milk_cardboard

Can

682 images

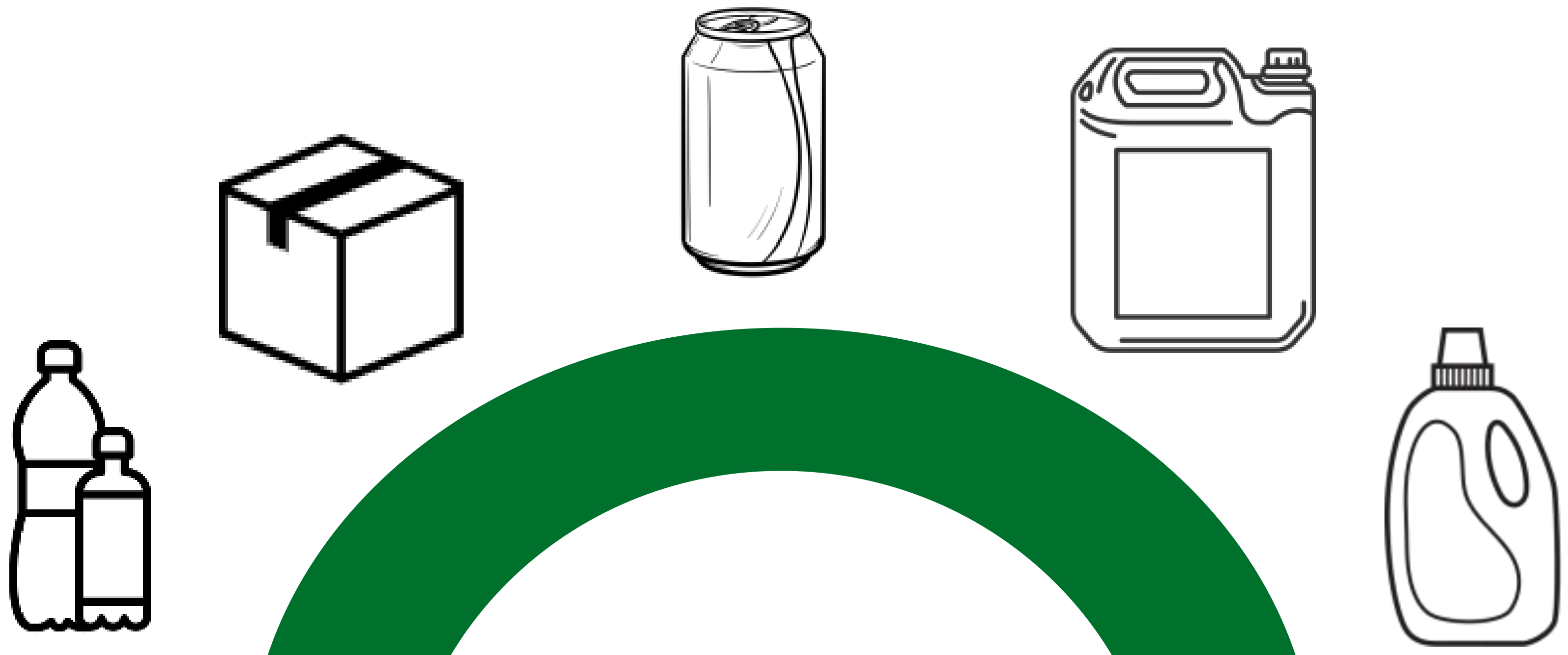
Canister

179 images

Detergent

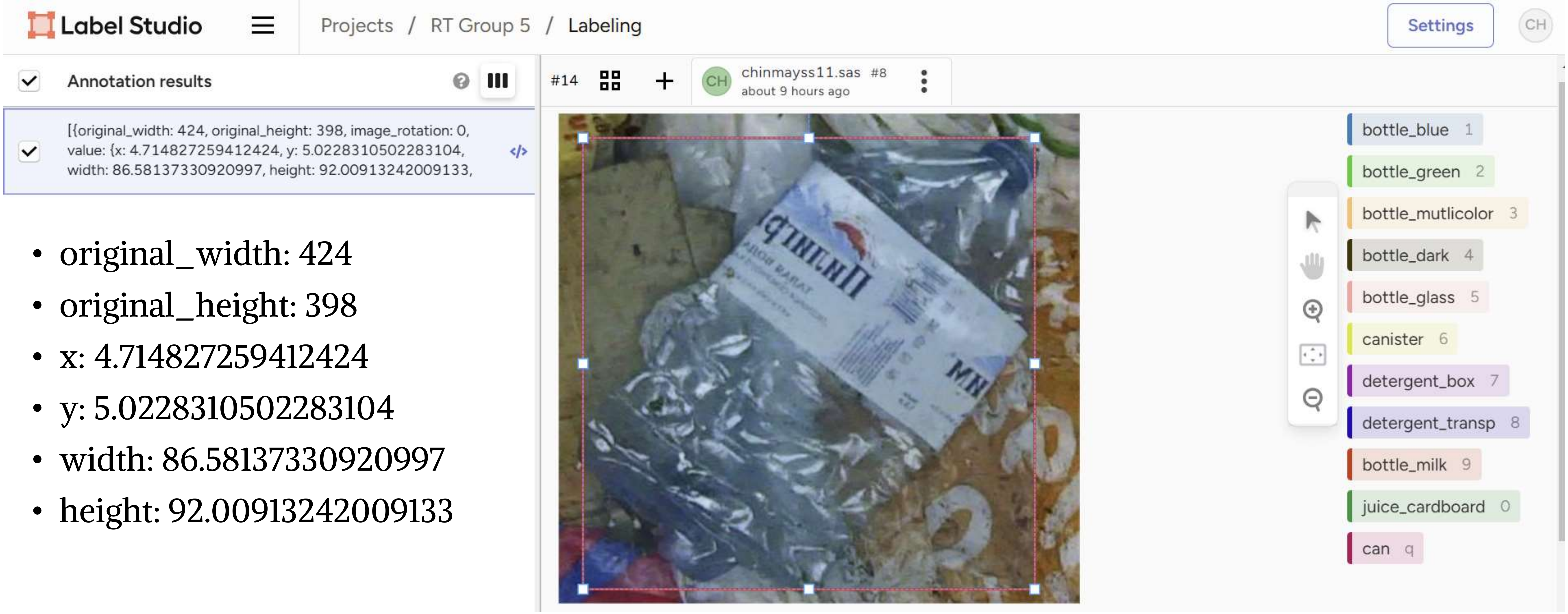
1090 images

- detergent_white
- detergent_colour
- detergent_transparent
- detergent_box



DATA ANNOTATION PROCESS

- Annotation involves labeling data, like tagging images, to identify objects or characteristics.
- This labeled data is essential for training AI models, helping them learn from examples and improving accuracy in tasks like object detection and classification.



- original_width: 424
- original_height: 398
- x: 4.714827259412424
- y: 5.0228310502283104
- width: 86.58137330920997
- height: 92.00913242009133

DATA SPLIT

Total No. of Images
2452

Train Data
1962 (80%)

Validation Data
490 (20%)

Test Dataset
522

MODEL TRAINING

Model Configuration

- Model: Pre-trained YOLOv8m model, a mid-sized version
- Pretrained: Initializes training with pre-trained weights

Training Setup

- Image Size: 640x640 pixels
- Epochs: 100
- Patience: 20
- Batch Size: 16

Optimization & Learning Parameters

- Optimizer: Automatically selects the best optimizer for YOLOv8.
- Weight Decay: 0.0005
- Learning Rate: 0.01

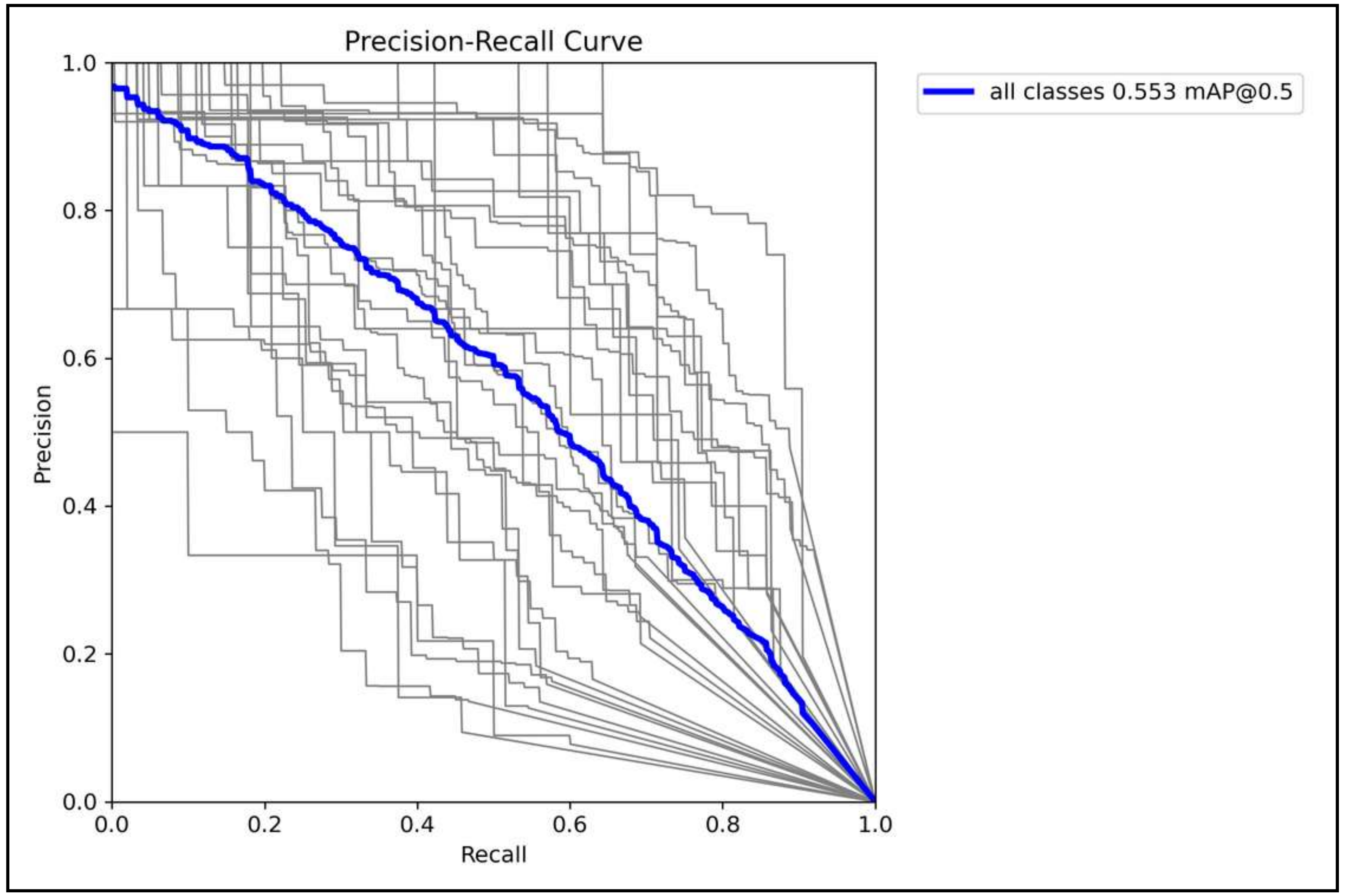
Augmentation and Regularization

- Translate: 0.1
- HSV Saturation: 0.7
- HSV Value: 0.4
- Overlap Mask : true

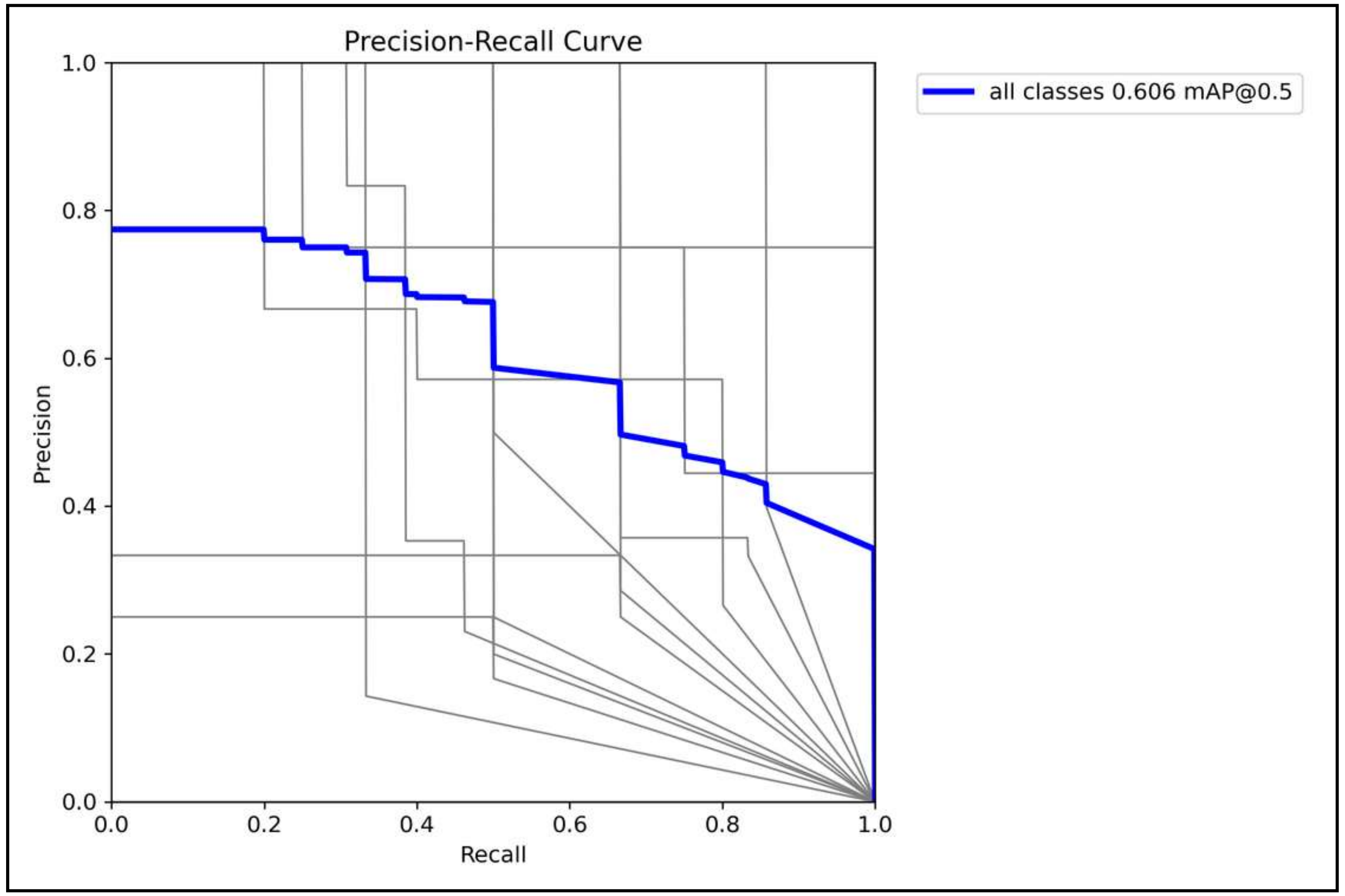
PRECESION-RECALL CURVE

- The curve shows the relationship between precision and recall across different confidence thresholds.
- A higher area under the PR curve (AUC-PR) indicates better model performance

Training Set



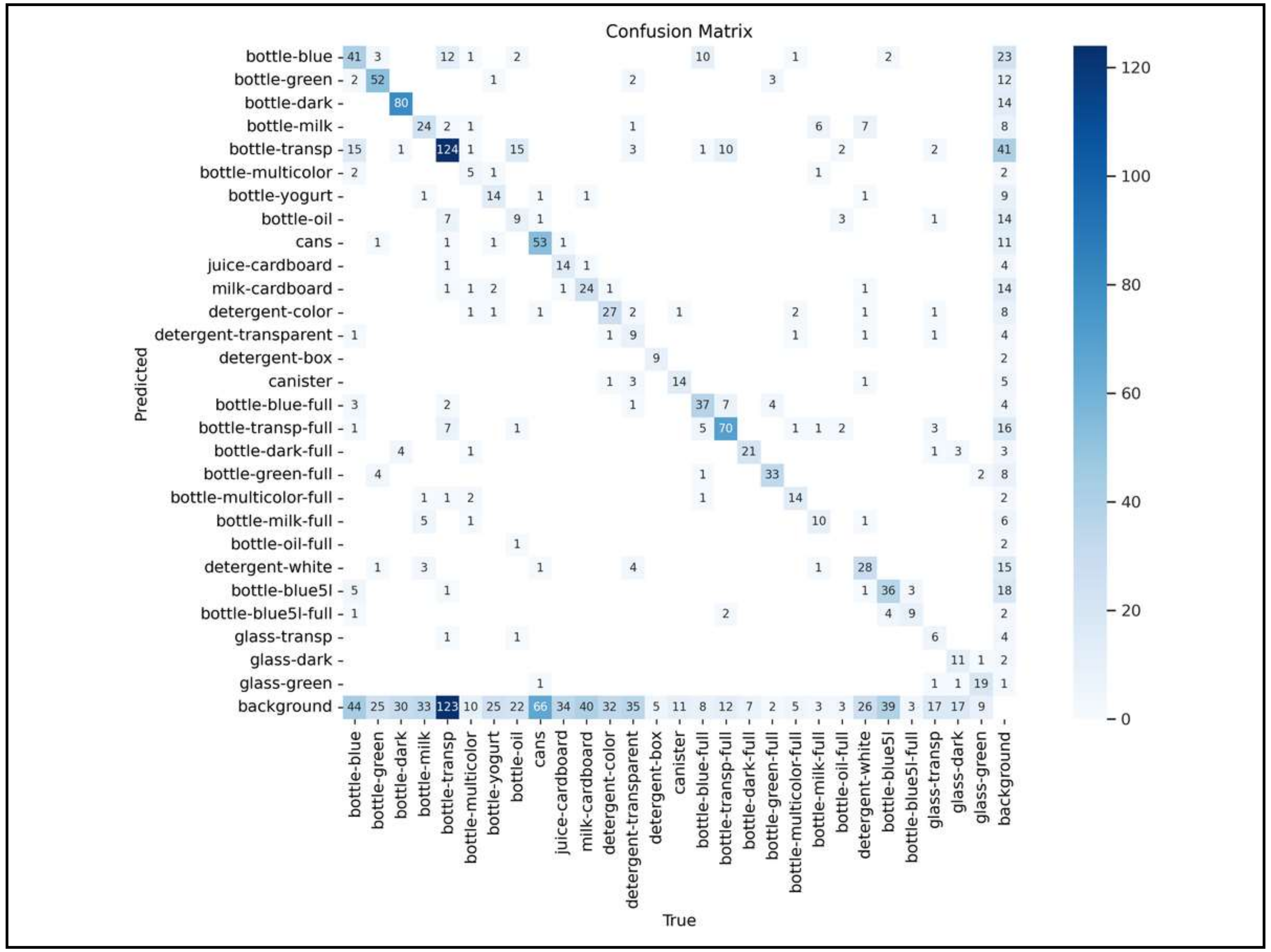
Validation Set



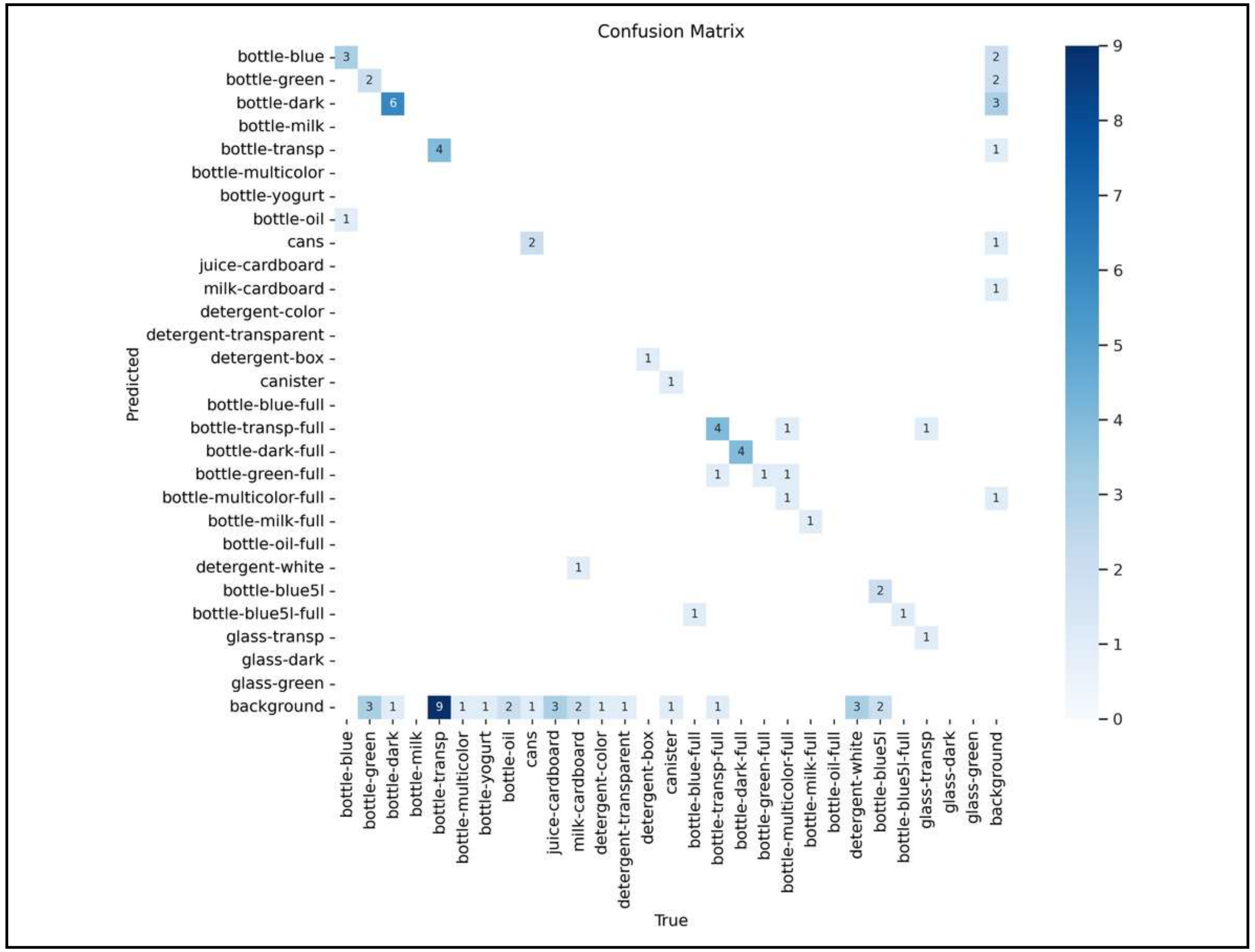
CONFUSION MATRIX

A table that compares predicted values to actual values for a dataset to evaluate the performance of a model.

Training Set



Validation Set



EVALUATION METRICS

Epoch	Accuracy	Precision	Recall	mAP@50	mAP@50-95
1	23.60%	0.3001	0.3576	0.2360	0.1752
10	50.00%	0.4936	0.5085	0.5006	0.3849
25	53.20%	0.5453	0.5111	0.5315	0.4155
50	52.10%	0.5392	0.5269	0.5215	0.4165
75	53.30%	0.5773	0.5106	0.5331	0.4284
100	55.30%	0.5791	0.5277	0.5532	0.4509

$$\text{Accuracy} = \frac{\text{Number of Correct predictions}}{\text{Total number of predictions made}}$$

$$\text{Precision} = \frac{\text{Number of True Positive predictions}}{\text{Total number of Positive predictions made}}$$

$$\text{Recall} = \frac{\text{Number of True Positive predictions}}{\text{Total number of Actual Positive cases}}$$

$$\text{mAP@50} = \frac{\text{Sum of Average Precision values for all classes}}{\text{Number of classes}}$$

$$\text{mAP@50-95} = \frac{\text{Sum of Average Precision values for IoU thresholds from 0.5 to 0.95}}{\text{Number of IoU thresholds}}$$

TEST PREDICTIONS

FUTURE SCOPE

Expansion to Diverse Waste Types

Adapt the model for broader waste categories, including hazardous, electronic, and biomedical waste, and test across varied environments (indoor, outdoor, urban).

Integration with Robotic Systems

Embed the model in robotic systems for real-time waste sorting, enhancing speed and accuracy with optimized edge processing.

Edge Deployment for Smart Waste Management

Deploy on smart bins and IoT-based systems to enable real-time waste categorization, aiding automated segregation and providing municipal data insights.

REFERENCES

WaRP (Waste Recycling Plant Dataset)
https://www.kaggle.com/datasets/parohod/warp-waste-recycling-plant-dataset

Solid Waste Detection Using Enhanced YOLOv8 Lightweight Convolutional Neural Networks
https://doi.org/10.3390/math12142185

Hierarchical waste detection with weakly supervised segmentation in images from recycling plants.
https://www.sciencedirect.com/science/article/abs/pii/S0952197623017268

Label Studio Documentation – Data Labelling and Annotation
https://labelstud.io/guide/labeling.html

YOLO Object Detection Explained
https://www.datacamp.com/blog/yolo-object-detection-explained

THANK YOU

FOR YOUR TIME & ATTENTION