Bottle Cap Detection using Yolov5

Objective:

- The objective of this project is to develop an automated system for detecting whether bottles have caps using the YOLOv5 object detection model.
- The project will evaluate the model's performance using metrics like accuracy and precision to assess its effectiveness in identifying capped and uncapped bottles.

Methodology:

Step 1: **Image Annotation**

The first step in developing a bottle cap detection system is to annotate data using labeling tools. Annotation involves marking or labeling images to indicate where objects of interest. This annotated dataset will enable the model to learn to recognize and localize bottle caps in new images.

Step 2: **Model Setup**

Pre-trained Weights:

- YOLOv5m Weights: Selected for moderate complexity tasks, offering a balance between model size, speed, and accuracy.

Why YOLOv5m:

- Versatility: Capable of handling various detection tasks efficiently.
- Performance: Provides a compromise between smaller models like YOLOv5s and larger models like YOLOv5x, suitable for this task's requirements.

Installation and Configuration:

- Download and Configure: Pre-trained weights are downloaded and configured to jumpstart the training process.

Step 3**:** **Dataset Preparation**

Dataset Characteristics:

- Image: Includes a diverse range of images showing bottles with and without caps.
- Annotations: Each image is annotated with bounding boxes.

Organizational Structure**:**

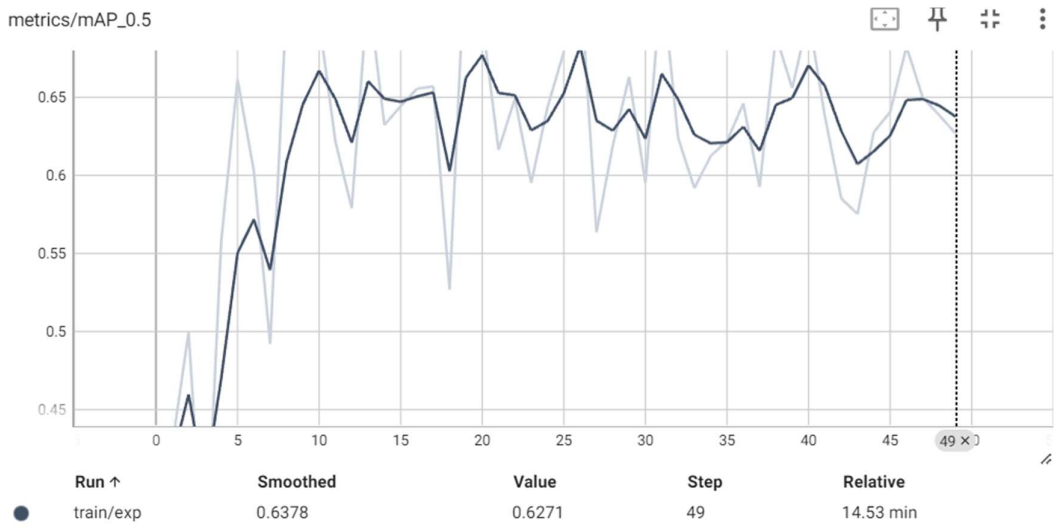
- Training Set: Contains the majority of the images for learning.
- Validation Set: Used for tuning model parameters and avoiding overfitting.
- Labels**:** Annotations also include class labels
- Test Set: Evaluates the model's performance on unseen data.

Step 4: **Fine Tuning the Yolov5**

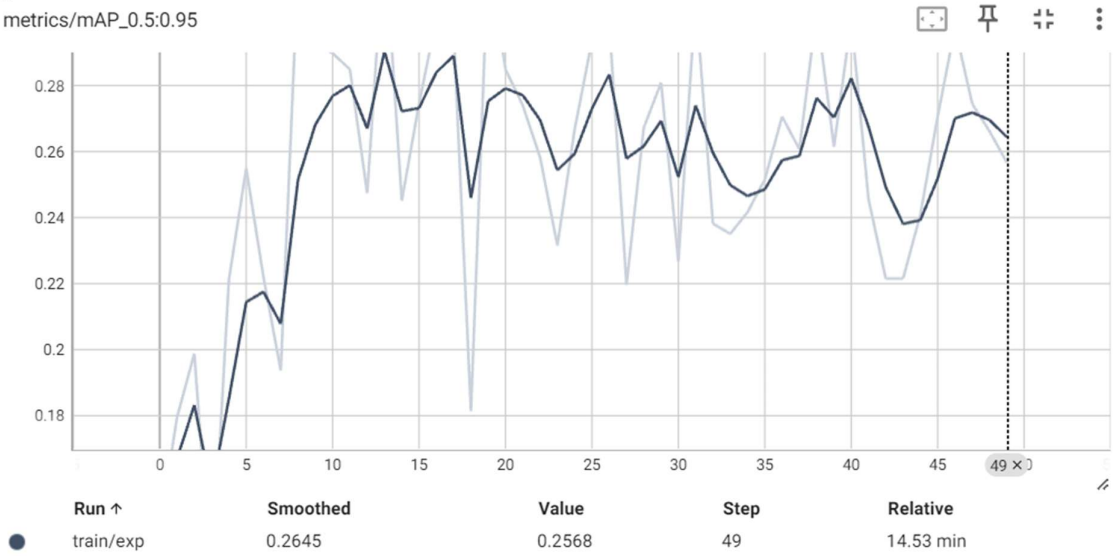
- The model was trained for 50 epochs to ensure sufficient learning without overfitting.
- A batch size of 8 was chosen for efficient memory usage and training iterations.
- Images were resized to 416x416 pixels to balance detection accuracy and computational load.
- Data, including images and annotations, was processed for training.
- The model learned iteratively, with periodic validation for fine-tuning and improved performance.

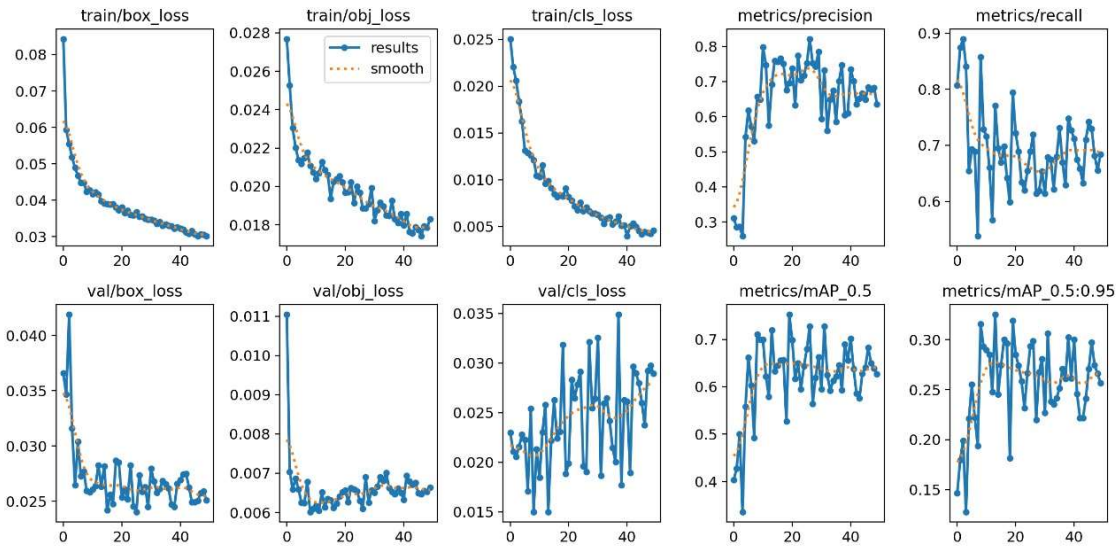
Step 5: **Evaluation**

Mean Average Precision(mAP) is a key metric for evaluating object detection models. It considers both how precise (correct) and complete (all objects found) the bounding boxes predicted by the model.



mAP@0.5 is 62.7% it represents Accuracy of predictions with at least 50% overlap with ground truth.





- **train/box_loss**: Shows a consistent decrease, indicating improved accuracy in bounding box predictions for bottle caps during training.
- **train/obj_loss**: Displays a downward trend, reflecting better detection of the presence of objects (bottle caps) in the training images.
- **train/cls_loss**: Gradually decreases, demonstrating enhanced accuracy in classifying bottle caps correctly during training.
- **metrics/precision**: Precision improves, indicating fewer false positives in bottle cap detection as training progresses.
- **metrics/recall**: Recall increases, showing the model's growing ability to detect most bottle caps without missing them.
- **val/box_loss**: Shows a sharp initial drop and stabilization, suggesting effective generalization in predicting bounding boxes on unseen data.
- **val/obj_loss**: Decreases and stabilizes, reflecting the model's capability to detect objects in validation images accurately.
- **val/cls_loss**: Fluctuates but trends downward, indicating improved classification of bottle caps on new data.
- **metrics/mAP_0.5**: Increases, demonstrating better overall accuracy in detecting and classifying bottle caps at an IoU threshold of 0.5.
- **metrics/mAP_0.5:0.95**: Shows an overall upward trend, highlighting the model's robustness in accurately detecting bottle caps across varying detection thresholds.

Precision is 63.6% it indicates Percentage of true positive detections out of all positive detections.

Recall percentage is 68.4 it indicates Percentage of actual objects correctly detected.

mAP@0.5:0.95 (25.7%) it indicates Average precision across multiple overlap thresholds, indicating overall model robustness.

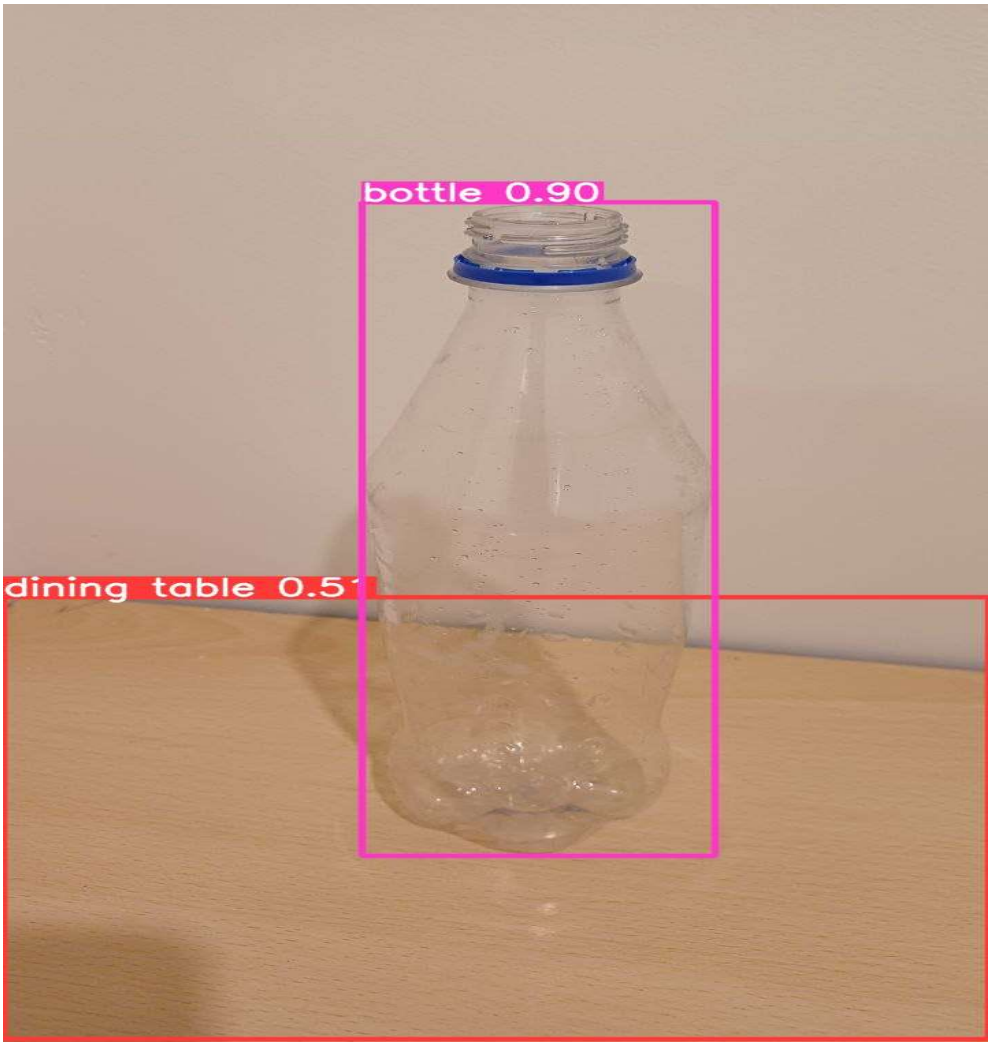
Step 6: **Testing:**

- Tested the model on a separate test dataset, confirming its effectiveness.
- Developed a user interface for real-time detection, enabling users to upload images and detect bottle caps.

Results on Test data


Bottle With Cap 0.76
Thums Up
CARBONATED WATER

Step 7: Interface



Code:

Link to Google Colab notebook

https://colab.research.google.com/drive/1idnmBTG-WbGbXF_x6cr2xGqMrIqFSADN#scrollTo=scmnS9hPM6Hh