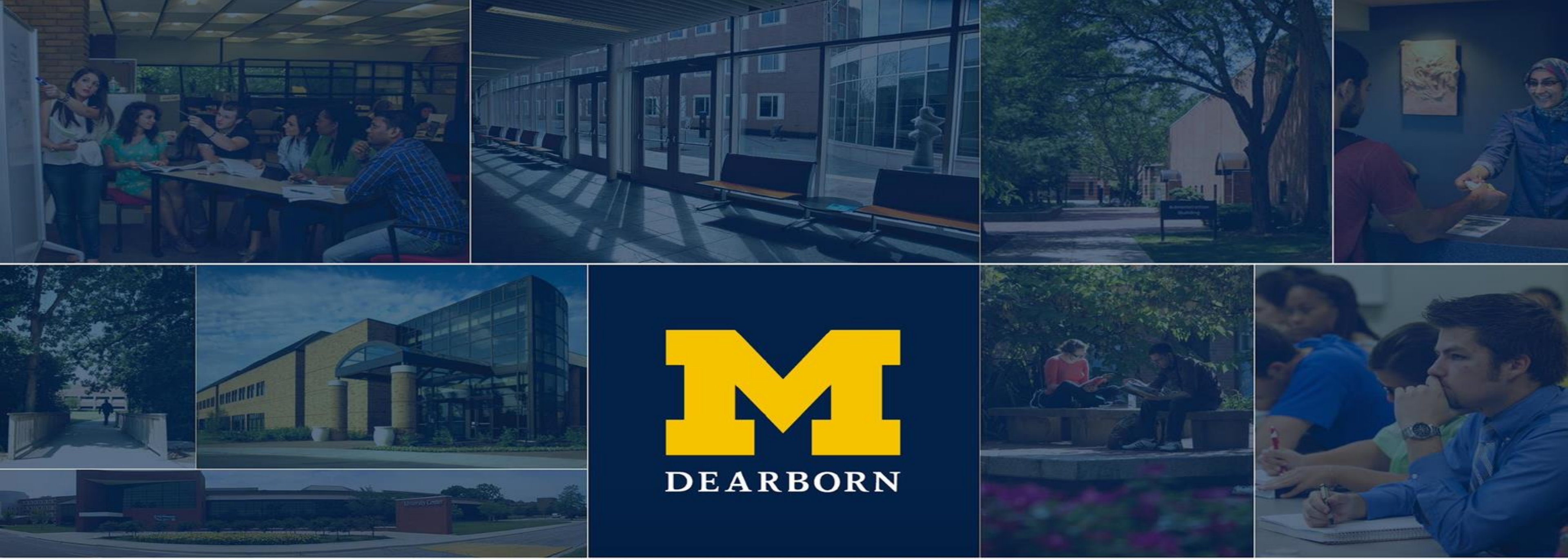

Detecting Plastic Bottles with YOLO v5: An Object Detection Approach for Recycling and Waste Management

CIS 585 - Advanced Artificial Intelligence

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CONTENTS

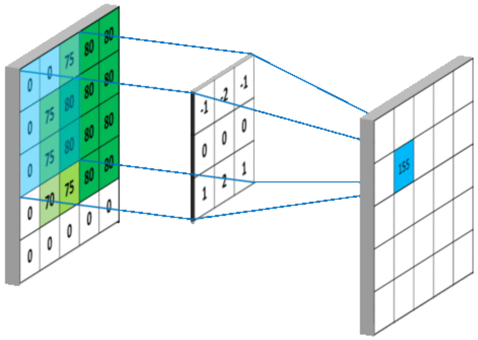
- Software Overview
- Convolution Neural Network
- Object Detection
- YOLO
- Find Bottle - My Work
- Results
- Challenges Faced
- Future Scope
- Project Demo

SOFTWARE OVERVIEW

The Find Bottle software utilizes YOLO v5, a cutting-edge object detection model, to detect plastic bottles in images or video frames. It processes input data, identifies regions of interest, and uses deep learning to accurately detect plastic bottles. The software is user-friendly, scalable, and aims to support waste management efforts and environmental conservation by identifying and quantifying plastic bottle pollution.

CONVOLUTION NEURAL NETWORK

Convolutional Neural Network (**CNN**) is a class of artificial neural network most commonly applied to analyze visual imagery. CNNs use a mathematical operation called convolution in place of general matrix multiplication in at least one of their layers.They are specifically designed to process pixel data and are used in image recognition and processing.



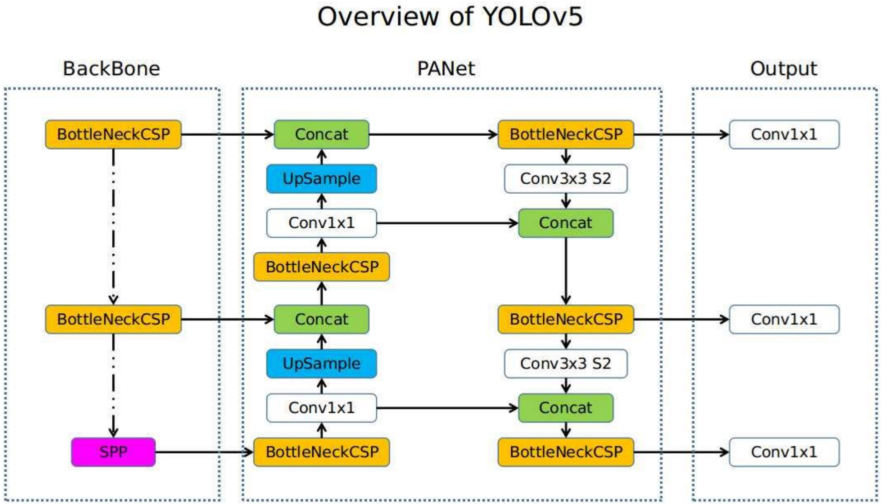
OBJECT DETECTION

Object detection is an important and challenging task with numerous applications, including autonomous vehicles, video surveillance, robotics, image retrieval, human-computer interaction, and augmented reality, among others. It plays a crucial role in enabling machines to perceive and understand visual information from the world.

Object detection typically involves multiple steps, such as region proposal generation, feature extraction, object classification, and bounding box regression. The output of an object detection model includes the detected objects' class labels, bounding box coordinates, and possibly additional information such as object scores or confidence levels.

YOLO

YOLO (You Only Look Once) is a real-time object detection model that has gained popularity in computer vision and deep learning communities. It is a single-stage object detection model, which means it performs object detection and classification in a single pass, making it extremely fast and efficient for real-time applications



MY WORK

- Answering the Why?
    - Why this project
    - Why this Datasets
    - Why this approach
    - Why Streamlit

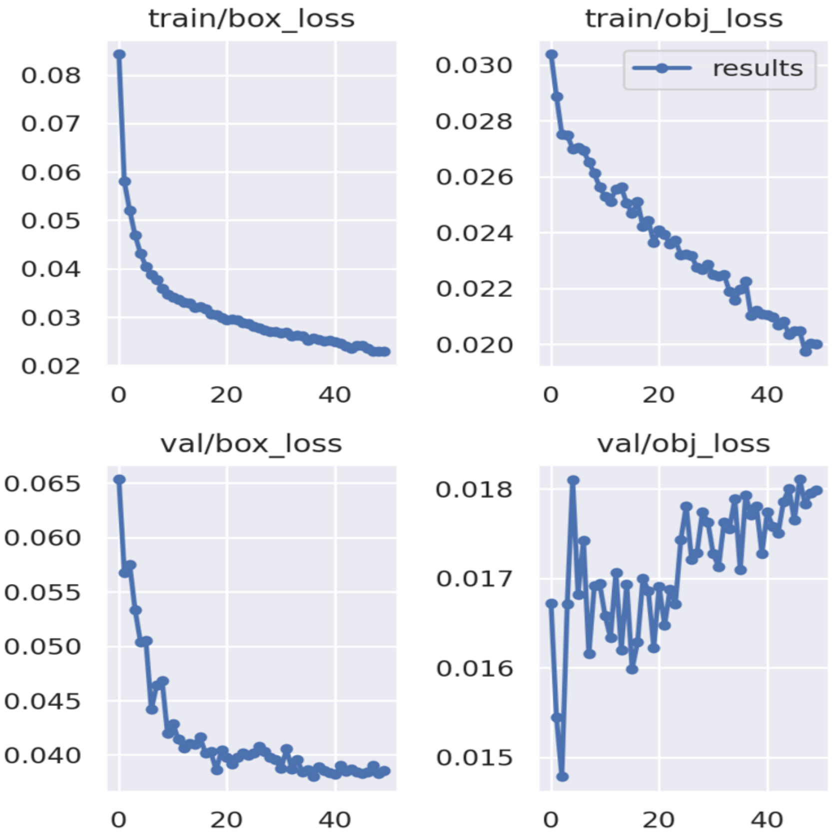
TRAINING LOGS & PLOTS

```
%%time
!python yolov5/train.py --img 416 --batch 16 --epochs 50 --data ./PlasticBottle/data.yaml --weights
yolov5/yolov5s.pt --cache
```

```
      Epoch    GPU_mem   box_loss   obj_loss   cls_loss  Instances       Size
      49/49      1.67G    0.02297    0.02002          0         53        416: 100% 136/136 [00:23<00:00,  5.76it/s]
                 Class     Images  Instances          P          R      mAP50   mAP50-95: 100% 37/37 [00:08<00:00,  4.47it/s]
                   all       1174       1550      0.573      0.554      0.423      0.278

50 epochs completed in 0.453 hours.
Optimizer stripped from yolov5/runs/train/exp3/weights/last.pt, 14.3MB
Optimizer stripped from yolov5/runs/train/exp3/weights/best.pt, 14.3MB

Validating yolov5/runs/train/exp3/weights/best.pt...
Fusing layers...
Model summary: 157 layers, 7012822 parameters, 0 gradients, 15.8 GFLOPs
                 Class     Images  Instances          P          R      mAP50   mAP50-95: 100% 37/37 [00:12<00:00,  3.07it/s]
                   all       1174       1550      0.584      0.571       0.45      0.301
Results saved to yolov5/runs/train/exp3
CPU times: user 25.2 s, sys: 3.24 s, total: 28.5 s
Wall time: 33min 10s
```


train/box_loss
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0
20
40
train/obj_loss
results
0.030
0.028
0.026
0.024
0.022
0.020
0
20
40
val/box_loss
0.065
0.060
0.055
0.050
0.045
0.040
0
20
40
val/obj_loss
0.018
0.017
0.016
0.015
0
20
40

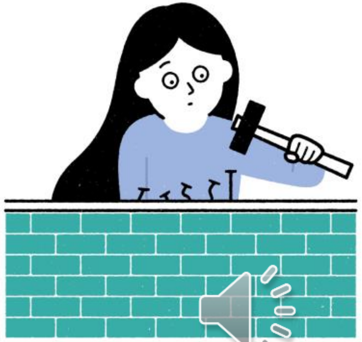
PREDICTION RESULTS FROM VALIDATION DATASET

CHALLENGES FACED

Video Display Issue in Streamlit for Object Detection:

During the presentation of the project, a challenge was encountered with video display in Streamlit. Despite multiple attempts, the video encoding in Streamlit was not successful, resulting in the inability to display the video output of the object detection process using Streamlit.

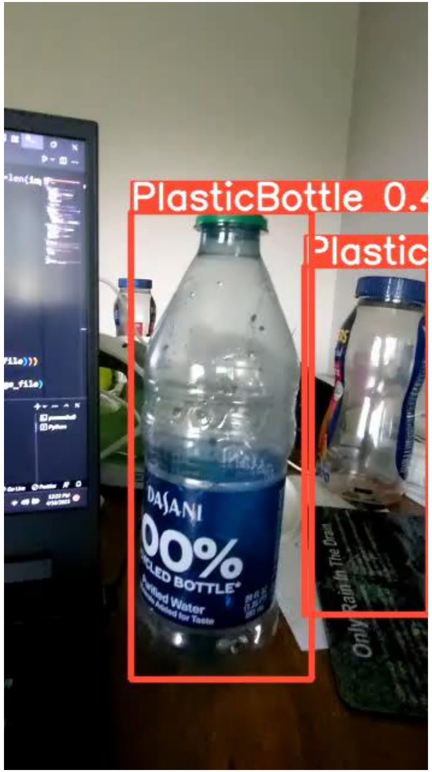
As a workaround, OpenCV was utilized as an alternative to display the video. OpenCV, a powerful computer vision library, was leveraged to process and display the video frames with the detected objects in real-time. While this approach allowed for successful video display, it required additional effort and time to implement and deviated from the initial plan of using Streamlit for visualization.



FUTURE SCOPE

- Improve video encoding in Streamlit for seamless video display.
- Enhance object detection accuracy through fine-tuning, hyperparameter optimization, and exploration of other object detection models.
- Expand the system to detect other types of waste items, beyond plastic bottles.
- Implement real-time monitoring and alerts for effective waste management enforcement.
- Optimize the software for deployment on edge devices for resource-constrained environments.
- Integrate the system with existing waste management systems for automated sorting and categorization.
- Develop educational materials and outreach programs to raise awareness about plastic pollution and sustainable waste management practices.

VIDEO RESULTS



SOFTWARE DEMO