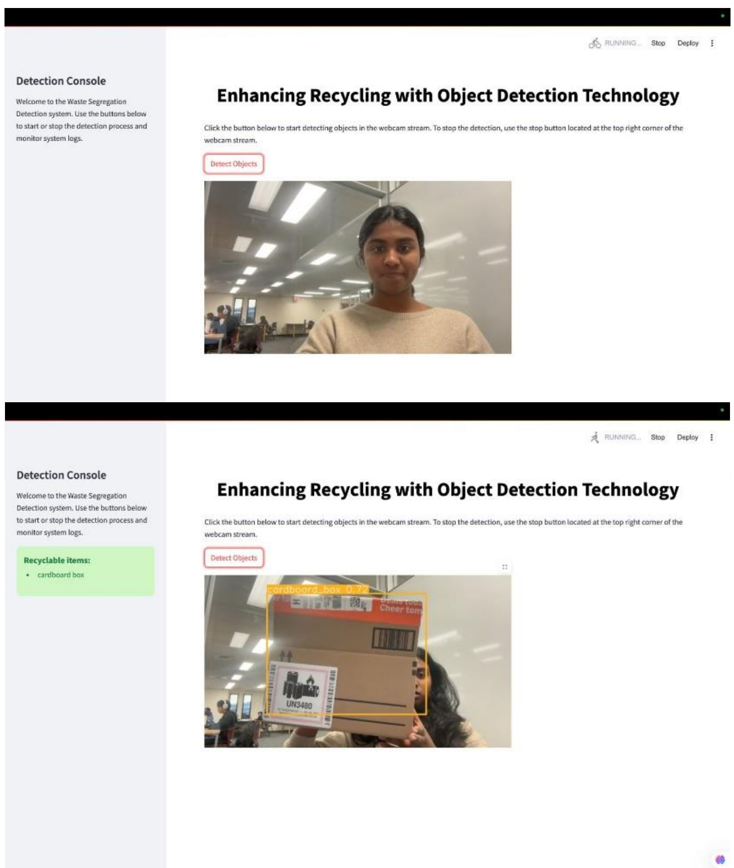
Enhancing Recycling with Object Detection Technology

• Abstract.

The rapid growth in waste production worldwide has resulted in substantial challenges for waste management, including the proliferation of landfills, pollution, and wasted energy. Manual waste segregation is a labor-intensive and time-consuming process, making effective recycling an imperative. We propose an automated system that utilizes object detection technology to improve recycling efficiency. Our real-time waste detection system uses a webcam to categorize waste into three groups: Recyclable, Non-recyclable, and Hazardous. The system, built using the advanced YOLOv8 object detection model, was trained on a custom dataset augmented with Roboflow and utilizes OpenCV for image processing. This system can be implemented in a variety of settings, including homes, parks, and recycling units, to promote eco-friendly practices and efficient waste management in diverse environments.



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• Introduction

A comprehensive system is urgently needed to effectively manage, detect, segregate, and recycle waste into various categories, thereby addressing the emerging issues of rapid waste growth, economic feasibility, environmental sustainability, and the widespread lack of awareness about the importance of waste management in our society. We have developed a sophisticated garbage detection system to address this pressing environmental problem, which accurately identifies and categorizes garbage into three specific types of waste, namely, recyclable, non-recyclable, and organic waste, thereby enabling effective waste management strategies. There are three main categories of waste: recyclable materials that can be reused and repurposed, non-recyclable waste that cannot be reused and must be disposed of, and hazardous waste that poses a significant threat to the environment and its ecosystem. We are currently in the process of training our model using a combination of datasets from Roboflow and custom data, which comprises a diverse range of images that will be thoroughly processed with OpenCV in order to achieve optimal results. For real-time object detection, we will utilize YOLOv8, a rapid and remarkably accurate system that is capable of detecting multiple items simultaneously, including plastic, plastic bottles, and paper, with impressive high precision and remarkable speed. We successfully fine-tuned YOLOv8, resulting in higher convergence and a significant increase in accuracy, which led to improved model performance. This project involved a comprehensive and intricate process of training and testing a model on a diverse range of 22 distinct waste categories, encompassing various types of recyclable and non-recyclable materials. Next, the training loop involves setting up distinct optimizers, learning rate schedules, and momentum, as well as a few other essential components, such as loss functions, batch sizes, and gradient clipping. To thoroughly evaluate the model's performance, the data is validated on 10% of the entire dataset, and its performance is comprehensively measured using a range of metrics, including Mean Average Precision (mAP), Intersection over Union (IoU), Precision, and Recall, in order to gain a more detailed understanding of its strengths, weaknesses, and potential areas for improvement.

• Approach.

For this project, we utilized code from the GitHub repository Waste Classification using YOLOv8 to implement the Streamlit-based user interface and integrate object detection capabilities. Specifically, the main.py file from the repository served as a reference for designing the front-end application. This included adapting the functionality for real-time waste detection using a webcam stream and providing an intuitive interface for users to interact with the detection model.

While the foundational structure of the main.py script was taken from the repository, significant modifications were made to tailor the application to our dataset and project requirements. For example, we customized the code to include the segregation of detected objects into categories (Recyclable, Non-Recyclable, and Hazardous) and adjusted the detection display to align with our YOLOv8-trained model. These adaptations ensured that the borrowed code met the specific goals of our project while enhancing its usability and effectiveness.

To tackle the waste detection problem, our project followed a systematic workflow involving data preparation, model selection, training, validation, and testing. The goal was to accurately classify and localize 22 different waste categories in images to aid in efficient waste sorting.

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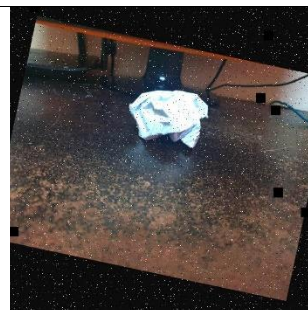
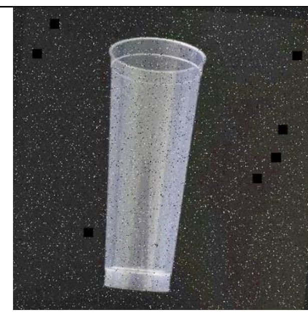
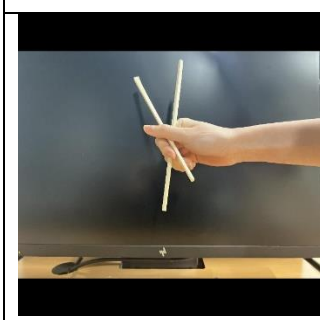
1. Data Preparation

We used a dataset from Roboflow that includes labeled images for 22 categories of waste such as plastic bottles, cardboard boxes, batteries, etc. The dataset was split into **train**, **validation**, and **test** sets in the following proportions:

- Train: 70%
- Validation: 20%
- Test: 10%

Each split contained images and corresponding annotations in YOLO format.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Challenges Faced:

A warning was encountered during validation indicating a mismatch between the number of bounding boxes and segmentation labels (len(segments) != len(boxes)). This suggested that the dataset contained mixed detect-segment labels.

- **Solution:** To address this, we removed segmentation labels and retained only bounding boxes, ensuring compatibility with the object detection task.

2. Model Selection

We utilized the **YOLOv8** (You Only Look Once, version 8) object detection framework, which is state-of-the-art for real-time detection tasks due to its speed and accuracy. YOLOv8's modular design allowed us to efficiently handle a multi-class detection problem.

- **Pretrained Weights:**
  We fine-tuned a YOLOv8 model pre-trained on the COCO dataset. This transfer learning approach enabled faster convergence and improved accuracy, given the large number of classes in our dataset.

3. Training Process

- **Hyperparameters:**
  - Optimizer: SGD (Stochastic Gradient Descent)
  - Learning Rate: 0.01
  - Momentum: 0.9
  - Weight Decay: 0.0005
  - Epochs: 50
  - Image Size: 640x640

- **Data Augmentation:**
  During training, data augmentation techniques like horizontal flipping, scaling, and random cropping were applied to improve the model's robustness to real-world variations.

- **Obstacles Faced:**
  - **Training Time**: The model took several hours (approx. 59 hours) to train on our hardware due to the large number of classes and dataset size.
  - **Solution:** To manage time efficiently, we monitored training progress via the YOLO logs and adjusted the batch size for optimal GPU utilization.

4. Validation and Testing

- **Validation Results:**
  After training, the model was validated on 1,857 images from the validation set. Performance metrics included:
  - mAP@0.5: **0.899**
  - mAP@0.5:0.95: **0.731**
  - Precision: **0.901**
  - Recall: **0.861**

  Per-class performance indicated excellent results for classes like chemical_plastic_bottle (mAP@0.5 = 0.995) and snack_bag (mAP@0.5 = 0.987). However, some classes like plastic_cup (mAP@0.5 = 0.505) and straw (mAP@0.5 = 0.825) had lower accuracy due to their high intra-class variability or overlapping features with other objects.
- **Testing Results:**
  Testing was performed on the test set to evaluate the final model. Predictions were saved to runs/detect/val/.

• Experiments and results.

1. Dataset and Experimental Setup

- **Dataset Details**
  The dataset was sourced from **Roboflow**, containing 22 distinct waste material classes. Each image included bounding box annotations in the YOLO format. The dataset was divided into the following subsets:
  - **Training Set**: ~7,000 images (70% of the dataset)
  - **Validation Set**: ~1,607 images (20% of the dataset)
  - **Test Set**: ~800 images (10% of the dataset)

- **Data Composition**
  The dataset encompassed a wide variety of objects, including:
  - **High-frequency classes:** plastic_bottle, scrap_paper
  - **Low-frequency classes:** plastic_cup, paint_bucket

  This uneven class distribution contributed to performance variation, as discussed in later sections.

- **Hardware Setup**
  - **Development Environment**: MacBook Pro (local training)
  - **Training Environment**: Google Colab (for GPU acceleration)

- **Model Architecture**
  - Model: YOLOv8 (pretrained on COCO dataset)
  - Rationale: Selected for its efficiency in multi-class object detection tasks.

2. Metrics for Evaluation

The following metrics were used to assess model performance:

- **mAP@0.5**: Mean Average Precision at IoU ≥ 0.5.
- **mAP@0.5:0.95**: Mean Average Precision averaged across IoU thresholds from 0.5 to 0.95 (in 0.05 steps).
- **Precision**: The fraction of correctly predicted positives.
- **Recall**: The fraction of true positives correctly identified.

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3. Experimental Results

- **Overall Validation Performance**
  After 50 epochs, the model's overall validation results were as follows:

- **Metric Value**

  mAP@0.5: 0.899
  mAP@0.5:0.95: 0.731
  Precision: 0.901
  Recall: 0.861

Per-Class Performance
The table below summarizes precision, recall, and mAP scores for individual classes:

Class	Instances	Precision	Recall	mAP@0.5	mAP@0.5:0.95
Battery	133	0.938	0.880	0.920	0.820
Cardboard Box	209	0.867	0.813	0.887	0.666
Chemical Plastic Bottle	111	0.995	1.000	0.995	0.894
Light Bulb	54	0.935	1.000	0.993	0.839
Snack Bag	142	0.992	0.986	0.987	0.841
Plastic Cup	148	0.667	0.520	0.505	0.426
Straw	114	0.869	0.728	0.825	0.500

- **Analysis**

- **Strong Performance**: Classes with distinct features (*chemical_plastic_bottle*, *light_bulb*) performed well.
- **Weak Performance**: High-variability classes (*plastic_cup*, *straw*) exhibited lower precision and recall due to poor representation or overlapping features.

4. Baseline Comparison

To establish a benchmark, we compared YOLOv8 with two naive approaches:

Comparison Results

Model	mAP@0.5	Precision	Recall
Random Classifier	~0.045	-	-
Majority Classifier	-	~0.11	~0.07
YOLOv8	0.899	0.901	0.861

YOLOv8 significantly outperformed the baselines, demonstrating its robustness for this task.

5. Hyperparameter Tuning

Several hyperparameters were explored during training to optimize performance:

Parameter	Value	Observation
Learning Rate	0.01	Balanced convergence; lower values caused slower learning.
Momentum	0.9	Stabilized training, and reduced oscillations.
Batch Size	16	Larger sizes caused memory issues; smaller sizes increased overfitting risk.
Epochs	50	Optimal trade-off between training time and performance.

- **Performance Trends**
  - Higher learning rates caused unstable training.
  - Increasing epochs improved performance but showed diminishing returns beyond 50 epochs.

6. Qualitative Analysis

- **Correct Predictions**
  - Objects like *lightbulbs* and *cardboard boxes* were detected accurately, even under partial occlusion.
- **Misclassifications**
  - Common confusion occurred between plastic bags and snack bags due to similar features.
- **Edge Cases**
  - Difficulties arose in detecting objects like paint buckets under poor lighting or partial cropping.
- **Illustrative Examples**
  - Placeholder: Add visual examples showing correct detections and misclassifications with bounding boxes and confidence scores.

7. Discussion

Expected Trends

- Classes with distinct visual features performed better (e.g., *chemical plastic bottles*).
- Increasing epochs improved detection but plateaued after 50 epochs.

Unexpected Trends

- Despite a relatively balanced dataset, *plastic cup* underperformed, likely due to poor representation or inconsistent annotations.

Segregation of Classes

The waste classes are grouped into the following categories for better analysis and application in waste sorting:

- **Recyclable**:
  - *cardboard_box*, *can*, *plastic_bottle_cap*, *plastic_bottle*, *reuseable_paper*
- **Non-Recyclable**:
  - *plastic_bag, scrap_paper, stick, plastic_cup, snack_bag, plastic_box, straw, plastic_cup_lid, scrap_plastic, cardboard_bowl, plastic_cultery*
- **Hazardous**:
  - *battery, chemical_spray_can, chemical_plastic_bottle, chemical_plastic_gallon, light_bulb, paint_bucket*

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• **Qualitative results.**

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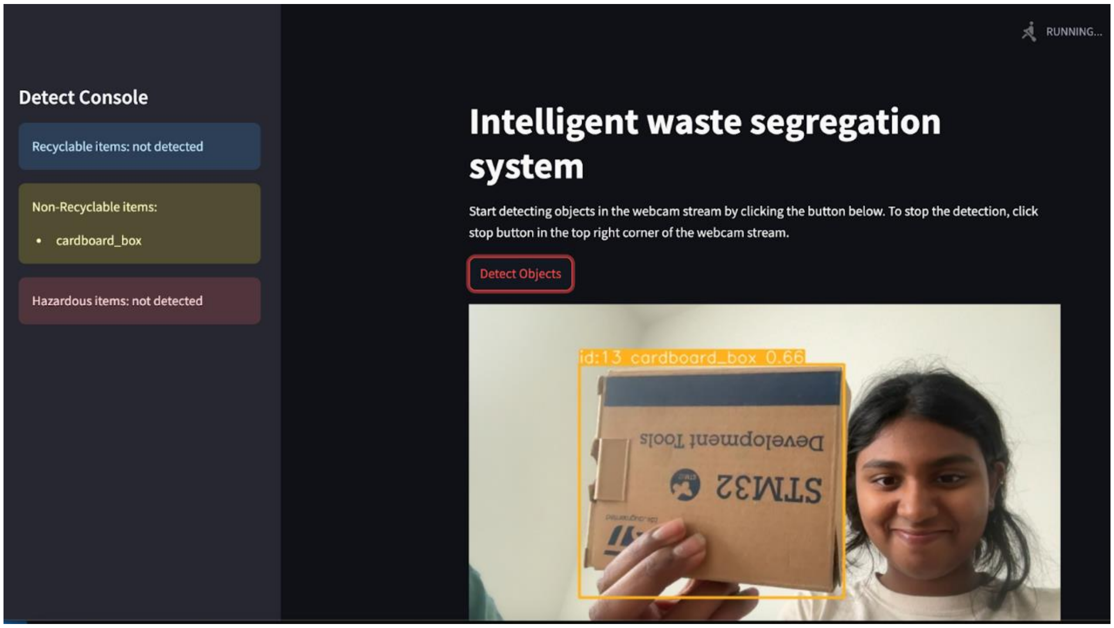
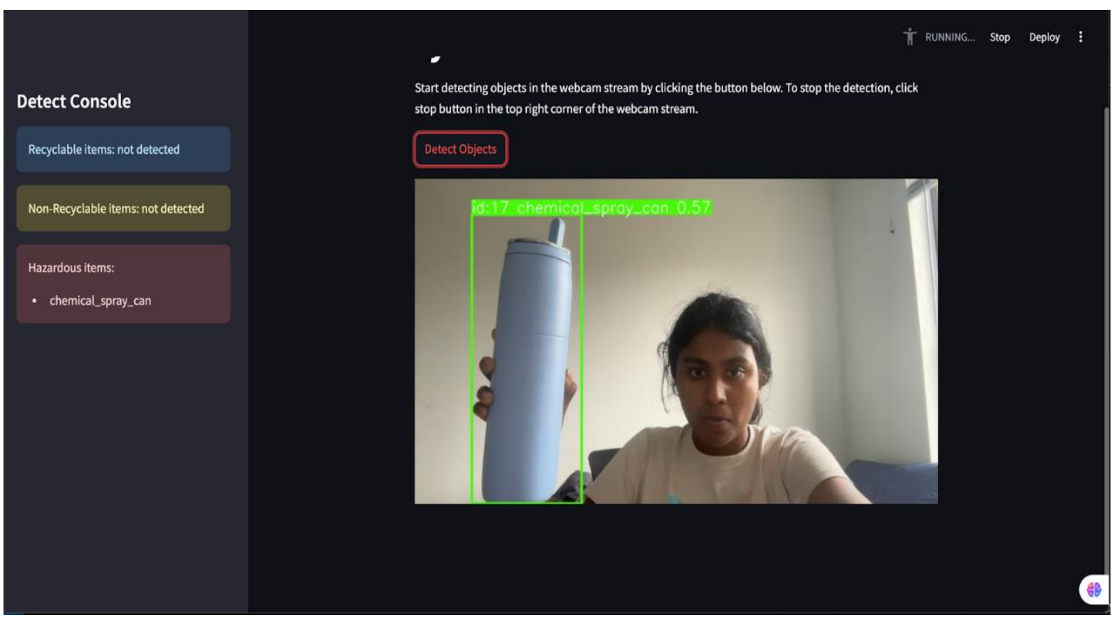
Success cases:





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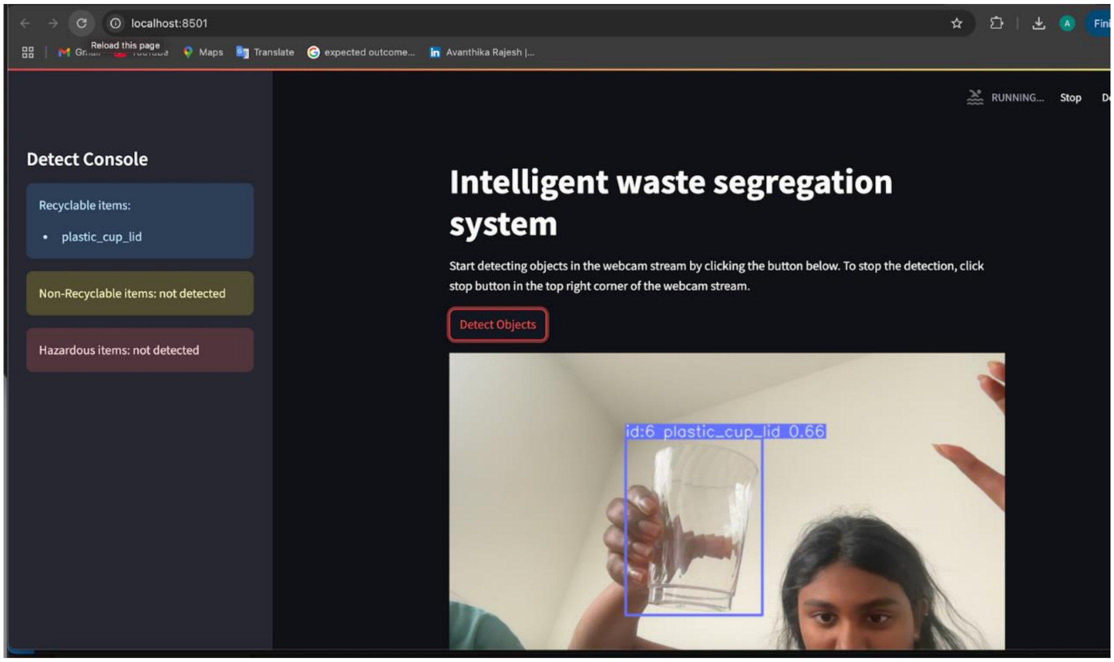

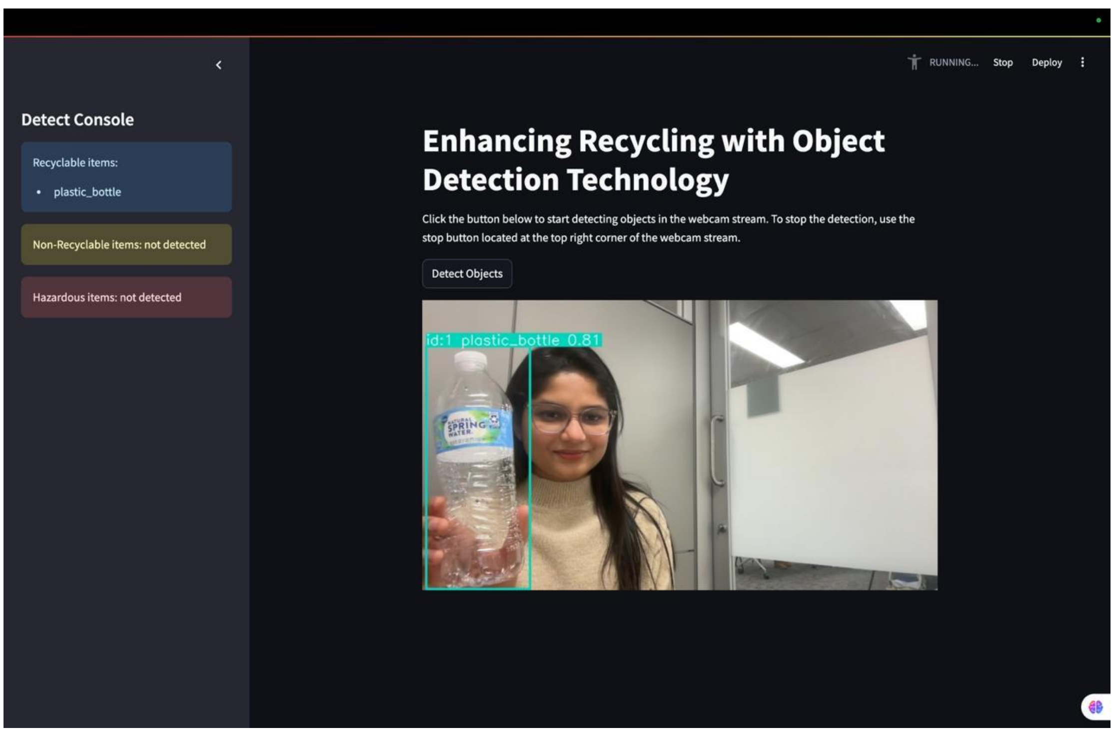

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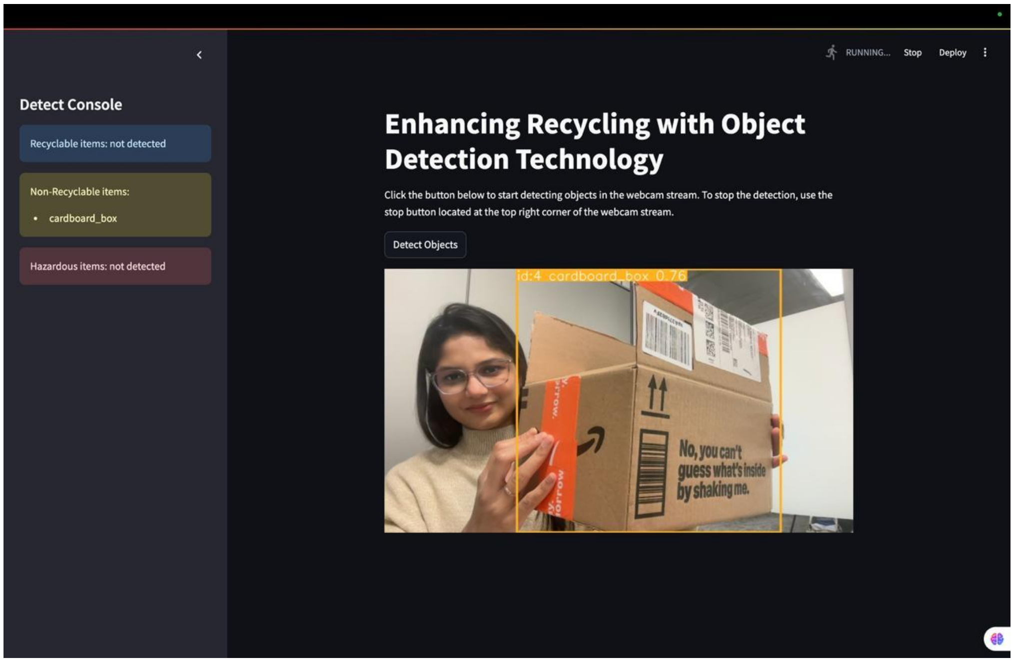

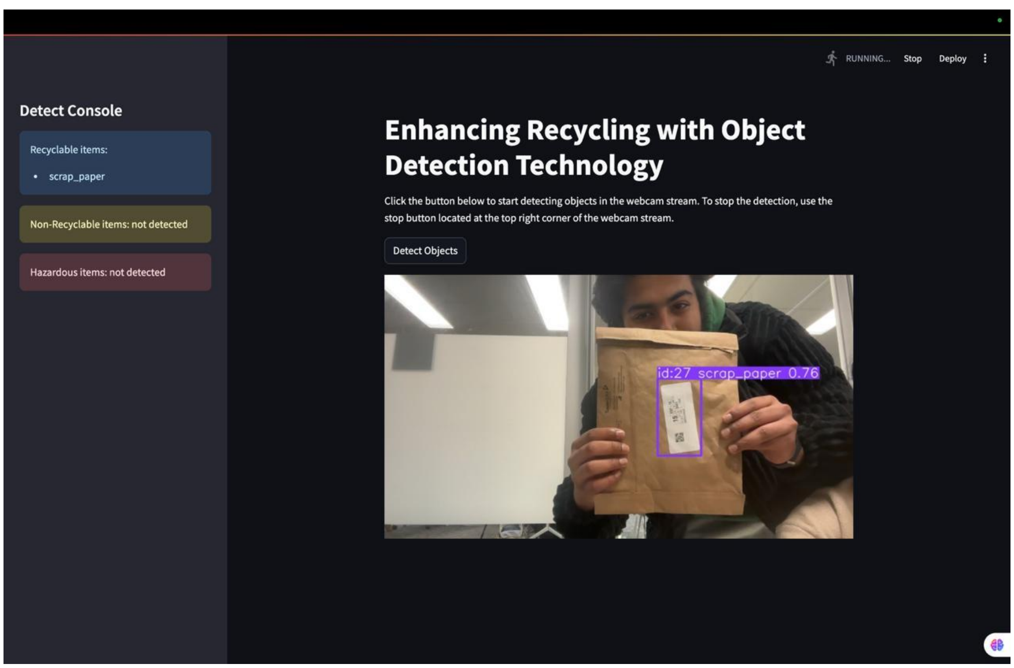

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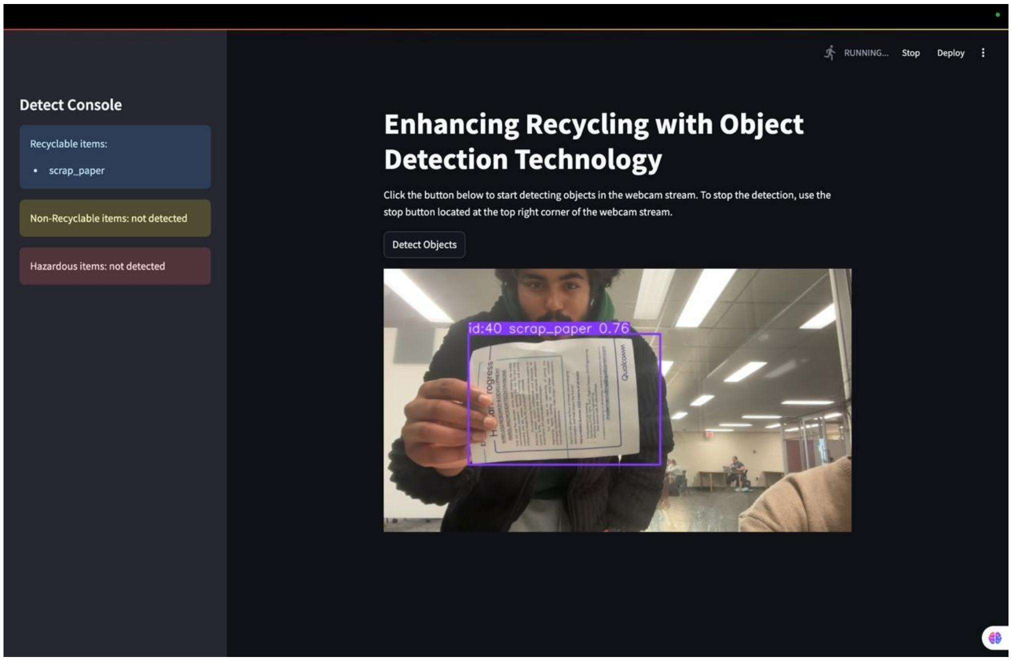

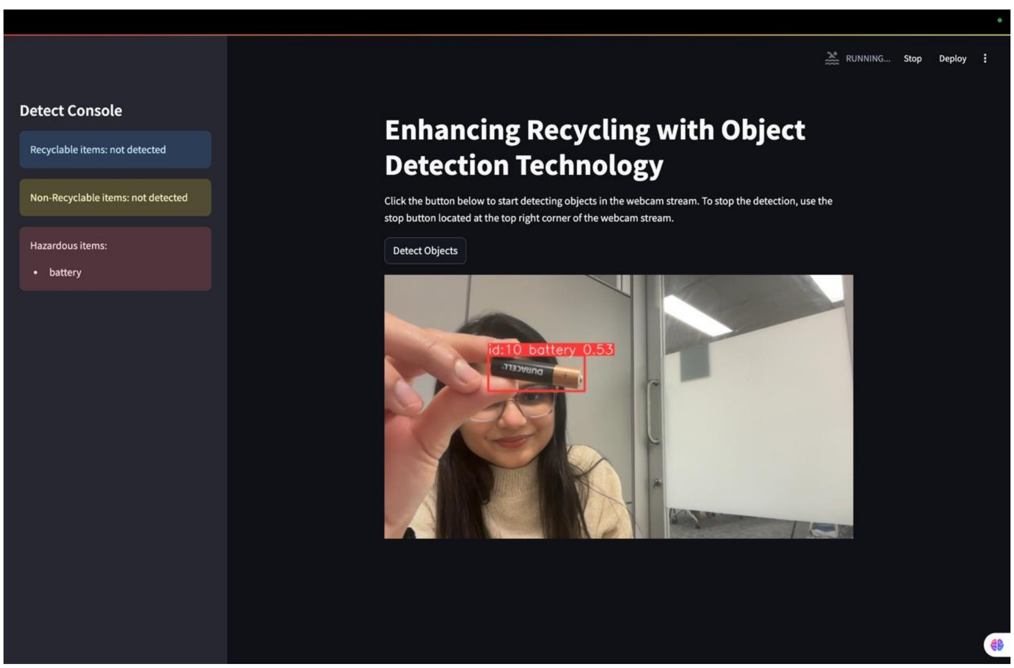

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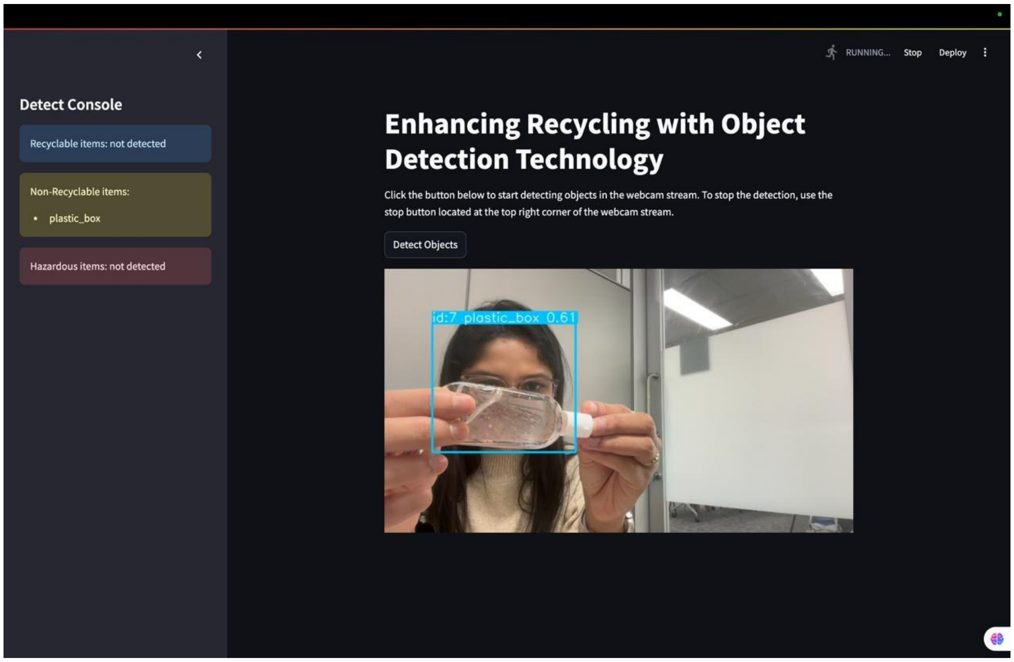

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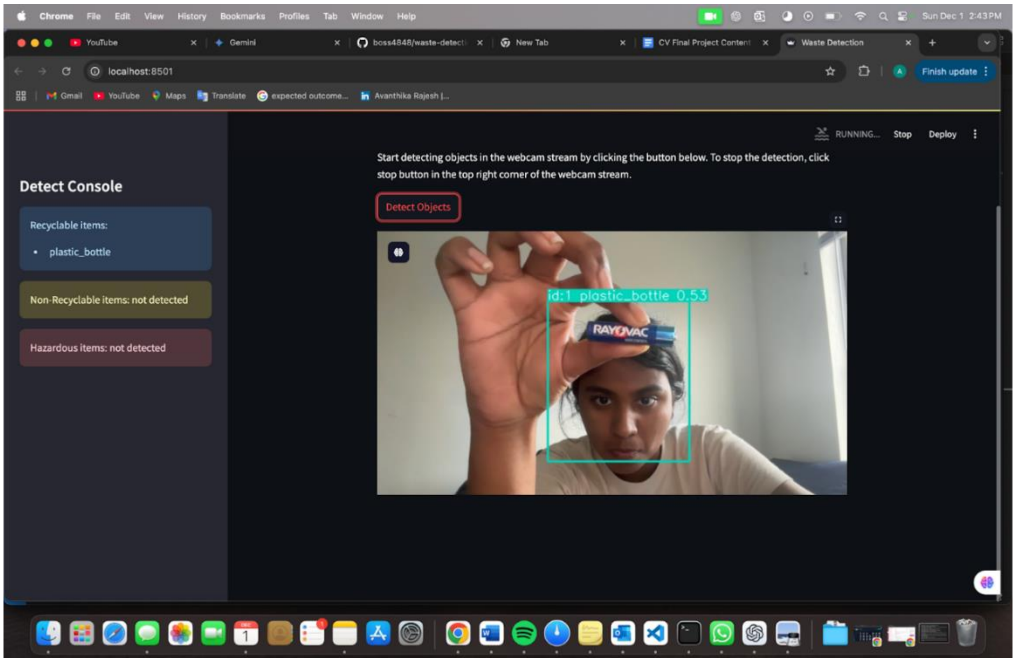
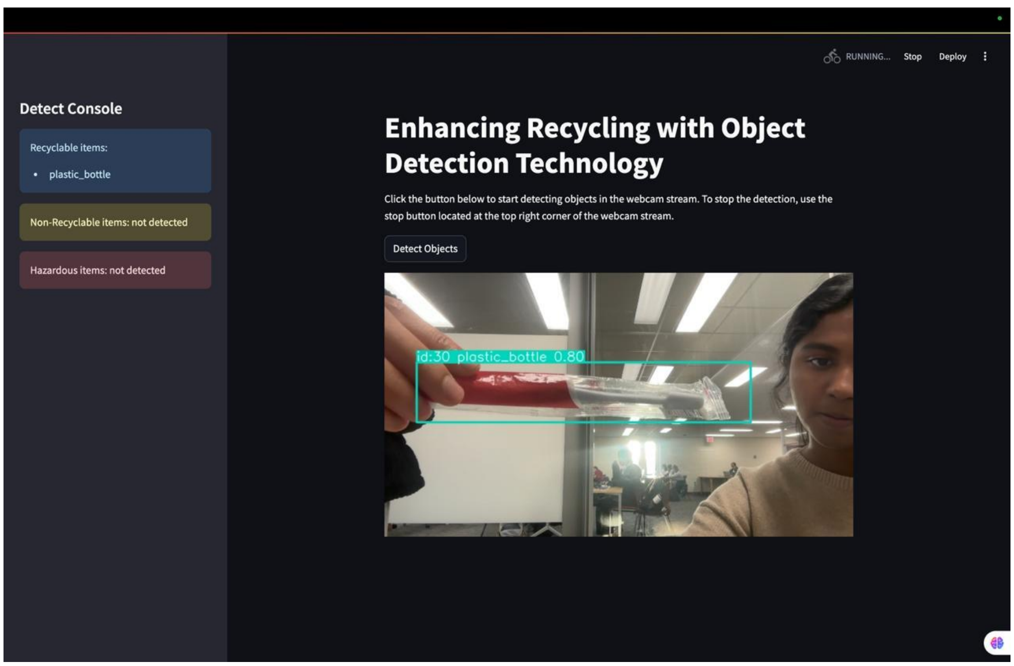
Failure cases:





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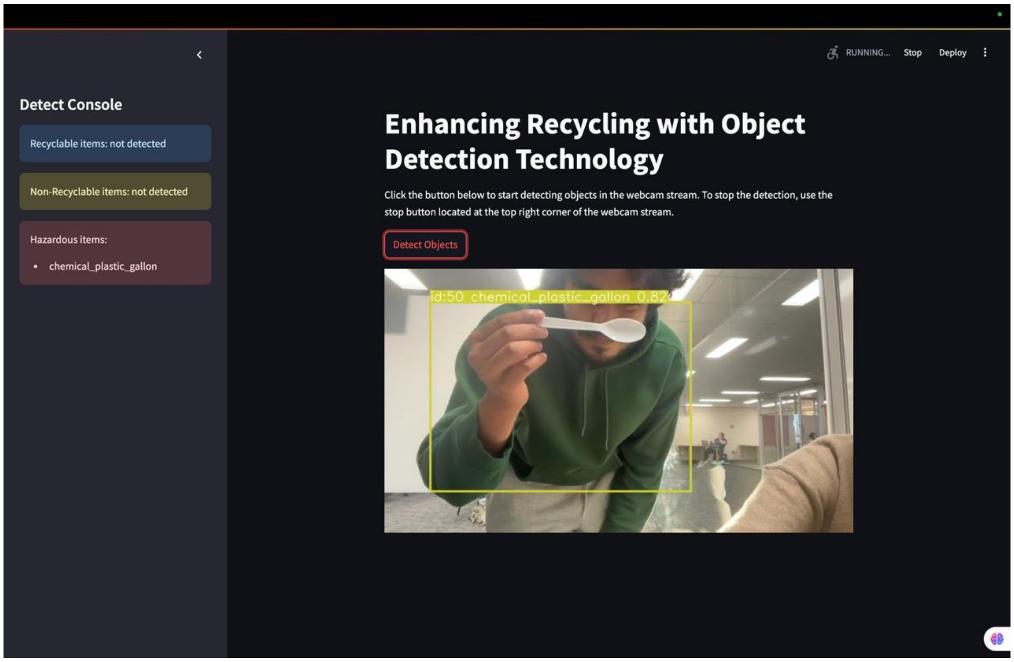

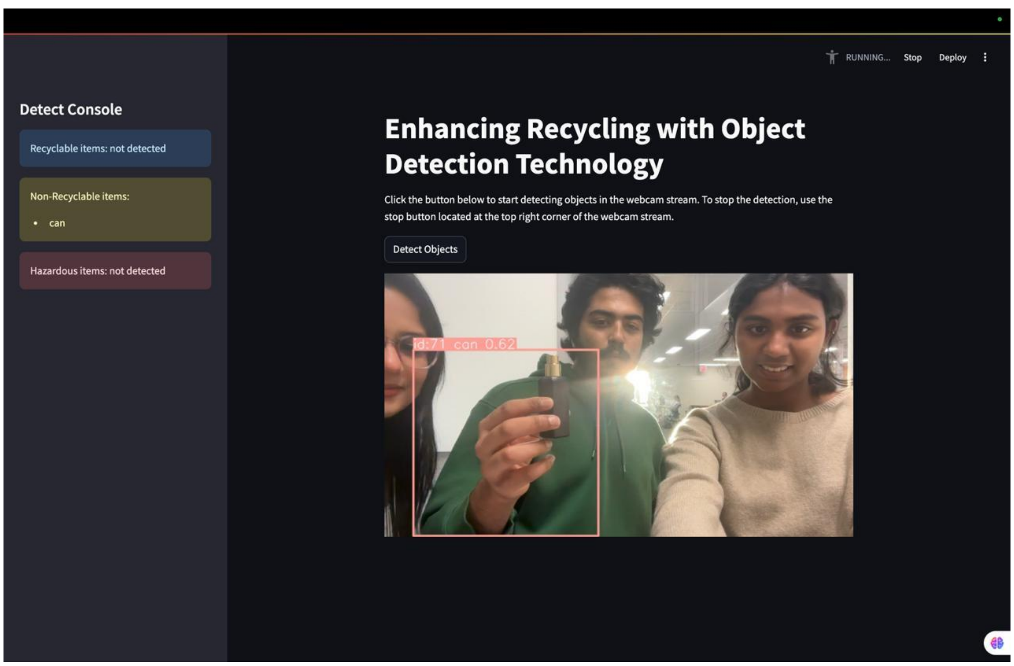

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Conclusion.

This comprehensive report thoroughly describes the process of developing the innovative garbage detection system, which leverages the advanced capabilities of YOLOv8, a cutting-edge object detection model. We trained, tested, and validated our model using different types of data from 22 diverse categories, and evaluated its performance with several metrics, namely, precision, recall, and accuracy. Precision, recall, mean average precision and other metrics are commonly used to evaluate the performance of machine learning models. This model achieves an impressive accuracy of 0.89, performing significantly better in detecting specific objects such as lightbulbs, chemical plastic bottles, and cardboard boxes than it does with objects like plastic bags or paint buckets. The items that are detected are further categorized into three distinct categories, namely Recyclable, Non-recyclable, and Hazardous, and this entire process occurs in real time.

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4. **Roboflow Dataset Tools**:

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Evaluation Metrics References

1. **Mean Average Precision (mAP)**:

   • Everingham, M., et al. (2010). “The Pascal Visual Object Classes (VOC) Challenge.” http://host.robots.ox.ac.uk/pascal/VOC/

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