Waste Detection and Segregation Using Computer Vision and Algorithms

TEAM: SHETA KE KPTAANZ

CONTRIBUTORS:

- Ayush Sheta
- Shivam Gupta
- Kavya Bhalodi
- Soham Sadavarte

PRESENTED TO: Dr. SACHIN CHAUDHARI

Under guidance of Ansh Shah (TA)

INDEX

OBJECTIVES :

The primary objective of this project is to develop an advanced waste management system that can:

- **Automatically detect and classify waste items** using advanced computer vision techniques and algorithms.
- Segregate waste into three broad categories, namely Recyclable, Non-Recyclable, and Hazardous waste, ensuring efficient disposal.
- Due to efficient waste detection and segregation, conclusively, enhance environmental sustainability by facilitating improved recycling processes.
- Utilize hardware and software integration to create a scalable and deployable solution for real-world waste management challenges.

This solution addresses India's growing waste crisis by providing an automated approach to waste segregation, reducing human intervention, and increasing recycling efficiency.

Proposed Solution: Smart Waste Segregator Model (SSM)

The proposed solution is the creation of a Smart Waste Segregator Model (SSM) that leverages modern deep learning algorithms, computer vision, and hardware integration to detect, classify, and direct waste to appropriate disposal bins.

Solution Pipeline:

1 **Data Input**

Real-time image capture of waste items using camera modules.

2 **Image Classification**

The captured images are fed into a YOLOv8-based computer vision model. This model classifies waste into one of the three categories:

Recyclable: Cardboard boxes, plastic bottles, aluminum cans, etc.

Non-Recyclable: Plastic bags, snack wrappers, plastic containers, etc.

Hazardous: Batteries, light bulbs,

3 **Waste Disposal**

After classification, the system directs the waste to the appropriate bin or disposal mechanism for processing, based on its category.

4 **Waste Segregation**

The waste is segregated into recycling bins for **recyclable materials** or processed accordingly for **hazardous and non-recyclable** waste.

Project Timeline and Progress

1

Data Collection (Completed)

Completed: Captured 1213 images of waste items from the IIIT campus and incorporated an additional 3000 images from public datasets, leading to a dataset of 4566 images.

2

Dataset Creation (Completed)

Completed: Annotated the dataset using Roboflow, classifying it into 15 waste classes, distributed among three main categories: Recyclable, NonRecyclable, and Hazardous.

3

Model Training (Completed)

Completed: Trained a YOLOv8 model using the dataset, after performing preprocessing and augmentation to enhance classification accuracy.

4

Dataset Expansion (In Progress):

In Progress: Continuously expanding the dataset to include more diverse examples, which will improve the model's robustness and generalization capability.

5

Model Testing (Completed) :

Completed: Testing the model's performance on various scenarios, focusing on real-world environmental conditions such as lighting and camera quality.

6

QIDK Kit Integration :

The trained model has been deployed on the Qualcomm Innovators Development Kit (QIDK) for real-time waste detection and sorting along with segregation.

7

Hardware Implementation (Upcoming):

Complete hardware integration to ensure real-time waste capture, classification, and disposal using the physical hardware architecture.

8

Model Optimisations and potential Improvements

(Completed) We decided to create another model on Roboflow that employs YOLO-NAS as the apt computer vision algorithm to achieve the required purpose.

9

WEB APP AND GRAPHICAL ANALYSIS :

A detailed performamce description of the model is provided with the help of graphs that truly capture the performance parameters of the model in the best possible way.

Waste Classification Categories

Hazardous

- battery
- light_bulb

Recyclable

- can
- cardboard_box
- scrap_paper
- plastic_bottle
- cardboard_bowl

Non Recyclable

- snack_bag
- plastic plastic_box
- plastic_cup
- plastic_cup_lid
- plastic_spoon
- plastic_bottle_cap
- straw

Tasks Completed (with conclusive evidences):

1

Data Collection

Over **4566** images of various waste items were gathered from the IIITH campus and public datasets resulting in formation of a comprehensive dataset covering 15 distinct waste classes.

2

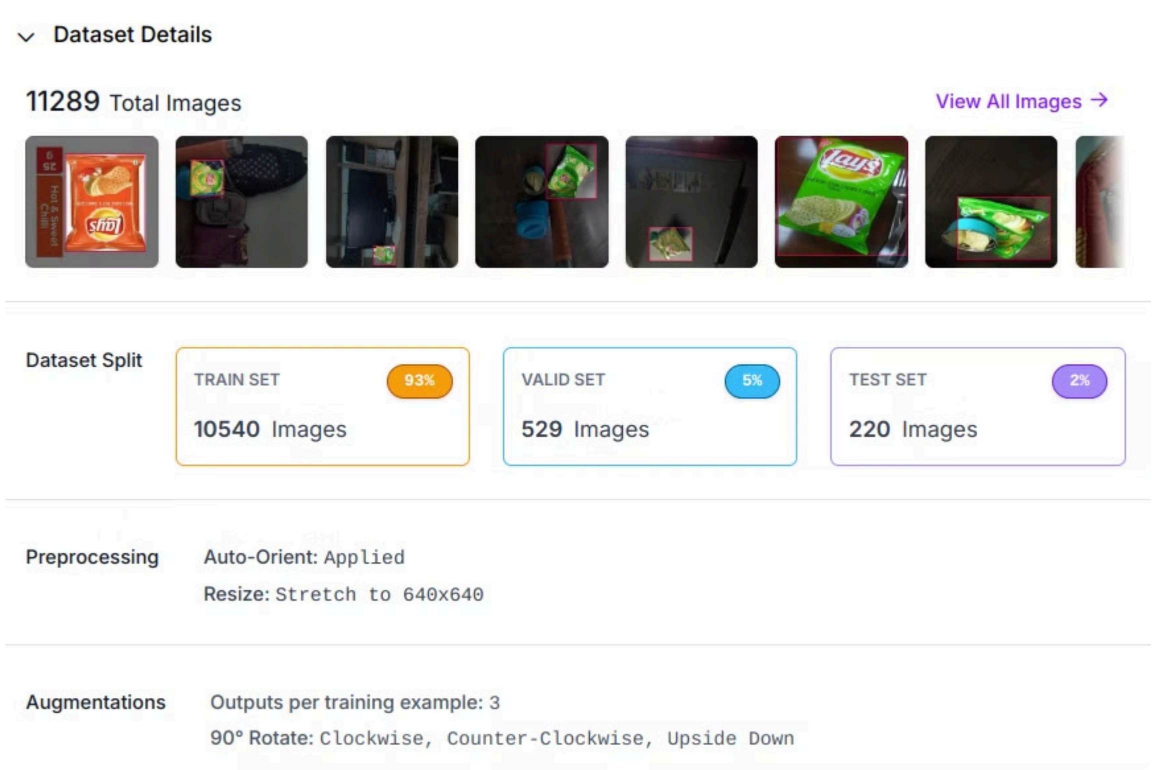
Annotation

The dataset was annotated using Roboflow, ensuring precise class labels for each image. Waste items were classified into **Recyclable, Non- Recyclable, and Hazardous categories.**

3

Preprocessing & Augmentation

The dataset was resized, oriented, and augmented using a 40% horizontal-vertical flip technique, resulting in **11289** training images. This augmentation step is essential to improve the model's generalization capabilities.



4

Model Training

The YOLOv8 model was trained on the augmented dataset. This model was chosen due to its efficiency in real-time object detection tasks and its suitability for resource-constrained hardware platforms.

5

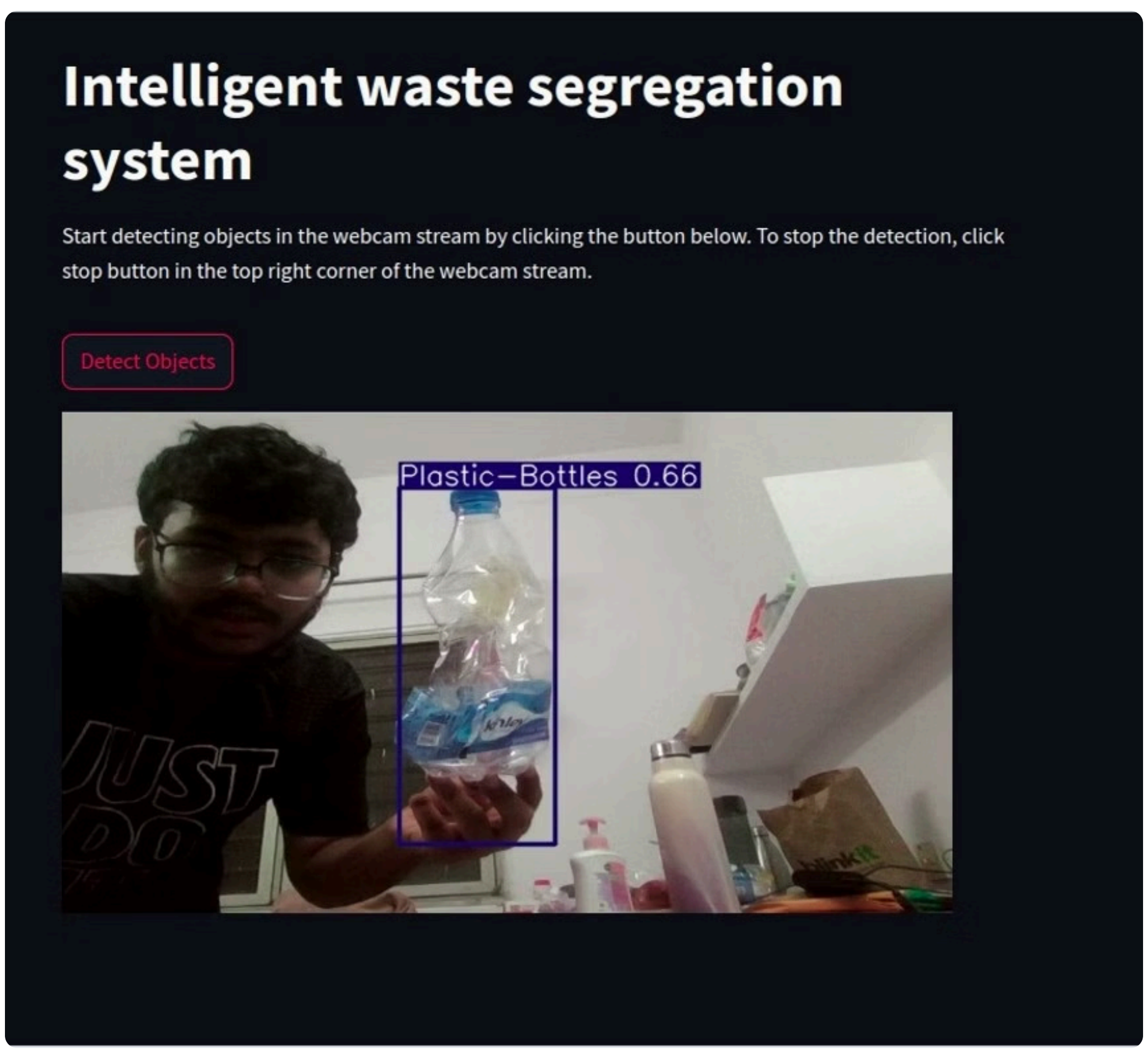
Model Deployment

After performing verifications and critical evaluations of our model, we successfully deployed our model on RoboFLow. (**Real-time model execution- Real time detection and class identification of waste articles. (can be used on smartphone sytems as well!!) ——> (link)**)

6

Complete Testing

Initial testing shows strong results, with the model achieving:



7

QIDK INTEGRATION

We made diligent efforts to develop a web-based app following the guidelines given in the Github repository hoisted on the official QIDK website . We were also successful in uploading it to the kits made available to us by Qualcomm, however, the visibility of the rectangular boundaries around waste articles is poor which is a major hurdle in the physical implementation of the project.

8

DEVELOPING WEB BASED APPLICATION TO PROVIDE AN END TO END SOLUTION WHICH CATERS TO THE NEEDS OF THE USER :

The streamlit based web application automatically creates rectangular boundaries around waste objects and the digital dashboard notifies the user to throw the waste in thre appropriate bin. We have also implemented a colour scheme for the bins that makes our app easy to use and user friendly.

9

DATA ANALYSIS OF WASTE USING GRAPHS :

Detailed model semantics are also enclosed within the ENDSEM PPT .

Analysis of Models Used & Outcomes:

Model Selection

The YOLOv8 model was selected due to its beneficiary strengths in object detection and its ability to process images in real time. Its single-shot architecture (YOLO = You Only Look Once) allows for rapid classification, making it ideal for deployment in a real-time waste management system. Further, we even created another model that employed YOLO-NAS so that model accuracy could be achieved to maximum extent.

Performance Metrics

Precision: The model achieves 71.3% precision in classifying waste, but there are areas requiring improvement, such as handling complex and diverse objects like snack bags.

Accuracy: Overall, the model boasts 95% accuracy, which is sufficient for real-time applications. However, further refinement is necessary to maintain high accuracy in diverse conditions.

Critical Analysis:

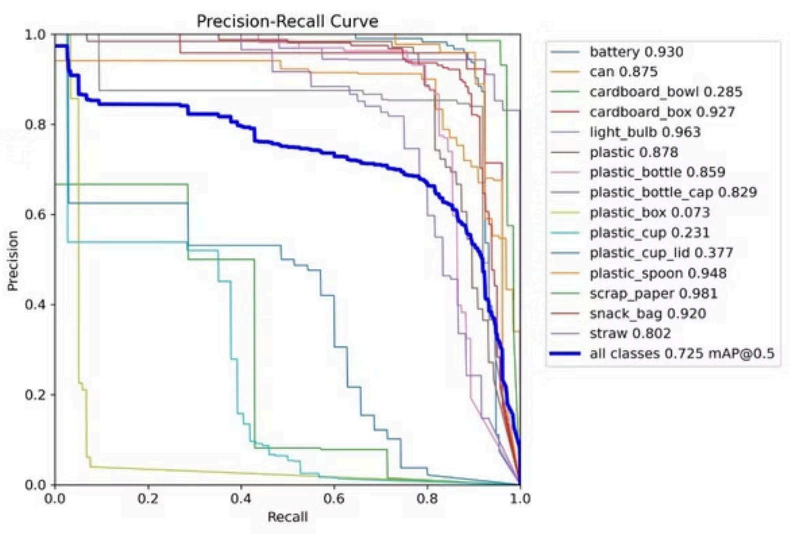
- **Complex Waste Types**: The model struggles to accurately classify waste items like snack bags, which exhibit varying shapes and textures.
- **Environmental Variability**: The model's performance dips in varying light conditions, necessitating additional optimization to handle real-world conditions.

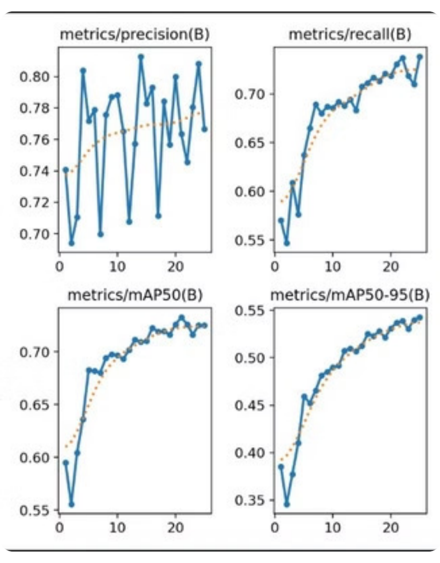
YOLOV8 PERFORMANCE METRICS :

We hereby present a mathematical and analytical perspective of our model with the help of appropriate graphs from which useful information can be inferred like precision and accuracy of detection of various waste articles along with other performance metrics.

Certain important definitive parameters such as accuracy and precision are enlisted below.

mAP 72.5% | Precision 76.7% | Recall 73.9%



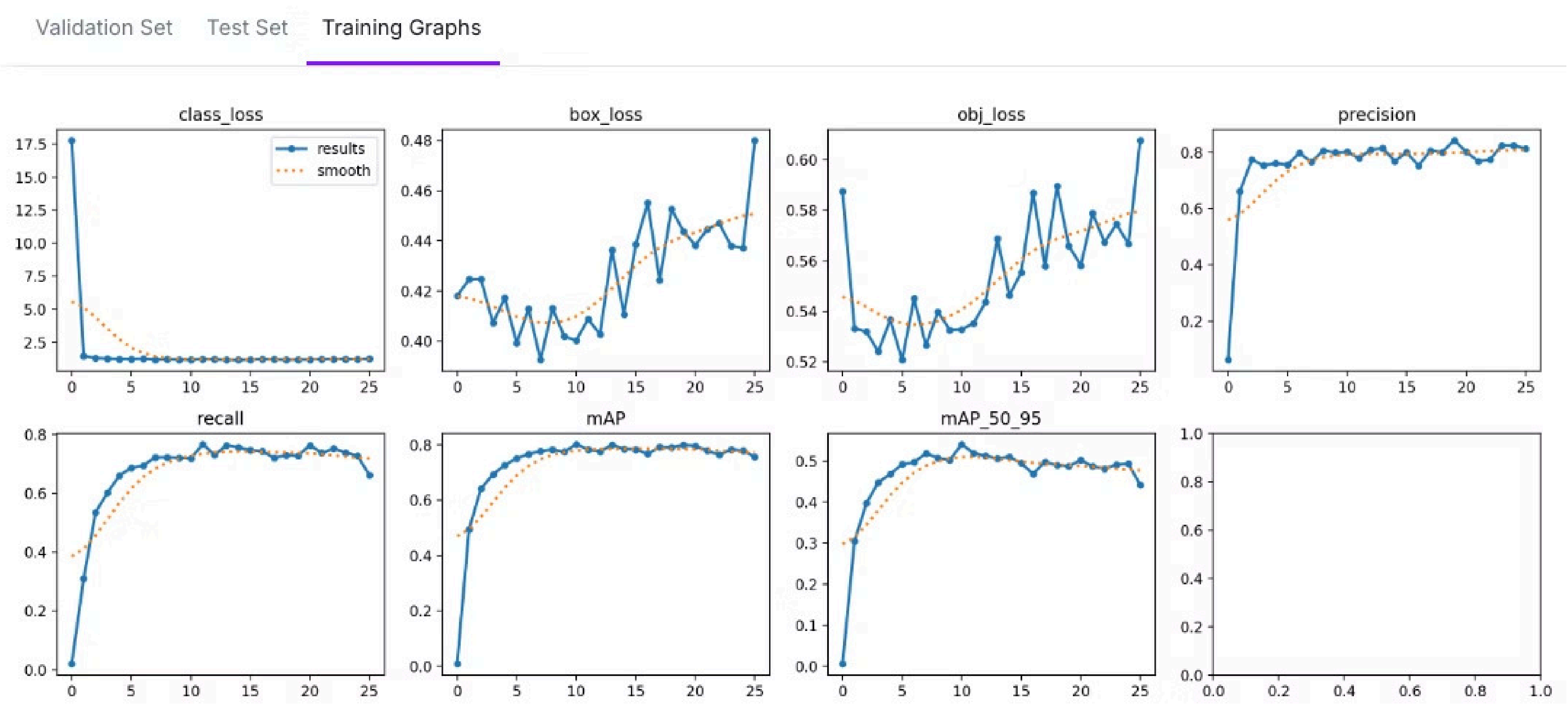


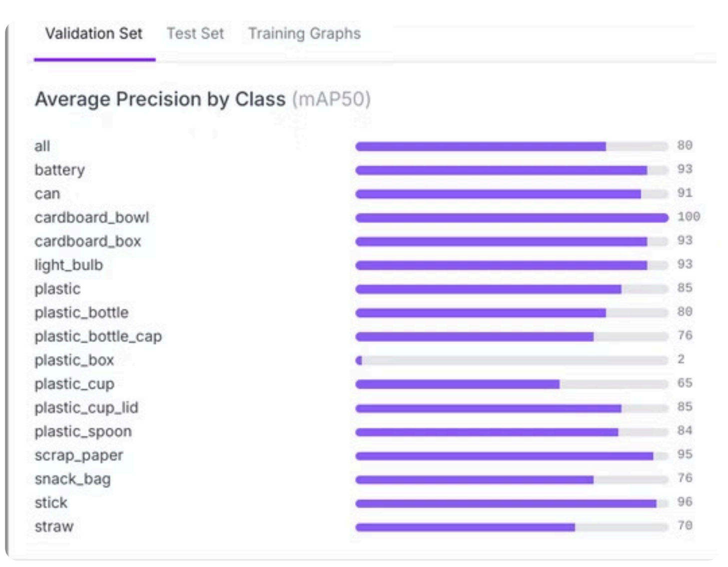
Class	Images	Instances	Box(P	R	mAP50	mAP50-95): 100% 34/34
all	529	1122	0.766	0.739	0.725	0.542
battery	70	133	0.889	0.91	0.929	0.853
can	37	66	0.695	0.909	0.874	0.648
cardboard_bowl	7	7	0.445	0.429	0.293	0.24
cardboard_box	22	26	0.837	0.923	0.927	0.769
light_bulb	45	54	0.706	1	0.963	0.856
plastic	30	87	0.882	0.805	0.878	0.583
plastic_bottle	77	103	0.831	0.825	0.86	0.65
plastic_bottle_cap	59	74	0.839	0.918	0.829	0.537
plastic_box	80	119	1	0.0327	0.0733	0.0364
plastic_cup	35	74	0.536	0.284	0.231	0.149
plastic_cup_lid	25	35	0.51	0.486	0.374	0.225
plastic_spoon	28	52	0.81	0.923	0.948	0.771
scrap_paper	22	70	0.942	0.957	0.981	0.715
snack_bag	103	162	0.861	0.895	0.92	0.641
straw	35	60	0.709	0.783	0.801	0.456

YOLONAS PERFORMANCE METRICS :

Some specifically necessary performance metrics are enlisted below:

mAP 80.2% | Precision 80.1% | Recall 71.8%





Challenges Faced

Technical Challenges

- **Over-Augmentation**: The augmentation process has resulted in some inaccuracies in the model's predictions, particularly when augmenting more complex images. Over-augmentation caused the model to misclassify certain items. As a result the outcome may not be as expected when demonstrating the model sometimes.
- **Hardware Constraints**: The QIDK kit is resource-constrained, making it difficult to deploy larger and more complex models, thus necessitating optimization of the model size and inference speed.
- **Lighting Sensitivity**: The model's performance is highly dependent on lighting conditions, making it difficult to maintain accuracy in low-light or highly reflective environments. Hence variable light condition turns out to be a deciding factor in determining the reliability and accuracy of the model.

Hardware Challenges

- **System Integration**: Implementing the trained model onto a physical hardware system proved to be more challenging than anticipated, especially in terms of aligning the classification output with physical waste sorting mechanisms.
- **Deployment on QIDK : For the true realisation of the physical interpretation of the model, its deployment on the QIDK kit is necessary which has been a major challenge throughout the course of the project.**

Miscellaneous Challenges

Class Imbalance: Certain waste categories (e.g., snack bags , plastic_box) were underrepresented in the dataset, leading to reduced accuracy for those classes.

Future Work and Further Scope

Despite our utmost and sincere efforts the model developed by us can undeniably be optimised more and there is stiil some scope of improvement. So we enlist here certain methods and ideas we could come up with to achieve the same:

1

Dataset Expansion

Began (and still continuing) collecting and annotating additional images to improve the diversity and robustness of the training dataset.

2

Model Optimization

Fine-tuned the YOLOv8 model to enhance performance on challenging waste types.

3

QIDK Kit Integration

Attempted and partially succeeeded in integrating the model onto the **QIDK** kit, ensuring seamless operation on the hardware platform.

4

Hardware Setup

There lies further scope in integrating this model on QIDK kit and have some real-life applications like waste detection and segregation at crowded places such as airports etc.

5

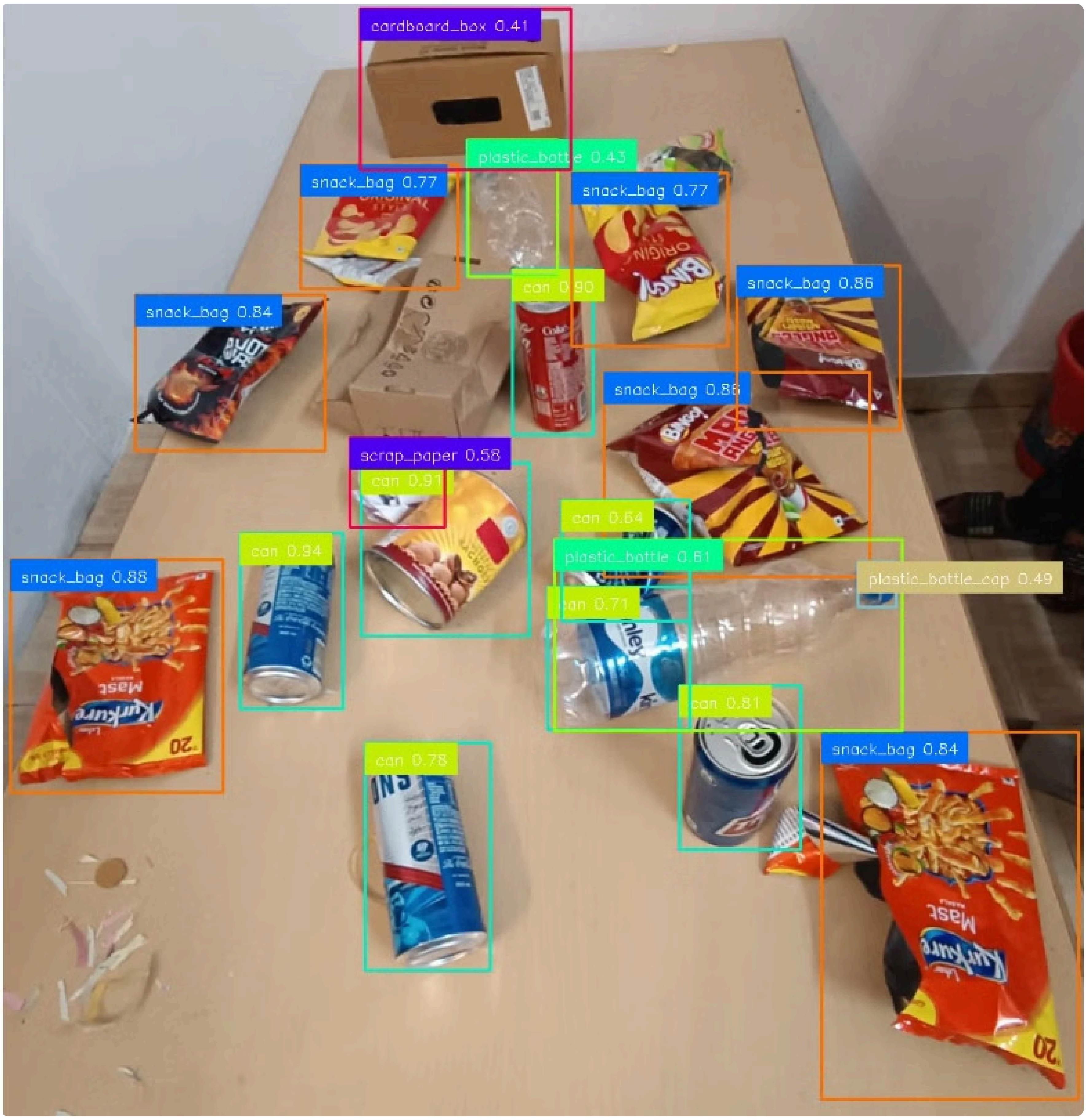
Light Sensitivity Adjustments

Optimized the model to handle varying lighting conditions, ensuring consistent performance regardless of environmental factors.

Conclusion and Resources Used

The project was finished as planned, with substantial progress made in data collection, model training, and initial testing. The **YOLOv8** model has shown strong results in classifying waste, though improvements are still needed to optimize performance in complex scenarios and on resource-constrained hardware.

With upcoming tasks focused on hardware integration and model refinement, the project is well on its way to achieving its objective of developing a fully functional, **real-time Smart Waste Segregation System.**



Resources Used (With Apt References):

- Roboflow: For image annotation and dataset management ([link](#)).
- YOLOv8 Framework: For training the waste classification model ([link](#)).
- QIDK Kit Documentation: For hardware integration and optimization ([link](#)).
- Public Waste Datasets: Used to expand the dataset and improve the model's performance.