EnviroScan

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Introduction

In an era marked by environmental degradation and resource depletion, effective waste management has become imperative for sustainable development. One significant aspect of waste management is the segregation of recyclable materials from non-recyclable ones, a process that traditionally relies heavily on manual sorting. However, manual sorting is labor-intensive, time-consuming, and prone to errors, leading to inefficiencies in recycling processes.

To address these challenges, our project focuses on developing an automated waste segregation system using computer vision technology. By harnessing the power of artificial intelligence and machine learning, we aim to streamline the process of sorting recyclable waste from non-recyclable waste, thereby enhancing the efficiency and effectiveness of recycling operations. Through this report, we present the methodology, implementation, and evaluation of our automated waste segregation system, highlighting its potential impact on waste management practices and environmental conservation efforts.

Motivation

As global populations burgeon and urbanization accelerates, waste generation surges to unprecedented levels, straining landfills and exacerbating environmental pollution. Amidst this backdrop, recycling emerges as a critical solution, offering multifaceted benefits to the environment, economy, and society at large. However, the efficacy of recycling efforts is hindered by inefficient waste segregation processes, which are laborious, time-consuming, and error prone. Manual sorting not only leads to contamination of recycling streams but also diminishes recycling rates. Recognizing these impediments, our project leverages advanced technologies such as computer vision and machine learning to revolutionize waste segregation, thereby bolstering recycling practices.

Moreover, our project aligns with broader objectives of promoting sustainability, conserving natural resources, and combating climate change. Recycling serves as a linchpin in reducing greenhouse gas emissions, conserving energy, and safeguarding biodiversity, making it integral to global sustainability endeavors. Through the development of an automated waste segregation system that is accurate, efficient, and user-friendly, we seek to empower individuals, communities, and organizations to actively engage in recycling initiatives. By inspiring positive behavioral changes, fostering environmental stewardship, and contributing to the collective pursuit of a greener, more sustainable future, our project aims to catalyze transformative change on both local and global scales.

Dataset

We used the open-source Trash Image Dataset from Roboflow [1] consisting of 16k annotated images of waste objects. The annotations contain class labels (categories) and bounding boxes for each object in the image. The objects are divided into 14 waste categories like plastic, metal, e-waste, etc. Each category is further labeled as ‘valuable’ or ‘non-valuable’ in terms of recyclability.

Methodology

The complete workflow of our project is shown in [Fig. 1].

1. Low risk problem: The first step of our project involved choosing a large and diverse dataset containing annotated images of waste objects. We worked with the dataset mentioned above and performed exploratory data analysis to study the distribution of waste categories [Fig. 2]. Since the original data contained only train and validation sets, the train set was again divided into train and validation subsets containing 20% and 80% images of each category respectively. The original validation set was kept as a test set.

2. Medium risk problem: After data preprocessing, we moved on to leveraging state-of-the-art models like YOLOv8 [2] and DETR [3] for object detection. Their backbone consists of convolutional neural networks (CNN) with DETR having a transformer encoder-decoder architecture for enhanced accuracy. As these models are pretrained, we finetuned them on our dataset. As per the model requirements, each dataset was loaded into appropriate formats. For YOLOv8 we passed .yaml data configuration and for DETR we used COCO data format. Both the models were finetuned for 10 epochs with learning rate of 0.01 and 0.0001 for YOLOv8 and DETR respectively. For finetuning, weights of the last layers of the models were updated keeping all other layers freezed. Models were evaluated on test dataset images where the expected output was to detect the waste objects and display their categories with recyclability status. A comparative analysis of performances was done between the two models using average precision as metric to select the better one.

3. High risk problem: Our high-risk problem statement was to develop a Streamlit application which can not only take images as input but also live feed from laptop webcam for real time waste object detection. After testing the finetuned models, we chose DETR as it had better predictions. The application interface gives the user an option to either upload an image or use the webcam as an input. For real time detection, Streamlit captures a frame from the camera footage and passes it as an input image to the model. The model outputs are the bounding boxes and category labels along with the confidence threshold which are overlaid on the input image and displayed to the user [Fig. 3]. We set a confidence threshold of 0.75 to consider a detected object as valid and include it in the final output.

Results

The evaluation metric used for comparing the models was average precision (AP) of Intersection over Union (IoU) which shows how well the prediction bounding box aligns with the ground truth box. We compared the AP values for different IoU thresholds (0.50 and a range from 0.50 to 0.95 with a step size of 0.05)

Model	**AP at IoU = 0.50**	**AP at IoU = 0.50:0.95**
Base YOLOv8	0.022	0.016
Finetuned YOLOv8	0.538	0.375
Base DETR	0.001	0.001
Finetuned DETR	0.578	0.412

Table 1. Performance Metrics

From the results we can see that the performances of both finetuned models were significantly better than the base models. This is likely due to the lack of waste/trash images in the pretrain dataset and highlights the importance of finetuning for downstream tasks. The finetuned DETR was slightly better than finetuned YOLOv8. In terms of computational cost YOLOv8 is faster and the training process is simpler whereas DETR is known to give better accuracy in certain complex scenes. For better accuracy, we decided to go with DETR.

Conclusion

In conclusion, our project titled “Enviroscan”,an automated waste segregation using computer vision technology , represents a step forward in waste management practices. By leveraging computer vision, we have successfully developed accurate waste detection models like YOLOv8 and DETR, as evidenced by our evaluation metrics, including average precision (AP) of Intersection over Union (IoU). Through comparing AP values for different IoU thresholds, we ensured robust performance across various criteria. The Streamlit application we developed allows for real-time waste object detection, making the system accessible and user-friendly. Through our efforts, we aim to contribute to sustainability goals by streamlining waste segregation processes, ultimately promoting environmental conservation and enhancing recycling rates.

References

[1] Trash Image Dataset
[2] YOLOv8
[3] DETR
[4] Finetuning DETR
[5] Finetuning YOLOv8
[6] DETRs Beat YOLOs on Real-time Object Detection, 2024. [Yian Zhao et al]

Appendix

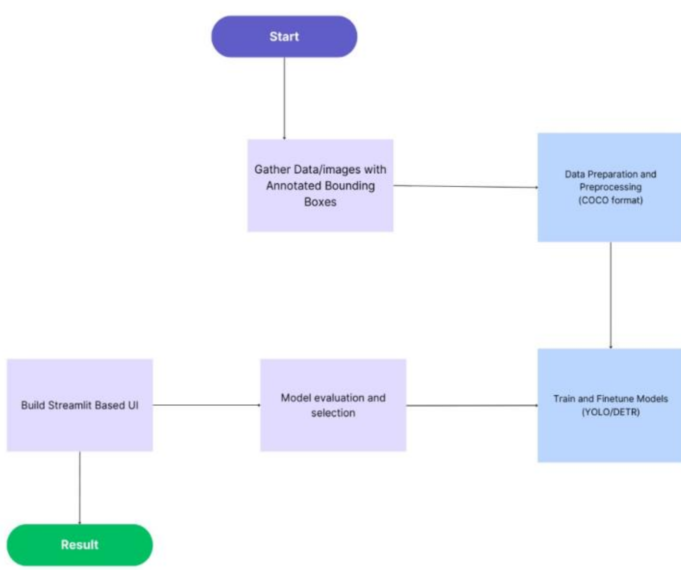

Fig. 1. Workflow Diagram

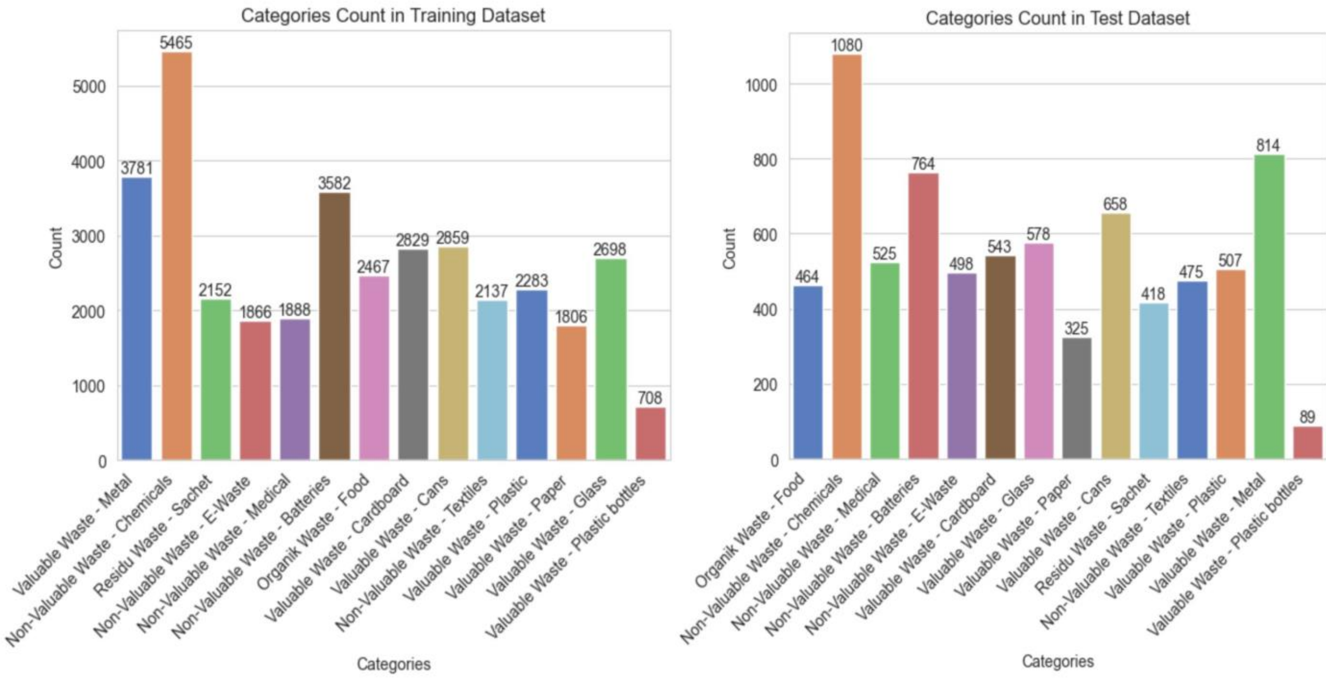

Fig. 2. Exploratory Data Analysis - Category Distribution

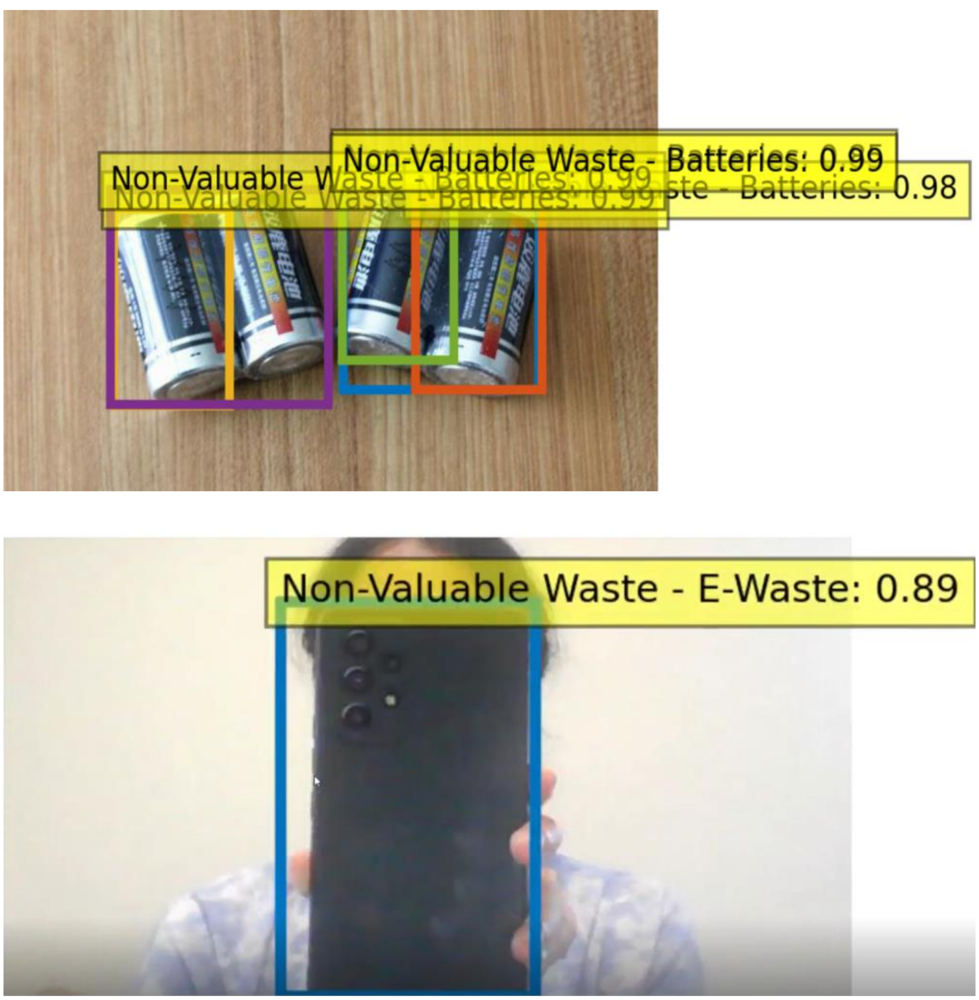

Fig. 3. Streamlit application - Image and real time object detection