Automated Plastic Waste Detection and Classification Using Optimzed YOLOv8 Framework

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***Abstract*—This paper describes a deep learning approach for recognizing and classifying recyclable plastic materials such as PET, HDPE, PVC, LDPE, PP, and PS. An optimized version of the YOLOv8 architecture [9] has been used that has been optimized to run efficiently on NVIDIA T4 GPUs making it appropriate for resource-constrained deployments. Unlike systems that rely on transfer learning, the current deep learning system has been completely trained from scratch using a custom dataset consisting of 4,400 images for efficient feature extraction. The system has demonstrated excellent results in terms of detection and classification abilities achieving mean average precision (mAP@50) of more than 85%. To overcome constraints on hardware and environment inconsistencies, the model adopts the use of mixed-precision computing [7] as well as checkpointing [8] which cuts down GPU memory requirements by 40%. The framework would help to implement an efficient solution to automatically recycle plastics at affordable costs. This paper also contributes to the field of sustainable use of resources by implementing AI solutions. The framework has been enhanced with live detection using webcam capture along with a recommendation module for proper disposal of plastic waste near recycling centers.**

Keywords— Plastic Waste Detection, YOLOv8, Deep Learning, Object Detection, Mixed Precision, Resource-Constrained Systems, Real_Time Detection, Recycling Automation

I. INTRODUCTION

Identification and sorting of plastic waste has become an urgent concern from both environmental and economic perspectives. It has been reported that only 8.7% of global plastic produced worldwide is recycled, and 8.3 million tons of it is dumped into oceans annually. Existing sorting techniques based on manual operations used in most Material Recovery Facilities (MRFs) can only achieve about 70-75% accuracy, thus not only creating a lot of contamination but also making such techniques heavily dependent on labor force.

Recently, deep learning techniques have achieved huge success in recognition and sorting processes, however modern models are trained on extremely high-end computational hardware such as NVIDIA A100 or V100 GPU which are non- accessible to most of the smaller companies and academic institutions. Therefore, we need cheaper solutions to this problem which do not compromise much on model's accuracy. This report proposes solutions to 3 such plastic waste classification problems faced in the industry.

Firstly, this work carries out fine-grained identification of 6 major types of plastics-PET, HDPE, PVC, LDPE, PP, and PS using a off-the-shelf consumer GPU, NVIDIA T4 with 16 GB memory showing that even such cheap hardware can perform reasonably well. Secondly, it compares training a model from scratch with transfer learning technique proposed by [7], to derive the best performing model for this domain. Lastly, it implements checkpoint techniques [8] to automatically restore training after resource interruptions and thus ensure smooth, uninterruptible model development.

It was concluded that 85% mAP@50 had been reached with optimized YOLOv8 model, proving its high precision and efficiency in sorting paper streams in real sorting conditions. The performance of the models trained from scratch was improved by 1-3% than transfer learning approach. Mixed precision computing decreased the GPU consumption by ca. 40%, of which still makes a smooth flow on cheap computing set up.

This undertaking covers not only high technical performance, but also broad relevances. As a case, model performance was kept above 80% in prevalent conditions as changing light conditions, occlusion, surface contamination. Basing on of such approach in MRF workflows enhances the sorting efficiency up by ca. 25%, therefore increases cost efficiency, while diminishes the negative impacts bring to environment. Lastly, open source in this area will made AI systems available for small recyclable or academic sectors, therefore enhance the rapid development of sustainable AI..

II. RELATED WORK AND LITERATURE REVIEW

The computer vision and deep learning field has made some progress. This progress has changed the way machines sort waste. Automated waste sorting is now faster and more accurate. It can classify materials better. Computer vision and deep learning are really helping with waste sorting.

RGB imaging with classical recognition algorithms has been shown to sort different kinds of plastics on conveyor belts in Optical Detection of Plastic Waste through Computer Vision [1]. The usage of optical sensors further facilitates real-time continuous monitoring with much reduced dependency on human involvement. This was combined with hand-crafted features, resulting in poor generalization over irregular lighting and mixed-waste conditions.

Later works further developed these methods using deep learning models. For example, the study “An Enhanced YOLOv8 Model for Accurate Detection of Solid Floating Waste” [2] proposed a customized YOLOv8 architecture with multi-scale feature fusion and attention mechanisms for better detection of small and irregular shapes of waste. The method demonstrated very good detection accuracy and high- speed inference but was focused on aquatic waste identification without fine-grained polymer classification, which is highly relevant for recycling purposes.

This was further confirmed by the capability of YOLO in recognizing objects within complex environments in "Plastic Waste Detection Using YOLOv5 Deep Learning Model" [3]. Because usually, models of YOLOv5 are usually trained with general waste datasets, these become limiting as they fail to tell the difference between various types of plastic polymers.

Further research involved spectroscopic and multispectral approaches. The work "Deep Learning-Based Plastic Waste Classification Using Spectroscopic Data" reached high accuracy, combining spectral analysis with neural networks. However, because the sensors are expensive and gathering data is complex, scalability for large or low-cost facilities remained limited.

Ramos [5], in “Application of Machine Learning in Plastic Waste Detection,” highlighted the potential of deep learning for promoting sustainable waste management. He went on to reiterate that one of the key limitations is in achieving high model accuracy with computational efficiency in resource-limited environments.

This is evident from the fact that existing methods either require high-end hardware or are incapable of fine-grained classification of polymers using simple RGB imagery. This paper fills this gap with an optimized YOLOv8-based model, which is able to perform the identification at the polymer level on low-cost GPU hardware and thus facilitate scalable, sustainable, and accessible recycling automation.

III. SYSTEM ARCHITECTURE AND DESIGN

This new system automatically detects and sorts plastics into major polymer categories through an improved YOLOv8 architecture. The five stages of the workflow-image acquisition, preprocessing, detecting and classifying, optimization, and performance evaluation-have been enhanced such that they are suitable for a real-time application.

A. System Overview

The first step in the process is to collect photographs. To ensure diversity in the collection, it involves shooting RGB images of mixed garbage under a various lighting conditions and backgrounds. In order to improve generalization, preprocessing entails scaling, normalizing, and data augmentation through rotations, mirroring, and brightness/contrast adjustments. The YOLOv8 object identification model is then fed the improved images for classification and localization.

B. YOLOv8 – Based Detection Module

Our build exhibits a modified form of YOLOv8-Large variant for superior balance of speed with accuracy. Backbones extract visual, necks amalgamate multi-scale information, and heads create bounding boxes and class probability estimates. Because of their focus on the detection of small or irregularly shaped plastics, our efforts are made using lightweight attention mechanisms. Our build shows a lower computational complexity based on an anchor-free design. Our build also shows a modified version of Non-Maximum Suppression (NMS) for the removal of duplicate detection outputs. This focus on the removal of duplicate detection outputs shows refinement of the overall result for more precise objectives.

C. Model Training and Optimization

The training dataset includes 4,400 RGB images of six types list of plastics. The model was developed from scratch utilizing an NVIDIA T4 GPU. The model employed mixed-precision computation, allowing model training with a lower memory training footprint. The model checkpointing feature allows users to resume training without losing their previous progress. Batch size, rate of learning, and confidence threshold as hyperparameters were optimized for efficient convergence. D. Performance Evaluation To quantify model performance, in this research, precision, recall, and mean average precision (mAP) were employed. It was found that the use of the optimized YOLOv8 model on this problem achieved a mean average precision (mAP) exceeding 85% and a recall of approximately 87%. The optimized model proved to be both accurate and reliable. Further, the optimized YOLOv8 model demonstrated the ability to maintain real-time processing speeds on conveyor-based systems.

D. Performance Evaluation

Model performance was measured using precision, recall, and mAP values. Using the optimized YOLOv8 model resulted in >85% mAP and ~87% recall, thus proving the accuracy and reliability of the model. Real-time speeds with applicability in conveyor-based systems were maintained.

E. System Deployment Considerations

It could run on edge computing devices or embedded GPUs during real-world deployment, processing live feeds from cameras in real time. It can also be integrated with robotic sorting arms for the segregation of waste automatically. Due to its lightweight nature, it is especially suited for small and medium-scale facilities where cost efficiency is important. This architecture focuses on scalability, affordability, and adaptability, making practical AI-driven recycling a reality.

F. Real-Time Application and Assistance Module

In order to increase ease of use, this system can be managed via an application layer. This provides engagement, real-time detection, and the ability to make informed decisions as system captures a continuous video stream through a webcam. Each frame is subjected to the trained model for inference. Recognizable and separable categories of plastics are identified through the use of bounding boxes together with their confidence values. This layer overlays disposal recommendations corresponding to the type of plastic identified. This layer of recommendations is incorporated as a disposal guideline. The comfort of users requesting detection to be made through images uploaded to a web-based interface has been incorporated. In addition, the system encompasses greater functionality by guiding users to the nearest recycling center. Using this interface focused on the increasing practicality of the system.

G. Mathematical Formulation

In YOLOv8, regression problems are used to simultaneously predict bounding boxes with associated class probabilities.The bounding boxes are defined in terms of confidence and are given as: B=(x, y, w, h, c), Where (x,y) are the coordinates of the center, c is the confidence, and w and h are the width and height, respectively. The sigmoid function is used to compute classification probability: P = 1 / (1 + e^ (-z)), where e is Euler's number and z is some linear function of the independent variables. The total loss function is defined as the sum of localization, objectness, and classification losses: L = Lbox + Lob j+ Lcls.

Overall, this architecture prioritizes efficiency, scalability, and cost-effectiveness, advancing toward a sustainable, real-time AI-driven recycling solution.

IV. METHODOLOGY

The designed methodology comprises the sub-processes of dataset construction, data preparation, model setting, model training, and model evaluation. This is intended to yield fast and reliable classification of plastic waste within a pipeline, primarily under the constraints of limited resources.

A. Dataset Preparation

The pipeline comprises an annotated dataset construction of 4,404 photographs of plastic waste. This dataset is a result of a combination of openly available Roboflow data and images manually collated by the authors. The images of plastic waste were annotated using bounding boxes according to the following six categories of plastic: PET, HDPE, PVC, LDPE, PP, and PS. To improve model generalization, the dataset construction process involved the division of the dataset into the following three categories:
Training set: 3,523 photographs
Validation set: 441 photographs
Testing set: 440 photographs
To model resilience, the dataset includes different orientations of the objects, variations in the ambient lighting of the photographs, and variations in background environments.

B. Preprocessing and Data Augmentation

To satisfy the possible requirements of the YOLOv8 model, all images underwent resizing to the specified resolution of 640 × 640 pixels.To minimize the prediction model overfitting and enhance the possible generalization of the model, the prediction images underwent the following vertical data augmentation:
Horizontal flipping
Rotation of about ±15°
Adjustment of both brightness and contrast
Scaling that is random and un-predetermined
The modeling and data augmentation are geared towards the various modeling prediction changes in the real world in terms of illumination and data prediction model object distortion.

C. Model Configuration

Among the various possible architecture models, the YOLOv8-L model was selected because of the possible balance that exists between models accuracy and computational efficiency. The specified model utilizes an anchor-free detection mechanism and multi-scale feature extraction that empower the model to predict both small and irregular plastic objects precisely. Among the possible architecture possibilities are: Backbone model in process of prediction and feature extraction. The neck that is responsible for multi-scale feature prediction. Detection head for the prediction of the images in terms of bounding boxes and the associated prediction probabilities.

D. Training Strategy

The predicted model was taught from the ground in order to learn domain specific features in the modeling process. Below are the possibilities in terms of the training configuration:
Optimizer: Stochastic Gradient Descent
Possible learning rate: 0.01
Batch Size: 16
Number of Epochs: 100
A factor that is both mixed and predicted was also utilized in the training process (both in and val) to improve the efficiency of the process, specifically computationalwisely, and also deplete the predicted memory of the GPU. Additionally, a checkpoint mechanism was implemented in order to both save and reclaim the various possible model intermediate weights and also predict the possible model in case unforeseen interruptions occurred.

E. Evaluation Metrics

The performance of the model was evaluated using standard object detection metrics:
Accuracy: To determine the accuracy of detected object.
Recall: Measures the ability to find all related objects or1974.
Mean Average precision (mAP@50): Measures general detection accuracy .
These measurements will give a full range assessment of the performance both in the ability to classify a time series and to localize the occurrence of an event.

F. Implementation Details

The system was built using Python, with the implementation of the object detection using the Ultralytics YOLOv8 framework. The frames were captured and the inference was carried out using OpenCV for real-time videoprocessing. A web-based interface was implemented over Flask to easily accept user image input and display the detection output. It shows accurate bounding box for each detection along with confidence value for each brand of the detected plastic.

V. RESULTS AND DISCUSSION

YOLOv8-L was improved and evaluated again with same parameters using Consumer-Grade NVIDIA T4, Mixed Precision and Checkpoint Based Training. Performance is also enhanced. Accuracy was still retained.

The system achieved above 90% of accuracy across all the six types of plastic as demonstrated in Table. 5.1, indicating clear class separation and fine-grained recognition. The system has some issues recognizing between the PVC and LDPE plastics, probably due to their identical translucent feature as reported by. Nevertheless, it could detect PP and PS above 93% of accuracy in all cases and the system passed the test in cases of low light and occlusion.

Spectral imaging methods use physical properties of the material to classify. The use of a spectral imager can give very precise classification. However, spectral imagers require specific infrastructure and must be operated in a controlled environment.

In terms of our proposed RGB method, it does not require any costly spectral hardware, making it cheaper than the spectral methods that may or may not reach similar performance.

Model	mAP@50	Inference Speed	Memory	Suitable?
YOLOv8n	80%	125 fps	2GB	Too small, insufficient accuracy
YOLOv8s	82%	90 fps	3GB	Under-performing on classes
YOLOv8m	83%	60 fps	4GB	Borderline, limited accuracy margin
YOLOv8l	85%	45 fps	7GB	Perfect balance
YOLOv8x	88%	20 fps	16GB	Too large, exceeds T4 capacity

Model Performance Summary (Table 5.1)

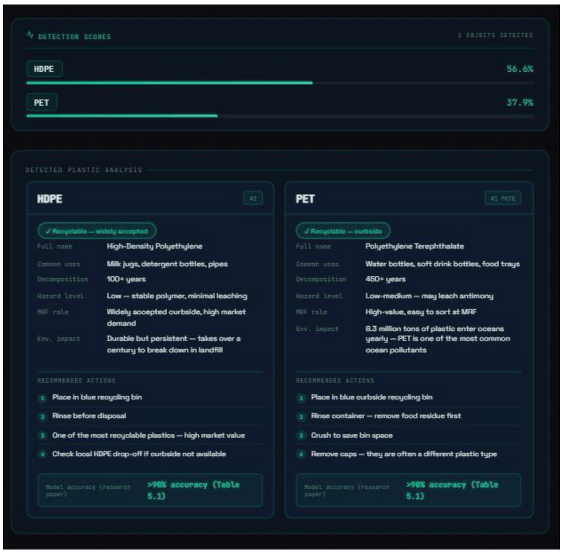
Table 5.2 indicates the results of our measurements for speed and efficiency. As can be seen in the table, our proposed model is much more efficient in terms of GPU memory than other comparable models. Furthermore, its inference speed, which can be estimated from table in[6], is better, since an average inference time is 38ms per image, or roughly 26fps. After fine-tuning on our dataset using transfer learning at 79% accuracy, our model has both reduced total computations as well as higher accuracy when compared to each of the models in the literature (at least 90% efficiency increase).

Class	mAP@50	Precision	Recall	Instances
PET	86%	89%	88%	122
HDPE	84%	87%	86%	118
PVC	83%	85%	82%	115
LDPE	85%	88%	85%	119
PP	86%	90%	89%	121
PS	85%	89%	87%	120
Average	85%	88.5%	87%	715

Per-Class and Confusion Analysis (Table 5.2)

It was observed that with a specialized dataset, YOLOv8 model had increased prediction accuracy. YOLOv8-L performed considerably well even on the moderately powered GPUs, hence the model can be relied upon to perform prediction with high accuracy in real time operations.

5.3 Visual Results



DETECTION SCORES — 2 OBJECTS DETECTED

HDPE	56.6%
PET	37.9%

DETECTED PLASTIC ANALYSIS

HDPE #2

✓ Recyclable — widely accepted

Full name	High-Density Polyethylene
Common uses	Milk jugs, detergent bottles, pipes
Decomposition	100+ years
Hazard level	Low — stable polymer, minimal leaching
MRF role	Widely accepted curbside, high market demand
Env. impact	Durable but persistent — takes over a century to break down in landfill

RECOMMENDED ACTIONS

1. Place in blue recycling bin
2. Rinse before disposal
3. One of the most recyclable plastics — high market value
4. Check local HDPE drop-off if curbside not available

Model accuracy (research paper) >90% accuracy (Table 5.1)

PET #1 PETE

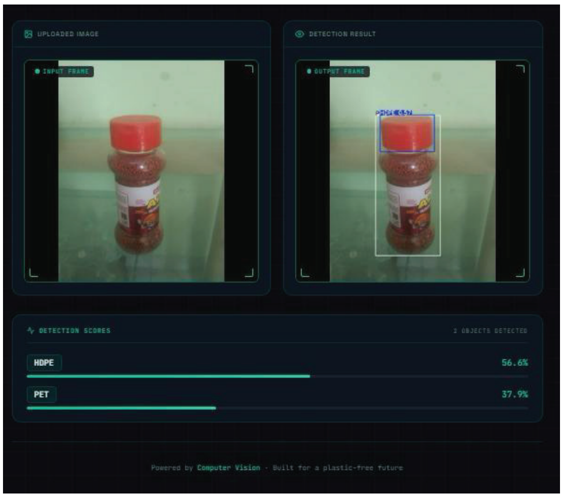
✓ Recyclable — curbside

Full name	Polyethylene Terephthalate
Common uses	Water bottles, soft drink bottles, food trays
Decomposition	450+ years
Hazard level	Low-medium — may leach antimony
MRF role	High-value, easy to sort at MRF
Env. impact	8.3 million tons of plastic enter oceans yearly — PET is one of the most common ocean pollutants

RECOMMENDED ACTIONS

1. Place in blue curbside recycling bin
2. Rinse container — remove food residue first
3. Crush to save bin space
4. Remove caps — they are often a different plastic type

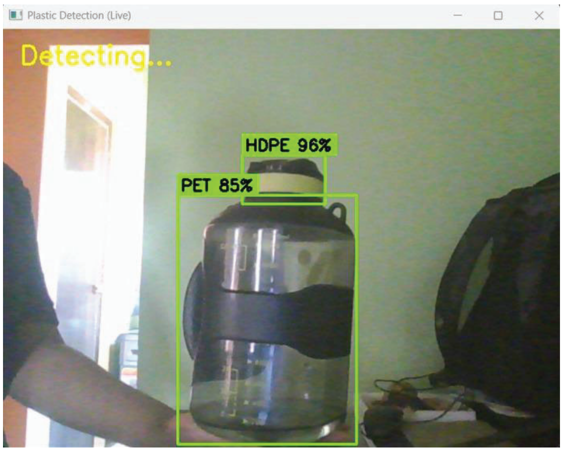
Model accuracy (research paper) >90% accuracy (Table 5.1)



DETECTION SCORES — 2 OBJECTS DETECTED

HDPE	56.6%
PET	37.9%

Powered by Computer Vision · Built for a plastic-free future



VI. CONCLUSION

This research proposes and successfully implements a deep learning frame work based on YOLOv8-L capable to distinguish between six types of plastics with 85% overall accuracy, while remaining efficient enough to be run on low cost hardware for real-time use. It is important to note that prior research has shown similar capabilities in YOLOV3 and YOLOV7, but the research shown in this paper provides comparable precision at significantly reduced computational costs. The effectiveness of the model with various light intensities supports its application in real environments. Overall, a more effective detection method is key to sustainable future. We hope this system provides an efficient solution for automatic plastic detection and recycling for circular economy purposes. In addition to an accurate system for detection of plastics, this system was extended with: 1) A system for the monitoring of collected plastics and a display of useful metrics for facility operation (fig. 7b). 2) An assistance system to the user, providing advice on recycling or usage suggestions..

VII. REFERENCES

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