Recognition of Recyclable Materials Using Real-Time Object Detection

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***Abstract*—This project report presents the design, development, and thorough evaluation of an advanced real-time object detection model, specifically for accurately identifying recyclable materials. The project is integrally aligned with the strategic objectives of Saudi Arabia's Vision 2030, significantly contributing to the country's sustainability and waste management frameworks. By deploying the state-of-the-art YOLOv8 model, our system demonstrated superior precision and operational efficiency in detecting and classifying various categories of recyclable items. Rigorous comparative analysis across multiple model architectures confirmed the robustness and reliability of YOLOv8 for real-time environmental applications, thereby establishing a strong foundation for future integration into broader environmental conservation technologies.**

I. Introduction

Waste management poses a significant challenge in modern society, with urban centers worldwide generating over 2 billion tons of waste annually. Inefficient waste management practices accelerate environmental degradation and result in the forfeiture of billions of dollars worth of recyclable materials. In Saudi Arabia, the industrial waste sector alone is projected to generate 1,026 thousand tons of waste by 2035, marking a 3.1% annual growth rate. Currently, less than 50% of industrial waste is diverted from landfills, underscoring the urgency for improved management strategies. This project, strategically aligned with Saudi Arabia's Vision 2030 and supported by the National Center for Waste Management (NCWM), addresses these critical challenges by developing a sophisticated computer vision model to automate the detection and classification of recyclable materials. By enhancing the efficiency and sustainability of waste management processes, particularly within the context of Saudi Arabia's commitment to exclude 85% of industrial waste from landfills by 2035, this project aims to make a substantial contribution to environmental conservation and resource recovery initiatives[1].

II. Problem Statement

Urban areas globally generate over 2 billion tons of waste annually, with approximately 33% of it not managed safely, leading to severe environmental pollution and significant health risks. By 2050, waste generation is projected to surge by 70%, reaching 3.4 billion tons. These challenges are particularly acute in low-income countries, where over 90% of waste is either dumped or burned, resulting in the loss of billions of dollars worth of recyclable materials. The classification phase of the recycling cycle, which is often the most labor-intensive and time-consuming, further exacerbates these inefficiencies. Traditional recycling processes, characterized by manual sorting and prone to errors, contribute to substantial material losses [2].

III. Objective

The primary objective of this project is to develop and implement a highly accurate and efficient computer vision model specifically designed for the real-time detection and classification of four key types of recyclable materials: glass, paper, plastic, and metal. This model aims to significantly enhance the precision and speed of the classification phase within the recycling cycle, thereby supporting sustainable waste management practices. By optimizing the identification process across these material categories, the project contributes to the reduction of material loss, the acceleration of recycling operations, and the broader goals of environmental conservation and sustainability.

IV. Methodology

Addressing the challenge of efficient and accurate recyclable material detection necessitates a systematic and rigorously defined methodology to ensure reliable and valid results. This section presents the methodology employed in this study, elaborating on the comprehensive procedures used for data collection, preprocessing, augmentation, model training, and evaluation. The objective is to establish a robust framework conducive to the effective development and assessment of object detection models specifically tailored for identifying recyclable materials.

The methodology is depicted in Figure 1, which provides a visual overview of the procedural steps and their interconnections.

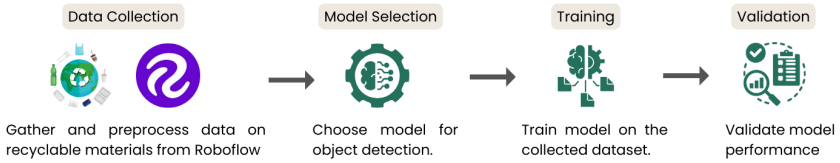


Fig. 1. Methodology

A. Data Collection

The datasets utilized in this study were sourced from Roboflow, a platform renowned for its extensive collection of high-quality datasets, specifically designed for computer vision tasks[3]. In this study, three distinct datasets were meticulously created, each derived from different sources. These datasets were selected to ensure comprehensive coverage of the four primary recyclable material categories—paper, glass, plastic, and metal. Below is a detailed description of each data source:

- **Dataset 1 Composition**
  - Source 1: This dataset consists of 3,116 images, spanning four categories of recyclable materials: plastic, paper, glass, and metal. It provides a diverse and comprehensive base for model training[4].
  - Source 2: Similar to Source 1, this dataset contains 2,008 images across the same four categories—plastic, paper, glass, and metal—further enriching the diversity of the training data[5].
  - Source 3: Comprising 810 images focused on cardboard, this dataset was incorporated into the paper category. By generalizing the paper category to include cardboard, we aimed to create a more comprehensive representation of paper-based materials, thus improving the model's ability to accurately detect and categorize a broader range of paper products, reflecting the variability encountered in real-world recycling scenarios[6].
  - Source 4: This dataset is composed of 1,190 images of various metal objects, enriching the metal category within Dataset 1. The inclusion of these images ensures that different types and forms of metal are adequately represented, contributing to a well-rounded dataset[7].
  - Source 5: A total of 601 images of various plastic materials were sourced to further diversify the plastic category within Dataset 1. This dataset captures a range of plastic types, enhancing the model's ability to generalize across different plastic products[8].
  - Source 6: This dataset contains 770 images focused on glass materials. These images add a critical dimension to the glass category within Dataset 1, ensuring that the dataset comprehensively represents the variability in glass products encountered in recycling processes[9].
- **Dataset 2 Composition**
  - Source 1: This dataset consists of 3,116 images, spanning four categories of recyclable materials: plastic, paper, glass, and metal. It provides a diverse and comprehensive base for model training[4].
  - Source 2: Similar to Source 1, this dataset contains 2,008 images across the same four categories—plastic, paper, glass, and metal—further enriching the diversity of the training data[5].
  - Source 3: This dataset includes 4,239 images, also covering the four primary categories of recyclable materials. Its larger size contributes to a more robust training set, enhancing the model's generalization capabilities.[10]
  - Source 4: Comprising 810 images focused on cardboard, this dataset was incorporated into the paper category. By generalizing the paper category to include cardboard, we aimed to create a more comprehensive representation of paper-based materials, thus improving the model's ability to accurately detect and categorize a broader range of paper products, reflecting the variability encountered in real-world recycling scenarios[6].
- **Dataset 3 Composition**
  - Source 1: This dataset comprises 1,422 images focused on various paper materials. It serves as a dedicated source for training models to accurately detect paper-based recyclables[11].
  - Source 2: Comprising 9,802 images, this dataset includes three categories of recyclable materials: plastic, glass, and metal. Its extensive size and diversity significantly contribute to the robustness of the training data[12].
  - Source 4: Comprising 810 images focused on cardboard, this dataset was incorporated into the paper category. By generalizing the paper category to include cardboard, we aimed to create a more comprehensive representation of paper-based materials, thus improving the model's ability to accurately detect and categorize a broader range of paper products, reflecting the variability encountered in real-world recycling scenarios[6].

After data collection, the individual datasets were

combined to create a comprehensive dataset covering plastic, paper, glass, and metal, ensuring diverse and representative training data.

B. Data Preprocessing

Roboflow facilitated the preprocessing of images to prepare them for model training. The platform's preprocessing tools enabled the following tasks:

- Auto-Orientation: Automated correction of image orientation to ensure all images were correctly aligned. This step minimized errors related to misaligned images and improved model training accuracy.
- Resize: Images were resized to a consistent dimension of 640x640 pixels. This standardization ensured uniform input sizes for the models, enhancing the consistency of training data.
- Filter Null: The platform's filtering capabilities ensured that only images with complete annotations were included. This step prevented the inclusion of incomplete data, which could negatively impact model performance.

C. Data Augmentation

Roboflow's augmentation tools were used to enhance the diversity of the dataset and improve model robustness. The augmentation techniques applied include:

- Horizontal Flip: To simulate different object orientations and improve the model's ability to recognize objects from various angles.
- Rotation: Images were rotated randomly between -15° and +15° to handle variations in object orientation.
- Shear: Horizontal and vertical shear transformations of ±10° were applied to introduce distortions that the model might encounter in real-world scenarios.
- Brightness Adjustment: Brightness levels varied between -15% and +15% to account for different lighting conditions.
- Blur: Gaussian blur with a maximum radius of 2.5px was applied to simulate varying levels of image sharpness and improve model resilience to blurred images.

D. Model Training

In this study, we evaluated several object detection models to determine the most effective approach for the real-time detection of recyclable materials. The models were assessed using three distinct datasets, each containing images of paper, glass, plastic, and metal. Below is an overview of each model:

- **Roboflow 3.0 Object Detection (Accurate)** is designed to achieve high precision and recall in object detection tasks. This model prioritizes accuracy, making it suitable for applications where precise detection is crucial[13].
- **Roboflow 3.0 Object Detection (Fast)** is optimized for rapid inference while maintaining a balance between detection speed and accuracy. It is designed for applications where real-time processing is important[13].
- **YOLO-NAS Object Detection (Accurate)** YOLO-NAS is a variant of the YOLO (You Only Look Once) series, tailored for accurate object detection with a focus on achieving high precision[14].
- **YOLOv8** is a sophisticated model in the YOLO (You Only Look Once) series, designed to enhance both detection accuracy and inference speed. It is highly effective for applications that require a balance of high performance and real-time processing capabilities[15].

E. Evaluation Metrics

1) Precision: It measures the accuracy of positive predictions, reflecting the proportion of true positives among all positive predictions[16].

$$\text{Precision} = \frac{\text{True Positive (TP)}}{\text{True Positive (TP)} + \text{False Positive (FP)}}$$

2) Recall: It measures the model's ability to identify all relevant positive instances, indicating the proportion of true positives among all actual positives[16].

$$\text{Recall} = \frac{\text{True Positive (TP)}}{\text{True Positive (TP)} + \text{False Negative (FN)}}$$

3) Mean Average Precision (mAP): is a key metric for evaluating object detection models, providing a comprehensive measure of performance by integrating both precision and recall across multiple classes and confidence thresholds[17]. Calculation Steps:

1) Precision and Recall: For each class, calculate precision and recall values at different confidence thresholds.
2) Average Precision (AP): Compute the area under the precision-recall curve for each class.
3) Mean Average Precision (mAP): Average the AP scores across all classes.

V. Results And Discussion

A. Results

TABLE I
COMPARISON OF OBJECT DETECTION MODELS ACROSS DIFFERENT DATASETS

Model	Data 1	Data 2	Data 3
Roboflow 3.0 Object Detection (Accurate)	mAP: 91.5% Precision: 90.1% Recall: 85.6%	mAP: 90.7% Precision: 89.5% Recall: 85.2%	mAP: 87.2% Precision: 87.5% Recall: 81.2%
Roboflow 3.0 Object Detection (Fast)	mAP: 87.6% Precision: 84.3% Recall: 83.9%	mAP: 91.2% Precision: 89.1% Recall: 86.4%	-
YOLO-NAS Object Detection (Accurate)	-	-	mAP: 76.5% Precision: 85.5% Recall: 63.7%
YOLOv8	mAP: 90.7% Precision: 90.6% Recall: 84.8%	mAP: 89.3% Precision: 89.0% Recall: 83.3%	mAP: 81.6% Precision: 84.6% Recall: 72.3%



Fig. 2. Roboflow 3.0 Object Detection (Accurate) on Data 1 Confusion Matrix

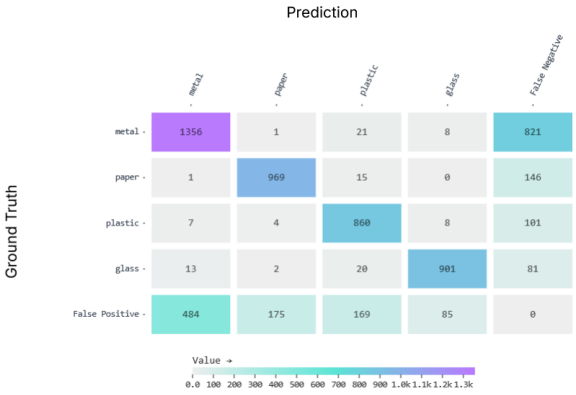


Fig. 3. Roboflow 3.0 Object Detection (Fast) on Data 1 Confusion Matrix

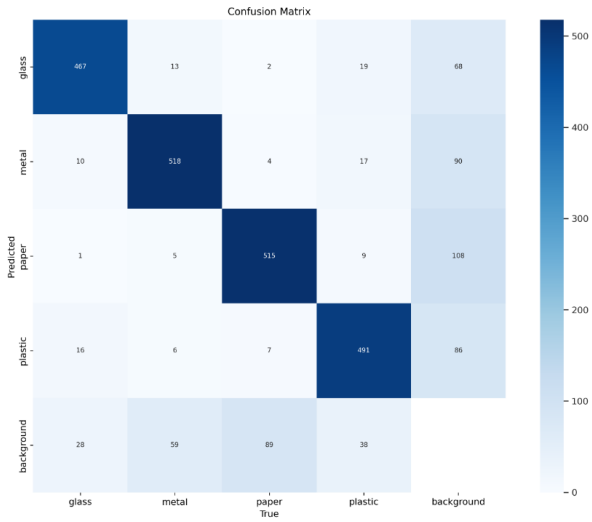


Fig. 4. YOLOv8 on Data 1 Confusion Matrix

B. Discussion

The performance of the object detection models varied across the datasets, as shown in Table I, demonstrating the significant influence of dataset composition on model effectiveness. The Roboflow 3.0 Accurate model achieved the highest mAP on Data 1, indicating its strong suitability for a diverse and balanced dataset. However, its performance slightly declined on Data 3, suggesting that this dataset's specific characteristics may not align as well with the model's detection capabilities.

The Roboflow 3.0 Fast model performed notably well on Data 2, surpassing the Accurate version in mAP, although it may trade off some precision and recall for speed.

YOLO-NAS, while showing high precision, had lower mAP and recall, indicating effective object identification but a tendency to miss relevant instances. YOLOv8 demonstrated robust performance, particularly on Data 1, but its metrics fluctuated across datasets, with lower results on Data 3, suggesting sensitivity to dataset-specific features.

In summary, while the Roboflow 3.0 Accurate model demonstrated strong overall reliability, the YOLOv8 model proved to be the most suitable for our project. Despite not achieving the highest accuracy, YOLOv8 excelled in precision, which is crucial for classification tasks. This makes YOLOv8 the most reliable model for our specific needs, with Roboflow Fast and Accurate models serving as viable alternatives depending on the application's specific requirements.

VI. Conclusion

This study assessed the performance of object detection models across three datasets of recyclable materials. Although the Roboflow 3.0 Accurate model demonstrated strong reliability, particularly with a diverse dataset, the YOLOv8 model emerged as the best choice for our specific project. It provided the highest precision, which is crucial for our classification tasks, making it the most suitable model. The Roboflow 3.0 Fast model and YOLO-NAS also offered competitive alternatives, particularly in scenarios where speed is essential. These findings underscore the importance of selecting the appropriate model based on the specific needs and goals of recycling detection tasks.

VII. Future Work

- Accuracy Enhancement: Further refine the model to improve accuracy and reliability in varied environmental conditions.
- Model Expansion: Extend the model to include additional material classes, thereby increasing its versatility in detecting a broader range of recyclables.
- Weight Estimation: Development of an integrated system to estimate the weight of detected objects based on image data.
- Application Integration: Deployment of the model within the "Recycling Bank" app to facilitate real-world applications and user engagement.

VIII. Github Link

The link for our project on GitHub: https://github.com/nsreen-hujjatullah/train-YOLOv8-object-detection-on-custom-dataset

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