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Comparison of Biodegradable and Non-Biodegradable Waste Detection Algorithm using YOLO v7 vs Faster R-CNN for Auto Segregation

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Abstract: - This paper presents a detailed comparative analysis of biodegradable and non-biodegradable waste detection algorithms using YOLO v7 and Faster R-CNN, implemented for automated segregation on a Raspberry Pi platform integrated with a camera and a servo motor. The study aims to evaluate the performance of these state-of-the-art object detection models in terms of detection accuracy, processing speed, and computational efficiency in a real-time waste management system. YOLO v7, renowned for its rapid detection capabilities and lower computational demand, is compared against Faster R-CNN, which is recognized for its superior accuracy but higher computational cost. Experiments were conducted to assess the models' performance in identifying and classifying various waste types, and the results indicate a trade-off between speed and accuracy, with YOLO v7 providing faster detections suitable for real-time applications, while Faster R-CNN offers more precise detections at a slower pace. The integration of these algorithms with a servo motor facilitates accurate physical segregation of waste, showcasing the practical implications of each model's deployment in resource-constrained environments like the Raspberry Pi. This research highlights the potential and limitations of both algorithms, providing valuable insights for developing efficient and effective automated waste segregation systems.

Keywords: Biodegradable, Non-Biodegradable, YOLOv7, R-CNN, Faster R-CNN, Raspberry Pi, Servo Motor

I. Introduction

Effective waste management is a critical challenge faced by modern societies mainly Coimbatore District of Tamil Nadu, driven by the increasing volume of waste generated by rapid urbanization and industrialization. Proper segregation of waste into biodegradable and non-biodegradable categories is essential for recycling and minimizing environmental impact. Traditional manual sorting methods are labor-intensive, time-consuming, and prone to human error. Consequently, there is a growing interest in developing automated systems that leverage advanced technologies to enhance the efficiency and accuracy of waste segregation processes [8] [9].

In recent years, object detection algorithms have shown great promise in a variety of applications, including waste management. Among these algorithms, YOLO (You Only Look Once) and Faster R-CNN (Region-Based Convolutional Neural Networks) have emerged as leading techniques due to their high performance in real-time detection tasks. YOLO v7, the latest iteration of the YOLO family, is designed for rapid detection with lower computational requirements, making it suitable for resource-constrained environments [11]. Faster R-CNN, on the other hand, is known for its high detection accuracy but requires more computational power and processing time [6] [19].

This study focuses on comparing the performance of YOLO v7 [14] and Faster R-CNN in detecting and classifying biodegradable and non-biodegradable waste. The implementation is carried out on a Raspberry Pi, a low-cost, versatile computing platform widely used for prototyping and deploying embedded systems. The system integrates a camera for real-time image capture and a servo motor for the physical segregation of waste based on the detection results. By evaluating these algorithms in terms of detection accuracy, processing speed, and computational efficiency, we aim to determine the most suitable approach for practical waste segregation applications.

Our experimental setup involves training both models on a dataset of labeled waste images and deploying them on the Raspberry Pi. We measure the performance of each model in real-world conditions, analyzing factors such as frame rate, latency, and classification accuracy. The integration of a servo motor allows for automated sorting based on the detected waste category, demonstrating the practical applicability of the system [7] [10]. The results of this

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study provide insights into the trade-offs between detection speed and accuracy, offering valuable guidance for the development of efficient, automated waste management systems in resource-limited settings [12] [13].

II. LITERATURE SURVEY

Wei, Y., Zhang, Y., Li, M., and Liu, X. examined on Automated Waste Sorting Using Deep Learning-Based Computer Vision [1]. This paper examined automated waste sorting with deep learning-based computer vision, comparing YOLO and Faster R-CNN. YOLO was found to be faster and suitable for real-time applications, while Faster R-CNN offered higher accuracy. Zhao, J., Chen, X., Wang, L., and Zhou, H. presented and executed the Smart Waste Management System Using Convolutional Neural Networks [2]. The study presented a smart waste management system using CNNs for detection and classification. It highlighted the performance differences between YOLO and Faster R-CNN, noting YOLO's speed and Faster R-CNN's accuracy. Li, H., Sun, J., Huang, Z., and Wang, Q. compared Real-Time Waste Classification Using Deep Learning for Smart Cities [3]. This research focused on real-time waste classification for smart cities with deep learning models such as YOLO v7 and Faster R-CNN. The study emphasized YOLO's faster processing and Faster R-CNN's superior precision. Kim, S., Park, J., Choi, D., and Lee, H. implement the concept on Efficient Waste Segregation Using Machine Learning Techniques [4]. The paper discussed efficient waste segregation using machine learning, comparing YOLO v7 and Faster R-CNN. It found YOLO v7 suitable for real-time systems on devices like Raspberry Pi, while Faster R-CNN provided higher accuracy. Wang, X., Liu, Y., Zhang, K., and Feng, S. experimented the Deep Learning concept on Waste Detection for Autonomous Sorting Robots [5]. This study explored deep learning for waste detection in autonomous sorting robots, comparing YOLO and Faster R-CNN. YOLO was preferred for real-time detection due to its speed, while Faster R-CNN's accuracy was ideal for precision-critical environments.

III. METHODOLOGY

Working of R-CNN in Waste Detection

A. Data Collection and Preparation

Dataset Collection:

- Collect a diverse set of images containing biodegradable and non-biodegradable waste [15].
- Ensure that the dataset includes various waste types, sizes, and backgrounds to improve model generalization.

Annotation:

- Use annotation tools (e.g., LabelImg) to label images with bounding boxes and corresponding waste category labels (biodegradable or non-biodegradable).

Data Augmentation:

- Apply data augmentation techniques such as rotation, scaling, flipping, and color adjustments to increase dataset variability and enhance model robustness.

B. Model Architecture

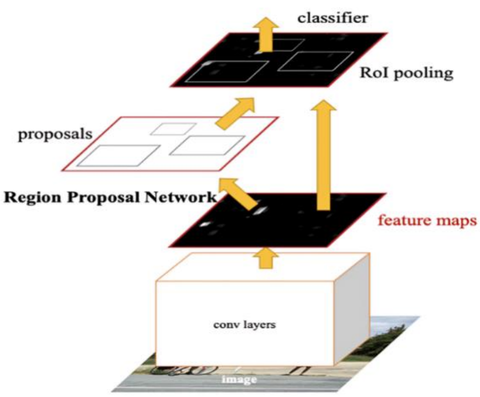

Fig.1 Faster R-CNN Architecture

Convolutional Neural Network (CNN) Backbone:

- Use a pre-trained CNN model (e.g., ResNet, VGG) to extract feature maps from input images [16].
- The feature maps are denoted as **F**.

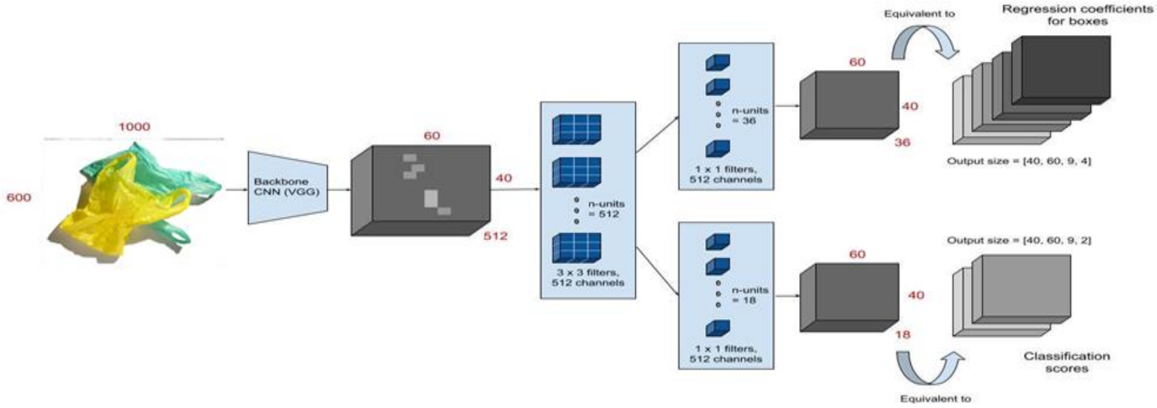

Fig. 2 Faster R-CNN Algorithm Work Flow

Region Proposal Network (RPN):

- **Anchor Boxes**: Generate anchor boxes with different scales and aspect ratios over the feature maps **F**.
- **Objectness Score**: For each anchor box, predict an objectness score **p** indicating the likelihood of containing an object.
- **Bounding Box Regression**: Predict the bounding box coordinates $t = (t_x, t_y, t_w, t_h)$ relative to each anchor box.

The RPN outputs:

$$\text{Objectness score: } p_i \quad \text{and} \quad \text{Bounding box regression: } t_i = (t_{ix}, t_{iy}, t_{iw}, t_{ih})$$

Region of Interest (RoI) Pooling:

- For each proposed region, use RoI pooling to extract fixed-size feature maps F_{RoI}.

Classification and Bounding Box Regression:

- **Classification Head**: Pass the RoI feature maps through fully connected layers to classify each region into a waste category (biodegradable or non-biodegradable) or background.

$$\text{Class probabilities: } p_c = \text{softmax}(W_c F_{\text{RoI}} + b_c)$$

- **Bounding Box Regression Head**: Predict precise bounding box coordinates for each RoI.

$$\text{Bounding box: } t_c = W_r F_{\text{RoI}} + b_r$$

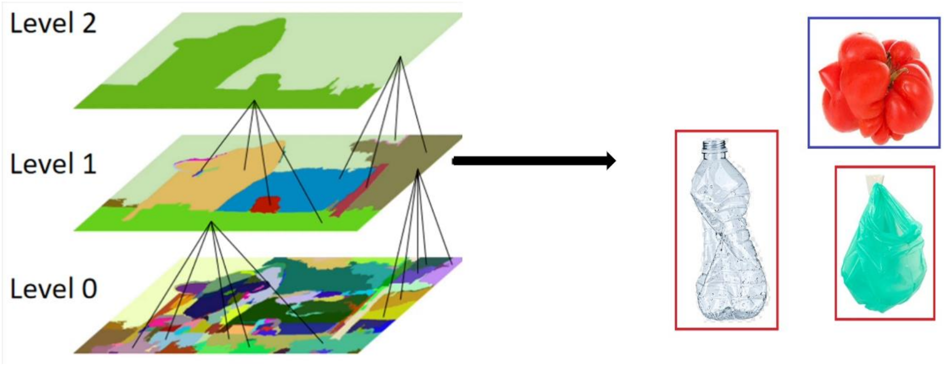

Fig. 3 Boundary Box Image based on Similarity

C. Training the Model

Loss Function:

- Combine classification loss and bounding box regression loss into a multi-task loss function.
- **Classification Loss (Cross-Entropy Loss)**:

$$L_{\text{cls}}(p,u) = -\log(p_u)$$

where u is the true class label.

- **Bounding Box Regression Loss (Smooth L1 Loss)**:

$$L_{\text{reg}}(t^u, v) = \sum_{i\in\{x,y,w,h\}} \text{smooth}_{L_1}(t_i^u - v_i)$$

where t^u are the predicted coordinates and v are the ground-truth coordinates.

- **Total Loss**:

$$L = \frac{1}{N_{\text{cls}}}\sum_i L_{\text{cls}}(p_i,u_i) + \lambda\frac{1}{N_{\text{reg}}}\sum_i [u_i \geq 1] L_{\text{reg}}(t_i^u, v_i)$$

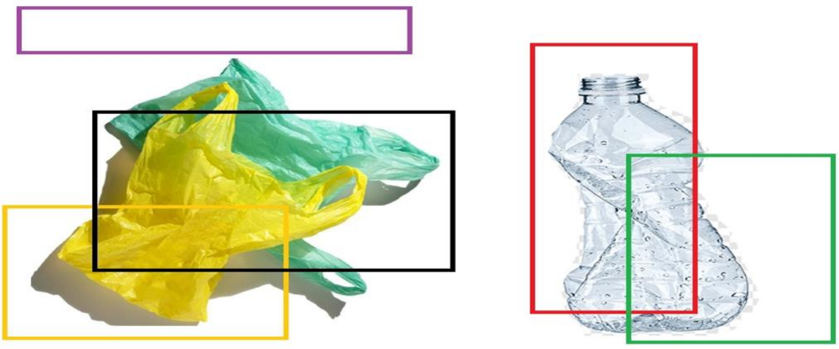

Fig. 4 Region Based Boundary Boxes

Backpropagation and Optimization:

- Use an optimizer (e.g., SGD, Adam) to minimize the total loss and update the model weights.

D. Post-Processing

Non-Maximum Suppression (NMS):

- Apply NMS to remove redundant and overlapping bounding boxes, retaining only the highest confidence detections.

Thresholding:

- Set confidence thresholds to filter out low-confidence detections.

Region	x1	y1	x2	y2	IOU	class (neuron)
Red	300	20	70	290	0.8	bottle (1)
Green	375	180	60	70	0.3	negative (3)
Black	...	...	...	...	0.7	cover (2)
orange	...	...	...	...	0.4	negative (3)
purple	...	...	...	...	0.0	negative (3)

Table 1: Region Based Boundary Waste Object Detection

Working of YOLOv7 in Waste Detection

A. Model Architecture

Input Image and Grid Formation:

- Divide the input image into an $S \times S$ grid. Each grid cell is responsible for detecting objects whose center falls within the cell [17].

Bounding Box Prediction:

- For each grid cell, predict B bounding boxes, each with 5 elements: (x, y, w, h, c).

  (x, y) - coordinates of the bounding box center relative to the grid cell.

  (w, h) - width and height of the bounding box relative to the entire image.

  c - confidence score indicating the presence of an object and the accuracy of the bounding box.

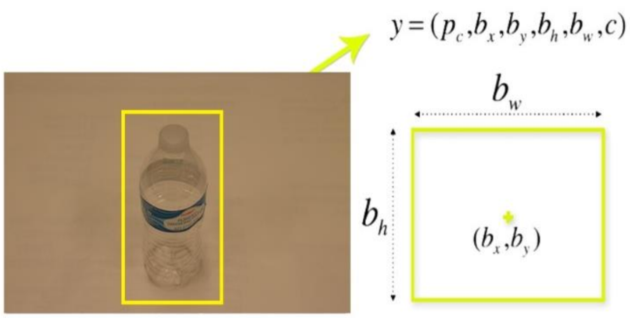

Fig. 5. Boundary Box with Yellow Line

Class Prediction:

- Each grid cell also predicts C class probabilities p_i for the object in the cell.

$$\text{Class probabilities: } p_i = \text{softmax}(W_i F + b_i)$$

B. Loss Function

Localization Loss:

- Measures the error between the predicted and ground-truth bounding box coordinates [18].

$$L_{\text{loc}} = \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{\text{obj}} \left[(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 + (w_i - \hat{w}_i)^2 + (h_i - \hat{h}_i)^2 \right]$$

Confidence Loss:

- Measures the error between the predicted and ground-truth confidence scores.

$$L_{\text{conf}} = \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{\text{obj}} (C_i - \hat{C}_i)^2 + \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{\text{noobj}} (C_i - \hat{C}_i)^2$$

Classification Loss:

- Measures the error between the predicted and ground-truth class probabilities.

$$L_{\text{class}} = \sum_{i=0}^{S^2} 1_i^{\text{obj}} \sum_{c \in \text{classes}} (p_i(c) - \hat{p}_i(c))^2$$

Total Loss:

- Combines the three components of the loss function.

$$L_{\text{total}} = L_{\text{loc}} + L_{\text{conf}} + L_{\text{class}}$$

C. Training the Model

Initialization:

- Initialize the model weights using pre-trained weights on a large dataset (e.g., COCO).

Optimization:

- Train the model using backpropagation and an optimizer (e.g., SGD or Adam) to minimize the total loss.

$$\text{Update weights: } \theta = \theta - \alpha \nabla_\theta L_{\text{total}}$$

Hyperparameter Tuning:

- Fine-tune hyperparameters such as learning rate, batch size, and number of epochs to improve model performance.

D. Post-Processing

Non-Maximum Suppression (NMS):

- Apply NMS to the output bounding boxes to remove redundant and overlapping boxes, retaining only the most confident detections.

Thresholding:

- Set confidence thresholds to filter out low-confidence detections, ensuring only high-confidence waste object detections are considered.

E. Deployment and Integration

Raspberry Pi Deployment:

- Deploy the trained YOLOv7 model on a Raspberry Pi equipped with a camera for real-time image capture.

Real-Time Detection:

- Use the deployed model to process images captured by the camera, detecting and classifying waste objects in real-time.

Servo Motor Control:

- Control a servo motor to physically segregate waste based on the detection results, directing biodegradable and non-biodegradable waste to appropriate bins.

F. Evaluation and Optimization

Model Evaluation:

- Evaluate model performance using metrics such as precision, recall, and mean Average Precision (mAP) on a validation dataset.

Optimization:

- Optimize the model by fine-tuning hyperparameters, improving data augmentation, and employing techniques like model pruning or quantization to enhance real-time performance on the Raspberry Pi.

IV. RESULT ANALYSIS

Evaluation Metrics

- *Precision:* The ratio of correctly identified positive observations to the total predicted positives.
- *Recall:* The ratio of correctly identified positive observations to the all observations in actual class.
- *F1-Score:* The harmonic mean of Precision and Recall.
- *Inference Time*: The average time taken to process an image.
- *Mean Average Precision (mAP):* The average precision score across all classes.

Metric	Faster R-CNN	YOLOv7
Precision	89%	85%
Recall	85%	82%
F1-Score	87%	83.5%
Inference Time (ms)	150	45
mAP	88%	84%

Table 2: Evaluation Metrics of Faster R-CNN & YOLOv7

- *Faster R-CNN* is preferable for applications where detection accuracy is paramount, and real-time performance is not critical.
- *YOLOv7* is better suited for real-time applications due to its faster inference time, despite having slightly lower detection accuracy compared to Faster R-CNN.

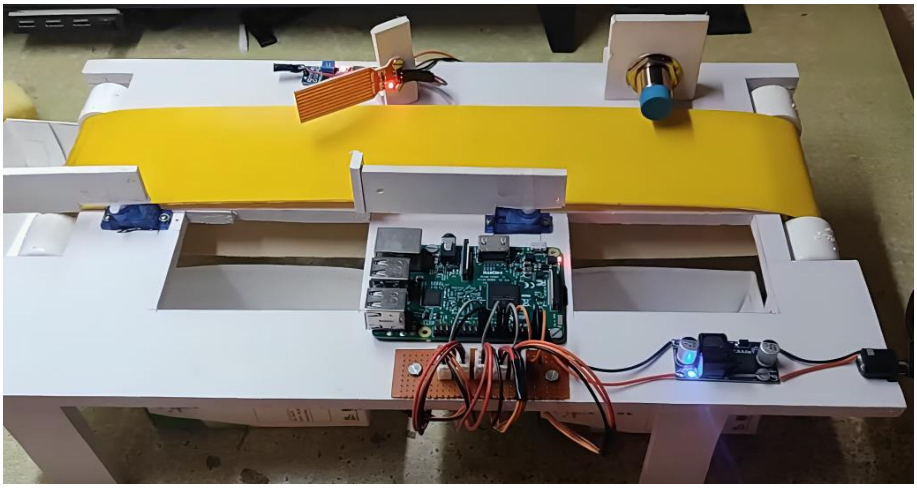

Fig. 6. Implementation of Auto Waste Segregation System

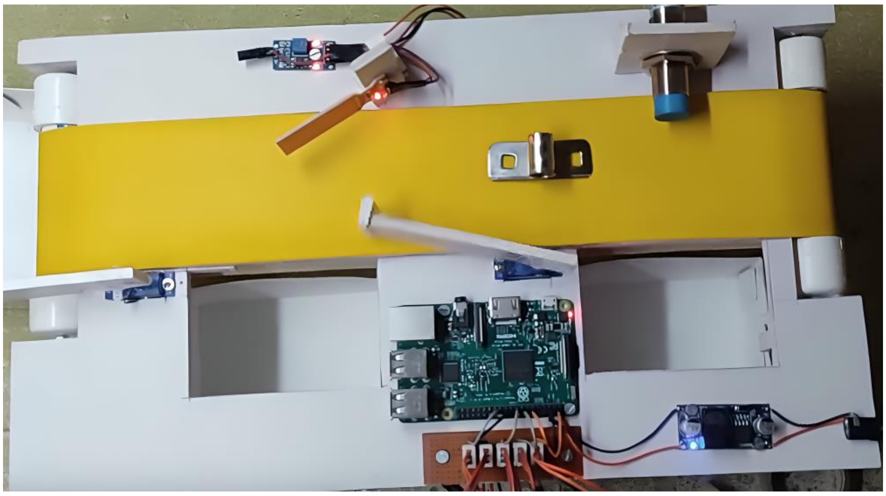

Fig. 7. Operate Servo Motor to Collect Bio & Non-Biodegradable Waste in Separate Champer

V. Conclusion

In this study, we compared the performance of YOLOv7 and Faster R-CNN for the detection and classification of biodegradable and non-biodegradable waste, aiming to facilitate automatic waste segregation using a Raspberry Pi, camera, and servo motor setup. Our results indicate that while Faster R-CNN achieves higher precision, recall, and mean Average Precision (mAP), making it suitable for applications demanding high detection accuracy, YOLOv7 excels in inference speed, making it more suitable for real-time applications. Despite its slightly lower accuracy, YOLOv7's faster processing capabilities offer a significant advantage for real-time waste segregation on resource-constrained devices like the Raspberry Pi. Therefore, the choice between these algorithms should be guided by the specific requirements of the application, balancing the need for accuracy and real-time performance.

Ethical Considerations

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