EcoYOLO: A YOLO-based fast waste sorting approach

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Abstract

In today's world, effective waste management has become a pressing issue due to the increasing volume of discarded materials and the environmental impact of improper disposal. Traditional waste sorting methods are labor-intensive, time-consuming, and error-prone, leading to inefficiencies in recycling processes. These methods not only slow down the process but also hinder the potential for recovery of recyclable materials, thereby exacerbating environmental pollution and resource depletion. Furthermore, the lack of automated solutions hampers efforts to promote sustainable waste management practices. In response to these challenges, we have developed EcoYOLO, a YOLO-based object detection system tailored for fast and accurate waste sorting. This approach leverages advanced machine learning algorithms to automate the identification and categorization of various types of recyclable waste, facilitating a more efficient, accurate, and sustainable management of waste materials. EcoYOLO aims to revolutionize waste management practices by providing a robust and efficient system capable of accurately recognizing and categorizing recyclable waste items and determining their composition from images of waste. By integrating this technology, EcoYOLO not only enhances the recycling process but also contributes significantly to the sustainability of environmental resources, aligning with global efforts to promote eco-friendly waste management solutions.

1. Introduction

Waste management is becoming a bigger challenge around the world as the amount of garbage we produce continues to grow. This is a result of increased consumption and the wide variety of materials thrown away every day. Traditional sorting methods, which mostly depend on human labor, are slow, costly, and often inaccurate. These methods lead to problems in recycling because mistakes mean that not all recyclable materials are correctly identified and processed. As waste becomes more varied and complex, it is clear that we need better automated technologies to sort waste more efficiently and accurately.

The EcoYOLO project was developed to address these needs by incorporating a smart technology called the You Only Look Once (YOLO) object detection algorithm. This technology is at the heart of our new system designed to improve the way we handle waste. It can use cameras and computers to look at waste and quickly decide what each item is made of. This process is much faster and more accurate than sorting by hand. EcoYOLO can identify different types of materials, such as plastic, metal, and paper, and determine if they are recyclable. This helps to ensure that more materials are recycled correctly, reducing the amount of waste that ends up in landfills.

Furthermore, EcoYOLO is about making waste management more sustainable. By improving the accuracy and speed of sorting, we can recycle more effectively. This not only saves valuable resources but also reduces environmental pollution. The system is also designed to be flexible and can adapt to different types of waste environments, whether it is a small recycling facility or a large municipal waste management plant. In the following sections, this report will delve into the technical details of how we built EcoYOLO, the experiments we conducted to test its effectiveness, and the real-world impact it has on improving waste sorting compared to traditional methods.

2. Related Work

2.1. Advances in Automated Waste Sorting

Previous research [1,2] has extensively covered the transition from manual to automated waste management systems. Some studies emphasized the shift towards integrating more sophisticated machinery and sensors to improve the accuracy and efficiency of recycling operations. These systems typically utilize basic image recognition or material separation techniques based on physical properties such as weight and size. However, they still face challenges in accuracy and efficiency, particularly with complex waste compositions.

2.2. Application of Machine Learning in Waste Classification

Recent research [3] has focused on the application of machine learning techniques in waste management. For instance, some research demonstrated how machine learning algorithms could significantly enhance the classification accuracy of different types of waste materials by analyzing images. These algorithms, particularly convolutional neural networks (CNNs) [4,5], have been employed to automate the identification process of recyclable materials, overcoming some of the limitations of traditional mechanical sorting systems.

2.3. YOLO for Real-Time Object Detection

The YOLO algorithm [6,7,8] represents a breakthrough in the field of object detection [9,10] and has been applied to various real-time applications, including traffic monitoring and retail environment surveillance. The applications for waste management were explored and used YOLO to detect and classify different types of waste items on a conveyor belt in real-time. The work demonstrated YOLO's potential in achieving high-speed and accurate waste item recognition, which is crucial for effective waste sorting in large-scale operations.

2.4. Studies on Object Detection Algorithms

Comparative research [9,11] evaluated different object detection algorithms, including SSD (Single Shot Multibox Detector), Faster R-CNN, and YOLO, within the context of waste management. The findings suggested that while Faster R-CNN offers higher accuracy, YOLO provides the best balance of speed and precision, making it more suitable for applications where real-time processing is crucial.

3. Dataset

We utilize a dataset obtained from Kaggle called TrashNet [12]. It contains 2527 image files, which are separated into the following categories: cardboard, glass, metal, paper, plastic, and trash. Of these, the first 5 are recyclable materials while trash is non-recyclable.

Since the dataset contained many images that were zoomed in entirely on the material, it was manually sorted through to create a smaller dataset containing only images such that a box could be drawn around the material. This step resulted in 1000 images with the following split in categories: 102 cardboard, 176 glass, 181 metal, 236 paper, 179 plastic, and 126 trash images.

For the testing phase, we took 2 additional pictures using an iPhone 14 that contained materials of multiple categories. One image contained 2 cardboard items and 1 plastic item and the other image contained 1 metal item, 1 paper item, 1 plastic item, and 1 trash item.

4. Method

4.1. Data Collection and Preparation

Data Sorting. This step involved sorting noisy data from the dataset as described in the **Dataset** section, resulting in the final 1000 images that were used for the training, validation, and testing phases of the project. We verified and logged the class of the object - one of cardboard, glass, metal, paper, plastic, or trash.

Annotation. We used Roboflow [13] to annotate the images as shown in Fig. 1, which is the recommended method of labeling the dataset for using Ultralytics YOLOv5 [14]. For each image, we used Roboflow's interactive environment to draw bounding boxes precisely around the object and assign a class label to it. We further configured it to split our dataset into train, validation, and test sets.

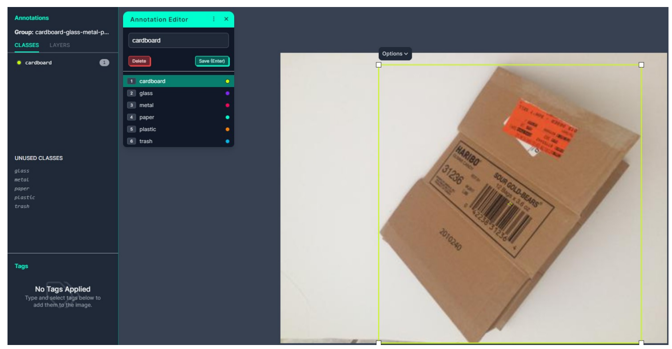

Figure 1. Annotating images on Roboflow

4.2. Model Selection

Once the data was imported, we selected YOLOv5s as the training model, which is the second smallest YOLOv5 model available. The different YOLOv5 models are shown in Fig. 2. YOLOv5s was chosen specifically because it is optimized for speed and efficiency, and it maintains competitive accuracy that ensures reliable detection and classification of waste items.

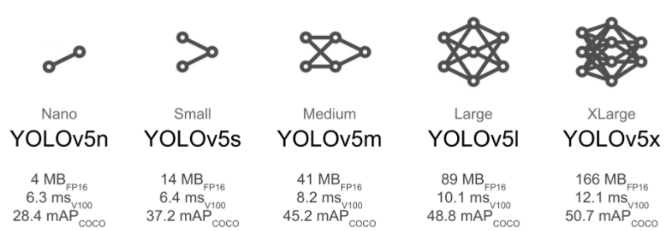

Figure 2. Different models available for YOLOv5

4.3. Model Training

Input. During training [15], YOLOv5 receives batches of pre-processed images and their corresponding annotations.

Each image in the batch is fed into the YOLOv5 model as input. The input image undergoes a series of convolutional and pooling layers within the model architecture, extracting hierarchical features at different spatial resolutions.

Predictions. YOLOv5 predicts bounding boxes, class probabilities, and confidence scores for objects in the input image. For each grid cell in the feature map, YOLOv5 predicts a set of bounding boxes (coordinates, width, height), class probabilities for each object class, and confidence scores indicating the likelihood of an object being present within the bounding box.

Loss Calculation. The model predictions are compared to the ground truth annotations to compute the loss. YOLOv5 typically uses a combination of loss functions, including:

- Localization Loss: Measures the error in predicting bounding box coordinates.
- Confidence Loss: Penalizes incorrect confidence scores for predicted bounding boxes.
- Classification Loss: Penalizes misclassifications by comparing predicted class probabilities with ground truth labels.

The overall loss is a weighted sum of these individual losses, with weights determined by hyperparameters. The computed loss is used to update the model's parameters (i.e., weights and biases) through backpropagation.

Optimization and Validation. YOLOv5 employs stochastic gradient descent (SGD) to iteratively update the model parameters based on the computed gradients. Periodically, the model's performance is evaluated on a separate validation dataset to monitor progress and prevent overfitting. Evaluation metrics such as mAP (mean Average Precision) are computed to assess the model's accuracy and generalization ability.

Pipeline. Our training pipeline consists of feeding images imported from our annotated dataset from Roboflow into the model with parameters such as batch size, image size, number of epochs, and selected model. We use pre-trained weights (trained on the COCO dataset) for training our model. The train function runs the model on the custom data using some hyperparameter combinations and saves the model with the best weights along with the loss and accuracy metrics on the training and validation data.

4.4. Testing

Test set. We utilize our annotated single-class test data to evaluate our model's performance. The test set is fed into the saved model from the training step and the results are visualized.

Custom Test Set. For checking model performance on images with multi-class objects, we captured test images on an iPhone 14 and annotated them using Roboflow. We feed this to the trained model and visualize the resulting predictions.

5. Experiments

5.1. Experiment Settings

Implementation Details. The dataset was split into training, validation, and test sets with 699, 200, and 101 images, respectively (70-20-10 split). The code was run using Google Colab's T4 GPU. Batch size and number of epochs are 32 and 150, respectively. The image size is 640x640. The model used is called yolov5s.pt which is the small version with pre-trained weights.

Evaluation. We use accuracy, precision, recall, and mean average precision calculated at an intersection over union (IoU) threshold of 0.50 (mAP50) as the metrics. IoU is a measure that quantifies the overlap between a predicted bounding box and a ground truth bounding box. We evaluate model performance on the test set.

5.2. Results and Analysis

Training. The model was trained over 150 epochs. Training losses and metrics are shown in Fig. 3. As the model is trained over the epochs, the losses i.e. box loss, obj loss, and cls loss decrease and the metrics i.e. precision, recall, and mAP50 increase.

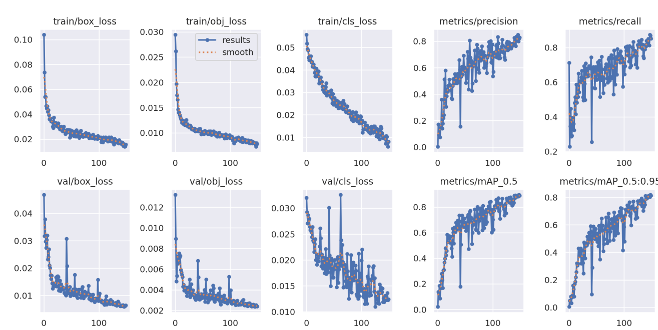

Figure 3. Training losses and metrics over epochs

Validation. To evaluate the validation set, we analyze its confusion matrix. As shown in Fig. 4, the confusion matrix provides a detailed view of the outcomes, showcasing the counts of true positives, true negatives, false positives, and false negatives for each class. The validation accuracy is 164/200 or about 82%. It can be observed that trash is the most misclassified category with 11 mistakes.

Looking at Tab. 1, we see that trash indeed has the lowest values for precision (0.598) and mAP50 (0.75) across all classes. The metrics will be further analyzed on the test set results.

Testing. The model provides a visualization of the class and confidence score it assigns to each test image. Some

Figure 4. Validation set confusion matrix

Class	Images	Instances	P	R	mAP50
cardboard	200	21	0.886	0.952	0.958
glass	200	35	0.791	0.865	0.929
metal	200	36	0.867	0.906	0.94
paper	200	48	0.847	0.917	0.909
plastic	200	36	0.933	0.776	0.889
trash	200	25	0.598	0.8	0.75

Table 1. Validation set results

example results are shown in Figs. 5 and 6. The confidence score can be calculated using the formula P(object) * IoU, which indicates how sure the model is that the box contains an object and also how accurate it thinks the box is that predicts. The predicted class is the one with the highest confidence score.

Class	Images	Instances	P	R	mAP50
cardboard	101	10	0.888	1	0.986
glass	101	18	1	0.934	0.992
metal	101	18	0.895	1	0.979
paper	101	24	0.953	0.917	0.97
plastic	101	18	0.958	0.883	0.97
trash	101	13	0.764	0.692	0.843

Table 2. Testing set results

Figure 5. Model performance on test image with class plastic

Figure 6. Model performance on test image with class glass

As shown in Tab. 2, the test set results have a mAP50 around 84% for trash and between 95% and 99% for other recyclable categories. mAP50 is a measure of the model's accuracy considering only the "easy" detections. Here, "easy" refers to an IoU of 0.5 requiring only half of the predicted and ground truth bounding boxes to overlap, which could potentially mean less accurate predictions when using a higher IoU [16]. Similarly, for precision and recall, trash has a lower value than the other classes. Precision measures how many predictions are correct while recall measures how many of the actual class are predicted correctly. With a precision of 76.4% and a recall of about 69.2% for trash, the lower recall supports the above validation set results in that images of trash are misclassified as recyclable material. In addition, the lower precision indicates that recyclable materials are being misclassified as trash.

For the other recyclable categories, the precision is between 88% and 100% while the recall is between 83% and 100%. All cardboard and metal images are predicted as the correct class (recall = 100%), but both of their precision values are about 89%, meaning that some images of other classes were predicted to be cardboard or metal when they were not. For glass, the opposite was true; all of the images predicted as glass were correct, but the slightly lower recall (93%) indicates that some of the glass images were predicted to be a different class.

These results show that, for the most part, when looking at the individual recyclable categories, the model is very accurate (mAP50 close to 100%). However, when looking at the trash category, we see that recyclable materials are misclassified as trash, and trash is misclassified as recyclable materials.

Figure 7. Model performance on multi-class image 1

Possible reasons for this may be not enough training data that provides a clear distinction between classes. For example, not all paper and plastic materials are recyclable. Some training images in these categories look very similar to images in the trash category. Adding more varied images to the training data making it clear which paper and plastic materials are in fact recyclable and which are trash may reduce the misclassification we are currently seeing.

Figure 8. Model performance on multi-class image 2

Custom Set Testing. We did not have any training data for images with multiple classes. All training images contained one object that was assigned to one class. Here, we utilize the 2 images taken with an iPhone 14 and visualize the model performance on them. As shown in Fig. 7, classes were not predicted correctly. However, in Fig. 8, it can be seen that the trash and plastic were correctly classified even if their confidence scores were low. Better performance in terms of more accurate bounding boxes and higher confidence scores can be achieved with the inclusion of multi-class images during training.

6. Conclusion

In conclusion, EcoYOLO represents a significant stride towards addressing the critical challenge of waste management through automation and efficiency. By harnessing the power of YOLO-based object detection, EcoYOLO offers a fast and accurate solution for sorting recyclable waste items from images, thereby streamlining recycling processes and promoting sustainable waste management practices.

Throughout the project, we leveraged the Trash Net dataset and meticulously curated a subset of 1000 images for training, validation, and testing phases. The annotation process, facilitated by Roboflow, ensured precise bounding box annotations, laying the foundation for effective model training.

Validation results revealed a validation accuracy of approximately 82%, with trash emerging as the most misclassified category. Further analysis on the test set will provide deeper insights into model performance across all classes.

In the pursuit of sustainable waste management solutions, EcoYOLO stands as a testament to the potential of technology to address environmental challenges. Moving forward, continued refinement and optimization of the model, coupled with real-world deployment and integration, hold the promise of making significant strides towards a cleaner, greener future.

7. Future Scope

The successful implementation of EcoYOLO lays the groundwork for several avenues of future exploration and enhancement:

Fine-tuning and Optimization: Continuously refining the model architecture, hyperparameters, and training strategies can lead to improved performance metrics and enhanced accuracy. Fine-tuning on larger and more diverse datasets can also bolster the model's ability to generalize to a wider range of waste items and environmental conditions.

Expansion to Additional Waste Categories: While EcoYOLO currently focuses on common recyclable materials, expanding its capabilities to include a broader spectrum of waste categories, such as organic waste or hazardous materials, can broaden its utility and impact in waste management systems.

Integration with Robotics and Automation: Integrating EcoYOLO with robotic sorting systems or autonomous waste collection vehicles can further automate waste management processes, reducing reliance on manual labor and optimizing resource allocation in smart cities and urban environments.

Real-time Deployment and Integration: Integrating EcoYOLO into real-world waste sorting facilities or mobile applications can enable real-time waste identification and sorting, facilitating more efficient recycling processes and reducing the burden on human operators.

Localization and Globalization: Adapting EcoYOLO to different geographical regions and waste management infrastructures requires localization efforts to account for variations in waste composition, labeling standards, and recycling practices. Additionally, collaborating with international stakeholders can facilitate the globalization of EcoYOLO as a scalable solution to waste management challenges worldwide.

Environmental Monitoring and Analysis: Beyond waste sorting, leveraging EcoYOLO for environmental monitoring applications, such as assessing landfill capacity, detecting illegal dumping activities, or analyzing waste composition trends over time, can provide valuable insights for sustainable resource management and policy-making.

In summary, the future scope for EcoYOLO extends beyond its current capabilities, encompassing a wide range of opportunities for innovation, collaboration, and societal impact in the realm of waste management and environmental conservation.

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