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Deep Learning for Waste Management: Leveraging YOLO for Accurate Waste Classification

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Abstract

This study presents a novel deep learning-based waste classification system using the state-of-the-art object detection framework You Only Look Once v8 (YOLOv8) to address urgent environmental concerns. Waste categorization is essential to efficient waste management because it allows different waste kinds to be separated for proper disposal, recycling, or composting. Our method uses YOLO v8's capabilities to identify and group waste materials into four classes: bio-degradable, paper, plastic, and metal. Utilizing the improved accuracy and real-time processing of YOLO v8, our system offers a workable automated garbage sorting solution. Convolutional neural networks (CNNs) are used to build the YOLO technique, which allows for real-time object recognition and classification. The model demonstrated high precision (0.94118) and recall (0.96622), indicating that waste items were thoroughly detected. It did well in recognizing items with moderate overlap (mAP@50 = 0.98252).Furthermore, when tested with images with various factors such as angle, position, lighting, and resolution, the results show that the model can classify objects with even higher accuracy.

Keywords

Deep Learning, Object detection, Waste classification, Waste sorting, YOLO

1. Introduction

1.1 Background

The World Bank predicts that trash generation might almost quadruple by 2050, with low- and middle-income nations seeing a 40% rise in waste generation per person [1]. To prevent environmental deterioration and advance sustainability, there is an urgent need for efficient waste management techniques given the exponential rise in garbage generation worldwide. Waste classification is an essential component of waste management that entails grouping waste materials into different classes according to the materials they contain to make recycling, composting, and safe disposal easier. Automated waste classification systems are a viable way to optimize this procedure, allowing for the effective and large-scale sorting of various waste kinds.

We provide a new waste classification system in this study, which is based on the You Only Look Once (YOLO) v8 object detection framework. Our technology uses deep learning and computer vision to automate the categorization process, in contrast to conventional waste sorting techniques that depend on human labour and are frequently prone to errors and inefficiencies. Through the utilization of YOLO v8's improved accuracy and real-time processing capabilities, our system can quickly identify and classify waste materials into four primary groups: paper, plastic, metal, and biodegradable materials.

Our work is driven by the urgent need to solve the problems caused by growing waste production and inadequate waste management infrastructure. By creating our waste categorization system, we hope to provide a dependable and effective waste sorting tool that will further sustainable waste management methods. Our solution increases the precision and consistency of garbage sorting processes while simultaneously lessening the workload for human operators by automating the classification process.

1.2 Problem Statement

Resource conservation and environmental sustainability depend on effective waste material recycling. However, Nepal has enormous waste management difficulties, particularly in metropolitan areas where limited infrastructure and fast population expansion put pressure on the country's already overburdened systems. The absence of adequate waste classification techniques is a major barrier to efficient waste management. Manual sorting procedures are labour-intensive, time-consuming, and error-prone, which results in wasteful resource use and contamination of the environment.

Furthermore, improper waste segregation at the source makes recycling operations downstream more difficult and reduces the possibility of sustainable waste management techniques. This problem is especially severe in Nepal, where the general public has little knowledge about recycling and garbage segregation. Only 4.1% of all garbage produced in Nepal is properly recycled, according to recent studies. The incorrect separation of waste materials is one of the main causes of the low recycling rate [2].

Effective waste segregation of paper, plastic, glass, metal, and biodegradable materials is hampered by the lack of automated technologies. Because of this, recyclables are frequently thrown into regular waste streams, which lowers recycling rates overall and limits the amount of material that can be processed again.

1.3 Objectives

The main objectives of the “Deep Learning for Waste Management” research is:

- To implement an automated waste classification system using YOLO technology to enhance waste management practices in Nepal.

2. Literature Review

The literature extensively discusses the use of deep learning in waste classification.These studies investigate the use of multiple AI algorithms and computer vision techniques for object detection and classification in waste management.

Research conducted by Rajesh et al. concluded that the sheer volume and complexity of waste materials make manual detection time-consuming and impractical. This study proposes a customized approach using an efficient object detection algorithm YOLO to address these challenges, with a focus on real-time object detection and classification of various waste items [3].

In article "A multi-label waste detection model based on transfer learning" Zhang et al. proposed method unlike previous research, which concentrated on single-category waste recognition,the YOLO model can quickly identify and classify multiple types of waste in images. Using a multi-label waste image dataset, the model achieves a mean Average Precision (mAP) of 92.23% and an average detection time of 0.424 seconds per image.When compared to other image classification algorithms, these results show superior classification performance and efficiency, providing new insights for efficient waste management in urban areas [4].

In Reference [5], authors employed YOLOX for real-time garbage detection, identifying seventeen types of garbage.The system automatically determines the type and location of detected garbage,which is then collected by mechanical jaws. TensorRT optimization allows the model to run on low-cost embedded devices without requiring a stable Internet connection. The dataset consists of 5000 labeled images,and evaluation metrics such as mAP, inference time, FLOPs, and model parameters are used. YOLOX outperforms other YOLO models, with a mAP0.5:0.95 ratio greater than 97%and an inference speed greater than 32 fps, providing high accuracy and speed for garbage classification in complex environments.

In [6] the study seeks to improve waste separation by detecting non-biodegradable waste (glass, metal, and plastic) in bins. To train a machine learning model, it collected and labeled 450-500 images in each category using the YOLO format. The model was first tested on a webcam before being implemented on a Raspberry Pi camera, with verified results and calculated accuracy. This approach shows promise for improving waste sorting efficiency.

In this research the authors have proposed a system capable of detecting 12 different types of waste, such as paper, plastic, polythene, glass, metal, bio, and e-waste. They gathered their data from a variety of open sources, with one-third of the images being their own, fully annotated images. Their highest classification accuracy is 73%, with an F1 score of 0.729 [7].

WasteDet, as described by the authors is a deep learning framework that includes convolutional neural networks. These networks perform both localization and classification tasks, with the results fed into an automated pickup planning system.Here the researches complied and annotated custom dataset to evaluate the model.The model when tested on eight classes, achieved a mean Average Precision (mAP) of 87.82%. When tested across all classes, it received a mAP score of 85.60%, outperforming the current state-of-the-art object detection algorithm by 4% in Average Precision (AP). Furthermore, the model can detect objects in real-time applications using live and recorded videos, with a frame rate of 49.6 fps on the authors’ video dataset [8].

The researchers on [9] proposes small object detection by integrating features at different layers, enriching available information, balancing positive and negative samples, and increasing small object instances. This paper [10] categorizes existing deep learning-based sonar image target detection algorithms into four types: candidate region-based, regression-based, Anchor Free, and search-based algorithms.Progress has been significant, with the emergence of high-performing algorithms combining deep learning and object detection methods. In [11] researchers uses one-shot object detection algorithm that aims to detect objects in an image in a single pass or with minimal computation and multi-object tracking to track multiple objects in a video sequence over time which makes it suitable for commercial purpose.

The researchers on [12] aimed to develop a waste classification and management system using the Faster R-CNN deep learning algorithm.The model was trained to recognize a variety of waste materials, including paper, cardboard, plastic, glass, metal, and organic trash. After 75 epochs of training, the model achieved 92% prediction accuracy. In [13] researchers uses a hybrid deep learning model and the features are then fed into a classification model, Support Vector Machine for precise classification.The researchers uses TrashNet Dataset that consists of images of garbage items that belong to different categories, such as cardboard, glass, metal, paper, plastic, and trash gave a very impressive accuracy of 99.84%.

3. Methodology

The methodology for carrying out the "Deep Learning for Waste Management: Leveraging YOLO for Accurate Waste Classification" entails several crucial phases, including the gathering of data, annotation, model training, and deployment.

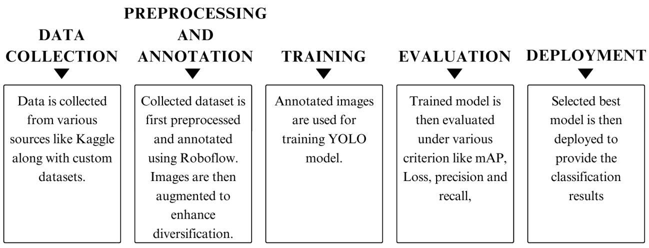

Figure 1: Workflow

3.1 Data Collection

The first stage in preparing datasets for training a trash categorization model is gathering pre-existing datasets from sites such as Kaggle and generating unique datasets by taking pictures of different types of rubbish. For the model to effectively generalize, these datasets should be varied, with samples reflecting various garbage kinds, lighting situations, and orientations.

To support our waste classification effort, we painstakingly assembled a large dataset with 2,350 garbage photos for our study project. By utilizing the extensive resources on Kaggle, we were able to obtain 2,100 high-quality photos that contained a wide range of trash products, including the well-known categories of paper, plastic, metal, and biodegradable waste. The photographs were carefully selected to guarantee that the sample was representative of the range of garbage types, sizes, forms, and environmental conditions that are frequently found in real-world situations.

We added 250 more photos of waste materials from nearby settings to the Kaggle dataset to more thoroughly enhance it and customize it to the particular details of our intended application in Nepal. These bespoke photos were taken in several locations throughout Nepal, showcasing the distinctive qualities and difficulties related to garbage management in the area.

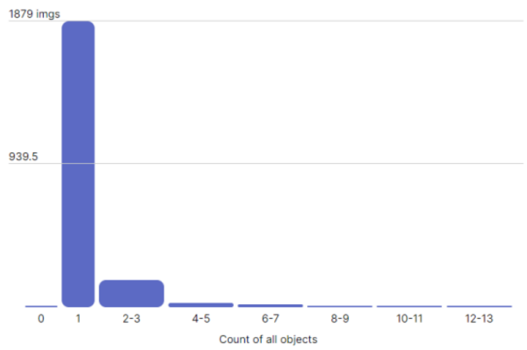

Figure 2: Histogram of Object Count by Image

3.2 Data Preprocessing and Annotation

Bounding boxes were made during the dataset preparation phase to precisely label items in photos. To enable supervised learning, each image in the collection was subjected to extensive annotation and tagging processes. Within each photograph, trash objects were identified and tagged carefully classifying them into the appropriate waste categories, such as paper, plastic, metal, or biodegradable materials. This painstaking annotation procedure made sure that we have ground truth labels, which are necessary for appropriate training and assessing our trash classification algorithm.

Rotating, flipping, resizing, changing contrast and brightness, adding noise, and cropping the photos are examples of common augmentation procedures. Following the pictures' annotation, from 2350 original images, 5872 annotated images were produced. With a median picture ratio of 512x384, the images were primarily broad and ranged in size from 0.03 megapixels to 16.04 megapixels on average. The sample included 890 biodegradable, 633 plastic, 556 paper, and 477 metal examples, evenly distributed across four classifications. The greatest number of photos with just one thing in them was in 1879, but pictures with just two or three objects were rare.

3.3 Training

The garbage categorization model was trained using the Ultralytics YOLOv8 (You Only Look Once) model, which is renowned for its real-time item identification abilities. Specifically, we implemented the architecture's image processing version, YOLOv8, which used TensorFlow and OpenCV, two deep learning frameworks. The model was trained using our annotated datasets, and its parameters were iteratively changed to improve the algorithm's ability to identify and classify various waste categories. Using YOLO's image processing efficiency and real-time item recognition capabilities, the goal of this technique was to develop a model that could quickly and accurately classify waste materials, hence contributing to more effective waste management solutions. The model's ability to distinguish between various types of trash was progressively enhanced. For training, the YOLOv8m model was employed. The model was trained with a batch size of 32 across 70 epochs.

3.4 Evaluation

Mean Average Precision at 50% Intersection over Union (mAP@50) and Mean Average Precision at Intersection over Union between 50% and 95% (mAP@50-95) were two common object detection metrics that we used to assess the performance of our garbage classification system.

The mAP@50 and mAP@50-95 scores offered insightful information about how well the algorithm performed in correctly categorizing waste products. Greater recall and precision were indicated by higher mAP scores, which demonstrated the model's capacity to accurately recognize and classify trash objects over a variety of IoU thresholds. To make sure the evaluation results were reliable and robust, the mAP ratings were compared to baseline performance metrics and confirmed against qualitative assessments.

We were able to gain a thorough grasp of the accuracy and reliability of the waste categorization model by employing mAP@50 and mAP@50-95 as assessment metrics. This allowed us to make well-informed decisions regarding additional optimization and refining of the model.

3.5 Deployment

With the use of a cell phone camera, our technology went beyond the classification of static images to identify waste in real-time. We used a two-pronged deployment strategy to accomplish this real-time capability. The initial layer was a web application developed using the Python framework Streamlit, which is renowned for its approachable data application creation process. A button to manage the live video feed from the camera and a dedicated display area showcasing the categorized waste type and confidence score for each frame in the video were likely among the aspects that Streamlit contributed to the creation of an intuitive user interface.

But OpenCV was doing the real-time magic in the background. Real-time video processing and categorization were made possible thanks in large part to OpenCV, a potent Python computer vision package. OpenCV functions were included in the Streamlit app and served as the bridge to access the live video stream that was provided by the mobile phone camera (via the Iriun application). Preprocessing was done on every frame that was taken from this video feed to make sure that it would work with the main waste classification engine, the YOLOv8 model. The pre-trained YOLOv8 model was then fed these preprocessed frames and it performed real-time analysis on them. YOLOv8 produced classifications and confidence scores by identifying and classifying waste objects that were present in every video frame. Lastly, the live video feed and these classifications were smoothly incorporated with the Streamlit interface.

4. Result and Discussion

4.1 Results

For training, the YOLOv8m model was employed. The model was trained with a batch size of 32 across 70 epochs. The outcomes that were attained are as follows:

Box loss	0.30762
Classification loss	0.23631
Distribution focal loss	0.92997

Table 1: Training losses

Box loss	0.34798
Classification loss	0.27666
Distribution focal loss	0.97204

Table 2: Validation losses

Precision	0.94188
Recall	0.96622
mAP@50	0.98252
mAP@50-95	0.92723

Table 3: Metrics

High precision (0.94118) and recall (0.96622) were attained by the model, demonstrating thorough and precise waste item detection. Strong performance in recognizing items with modest overlap is demonstrated by the mAP@50 score of 0.98252. Nonetheless, the marginally reduced mAP@50-90 score of 0.92723 indicates challenges in identifying items with greater overlap. The model can be improved in handling objects with more overlap, but overall it recognizes and classifies trash items successfully.

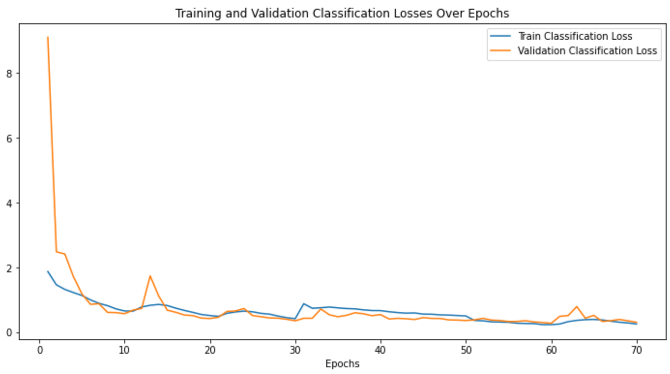

Figure 3: Classification loss over epochs

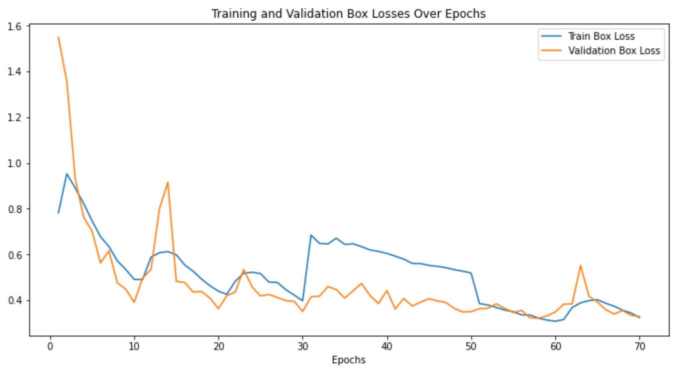

Figure 4: Box loss over epochs

The choice of short training epochs is the main cause of the spiking behavior seen in our model training graph. Our computers become overly constrained when we use big epochs, and they may crash.

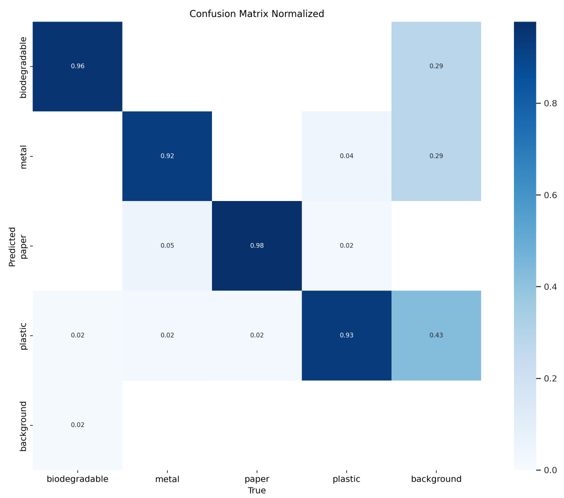

Figure 5: Normalized confusion matrix

4.2 Discussion

The mAP scores that were attained were quite encouraging and demonstrated how well the system classified waste materials. A very high accuracy for detections with a great degree of confidence (IOU greater than 50%) was shown by the mAP@50 value of 0.98252. This indicated that when there was a substantial overlap between the anticipated and ground truth bounding boxes, the model could probably classify most of the waste items in the test set.

The model's capacity to handle detections with a slightly smaller IoU range (between 50% and 95%) was further proved by the mAP@50-95 score of 0.92723. This suggested that even in situations where the bounding boxes were not exactly aligned, the system could still categorize waste items well, possibly capturing a greater diversity of waste products in real-world circumstances.

5. Conclusion

The remarkable outcomes of our real-time trash classification system utilizing YOLOv8 show that it has the potential to be an important instrument for better waste management procedures. The integration of mobile phone cameras and the user-friendly Streamlit interface provided a workable solution for real-time garbage identification. This study paved the way for a more sustainable future by providing access to deep learning applications in trash management.

References

[1] Amani Maalouf and Antonis Mavropoulos. Re-assessing global municipal solid waste generation. *Waste Management & Research*, 41(4):936–947, 2023.

[2] Aisha Khatoon. Waste management—a case study in nepal. *Solid Waste Policies and Strategies: Issues, Challenges and Case Studies*, pages 185–196, 2020.

[3] Rajesh Y A, Rahul S, Puneeth Kumar T R, and S. N. Waste and vehicle detection using yolo. *International Journal For Science Technology And Engineering*, 10(5):3587–3590, 2022.

[4] Qiang Zhang, Qifan Yang, Xujuan Zhang, Wei Wei, Qiang Bao, Jinqi Su, and Xue-Zheng Liu. A multi-label waste detection model based on transfer learning. *Resources Conservation and Recycling*, 181:106235–106235, 2022.

[5] Yolox on embedded device with cctv & tensorrt for intelligent multicategories garbage identification and classification. *IEEE sensors journal*, 22(16):16522–16532, 2022.

[6] Aishwarya Aishwarya, Parth Wadhwa, Owais Owais, and Vasudha Vashisht. A waste management technique to detect and separate non-biodegradable waste using machine learning and yolo algorithm. pages 443–447, 2021.

[7] Object detection based management system of solid waste using artificial intelligence techniques, 2022.

[8] Wastedet: An anchor free novel detection algorithm for improving waste management. 2022.

[9] Wei Wei, Yu Cheng, Jiafeng He, and Xiyue Zhu. A review of small object detection based on deep learning. *Neural Computing and Applications*, 36:1–21, 02 2024.

[10] Xu Liu, Han-Hao Zhu, Weihua Song, Jiahui Wang, Zhigang Chai, and Shaohua Hong. Review of object detection algorithms for sonar images based on deep learning. *Recent Patents on Engineering*, 18, 10 2023.

[11] Hyun Yoo, Seo-El Lee, and Kyungyong Chung. Deep learning-based action classification using one-shot object detection. *Computers, Materials & Continua*, 76:1343–1359, 08 2023.

[12] Patrick Mole and Beverly Ferrer. Trashscan: A deep learning-based waste identification and classification model. 07 2022.

[13] Shivendu Mishra, Ritika Yaduvanshi, Prince Rajpoot, Sharad Verma, Amit Kumar Pandey, and Digvijay Pandey. An integrated deep-learning model for smart waste classification. *Environmental Monitoring and Assessment*, 196, 02 2024.