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A DEEP-LEARNING BASED METHOD FOR WASTE DETECTION

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Abstract

The integration of advanced deep-learning techniques and object detection architectures represents an advanced methodology for waste detection. Considering the importance of recycling and environmental protection in sustainable waste management, automation of such processes becomes an essential task to improve efficiency and accuracy in various industrial and environmental applications. In this study, a system based on convolutional neural networks is proposed for the identification and classification of different types of waste, such as paper, metal, plastic, or glass. An extensive dataset was used to train and evaluate the proposed models using digital RGB images. Following the experimental results, the implementations of this study demonstrated a detection accuracy of over 90%, highlighting the effectiveness of these models and providing modern solutions for correct waste management and manual sorting errors. Efficient recycling is important for ensuring good environmental sustainability practices and automating the process using deep-learning systems is an important step in this direction.

Key words: *image processing, object detection, waste management, pollution.*

INTRODUCTION

Effective waste management is a critical issue for modern society around the world. In recent years, due to globalization, rapid population growth, excessive consumption has led to the emergence of serious problems represented by the generation of massive amounts of waste (Virsta et al., 2020). Solving these problems requires the adoption of innovative and effective solutions (Abdu & Mohd Noor, 2022; Majchrowska et al., 2022). One of these solutions, which promises to revolutionize this field, is the deep learning development area (Mohammed & Kora, 2023; Petrea et al., 2023). As a branch of machine learning, as a part of the whole set of artificial intelligence, deep learning is based on the integration of deep artificial neural networks with multiple layers and important architectural features (Janiesch et al., 2021). These innovative models are capable of learning complex and abstract features from massive amounts of raw data, eliminating manual intervention to extract the desired information. Based on these characteristics, deep learning architectures demonstrate remarkable performance in recognizing patterns and features of visual data, such as images and videos, being an important research topic (Martin et al., 2013).

The automatic detection and identification of waste is an important field that can capitalize on the modern characteristics of deep learning in the efficient management processes. Quickly identifying the type of waste allows efficient sorting and recycling (L. Zhou et al., 2023). These integrations come in the context of managing a large volume of waste where traditional methods are inefficient, expensive, and time-consuming (Meng et al., 2021). Automating these processes can bring significant efficiency and cost benefits (Zhou et al., 2023).

By optimizing deep learning architectures, applications are numerous in waste detection. A popular research topic in the use of deep learning for waste management focuses on digital image classification for waste identification (Meng et al., 2021). Convolutional Neural Network (CNN) models are the basis of such processes, aiming at training and validating large data sets. Based on these processes, trained models can successfully classify digital images of waste with high accuracy (Feng et al., 2020; Lubura et al., 2022).

Deep learning models such as Faster R-CNN, SSD, and YOLO are popular for detecting garbage objects from digital images and videos (Ren et al., 2022; Zhou et al., 2023). This step involves techniques that allow the identification and localization of individual objects in digital images and is essential for real-time applications and continuous monitoring (Terven et al., 2023). Unlike traditional methods, deep learning models can process large amounts of visual data much faster and more accurately. This feature brings to the fore more efficient sorting and a higher recycling rate (Mao et al., 2022).

Looking at the state-of-the-art or related works branch, notable works that satisfy waste management problems using up-to-date deep learning technologies are highlighted. Ongoing research highlights the limitations of manual and expensive waste identification and sorting and applies innovative techniques to create automated detection systems.

In the authors' work (Zhou et al., 2023) the detection of SWAD - solid waste detection - from aerial images was pursued. The authors note that manual identification is expensive and inefficient, especially for large images and wide coverage areas. A model named SWDet is presented as part of this study, optimized for the detection of waste from aerial images and integrating an anchor-based object detector. Moreover, the model integrates an ADA-type structure (asymmetric deep aggregation) to extract the image characteristics as best as possible and at the same time efficient attention fusion pyramid network (EAFPN) to solve the problem of image blur of waste, a problem that can appear due to the shapes of irregular waste. The authors proposed a proprietary dataset in this study, and the experiments performed demonstrate notable mAP metrics, with tests also performed on the TACO dataset, surpassing existing research. This study demonstrates the ability of deep learning techniques to extract data from high-resolution images for accurate waste detection.

In another study, the authors (Ren et al., 2022) propose a coastal waste detection model by improving detection speed and small object detection. A proposed model, Multi-Strategy Deconvolution Single Shot Multibox Detector (MS-DSSD), integrates feature fusion, focal loss, and dense block models as an important part of a feed-forward, end-to-end trained network. Focal loss solves the problem of class imbalance, similar to the state-of-the-art RetinaNet model technique, dense blocks improve complex feature extraction, and fusion modules improve feature extraction for small objects. A data set is proposed for this study, and the obtained results validate the efficiency of the implemented architecture. Finally, optimization methods by growing the data set and by optimizing the fusion method for detection efficiency and speed are noted.

A study by the authors (Fan et al., 2023) leverages the characteristics of a model from the YOLO family for accurate waste identification as part of sorting processes and at the same time by integrating data augmentation techniques. The authors noted a lack of datasets for multi-class debris detection and propose a DCGAN model for image generation using these structures by convolutional adversarial generative networks. At the base of the detection model is a YOLOV4 architecture, modified by introducing an EfficientNet model as a feature extraction network. The proposed implementation had the role of increasing the detection speed and efficiency but also to reduce the number of parameters. In the same context, a feature extraction model with CA - coordinated attention is introduced, reconstructing the classical MBConv model of the architecture. The key points of these implementations are to improve the detection of small and medium objects and increase the generalization and global detection capability of the augmented data model. On the proposed dataset with the mentioned modifications, the model achieves a considerable mAP metric of over 96% and can be successfully applied in automatic waste detection tasks.

The study by the authors (Majchrowska et al., 2022) emphasizes the problem of global pollution as part of the improper management of waste resulting from production activities. The authors analyze important datasets and information related to these issues and present a critical analysis of waste detection methods using deep learning. On the other hand, the authors introduce two datasets named: detect-waste and classify-waste for the tasks of waste detection and classification, analyzing several open-source datasets, covering a vast list of waste classes, with the annotations attached. An EfficientDetD2 detection model is proposed, as well as an EfficientNet-B2 classification model, for seven categories and in a semi-supervised manner. The authors' experiments demonstrate remarkable performance in multi-class detection and identification, with average accuracy values of 70% for the detection task and 75% for the classification model. The authors note that a quality dataset with properly annotated images, as well as optimized detection and classification models can have a positive impact on the global and modern sustainability of automated waste detection systems of various types.

According to studies dedicated to this field, clear methods of implementing automatic waste detection systems are observed. Datasets for training and validating networks are as important as optimizations to the architectures used for detection. Starting from this aspect, a modern method is presented in the present study and explores the use of deep learning models for waste detection and highlights the benefits and novelty of the methods used. The new, modern YOLO architecture, versions 8, was used for this study and each version was optimized for the associated task. After the introduction part, a materials and methods chapter present the data set used, the proposed models and the settings in which the experiments were performed. In another section, the experimental results and the discussions related to the performances obtained and the methodology approached are presented. At the end of the paper, the conclusions and future research directions are presented.

MATERIALS AND METHODS

To develop a deep learning system for waste detection, several elements and methodologies are considered - a robust and detailed dataset, a high-performance hardware and software architecture, and a series of convolutional neural networks optimized for the object detection task. This chapter presents the details for each individual case.

The dataset for a waste detection system is essential for training and evaluating these detection models, being trained to recognize the various features and information attached to each type of waste. Such a dataset was used for the implementation in the present work and included images captured from various contexts to ensure the detection system's basis, variability, and robustness. The composition of the dataset shows various categories of waste. The dataset used included RGB images in JPEG and PNG format, with variable resolutions that could simulate various real or usage conditions. Figure 1 shows examples of images from the dataset used for the present work.

Figure 1. Example images from the waste dataset

To standardize the input data, the dataset went through normalization operations and at the same time augmentation techniques to increase the size of the dataset, being applied transformations and various changes such as rotation, contrast and brightness changes and geometric transformations.

Further, the object detection models used were trained on this dataset by tracking the performance of each model at various stages - training, validation, and testing. The division of the dataset was done with respect to these features and included carefully labelled images. The final dataset includes a total of 1300 images: 780 images for the training area (60%), 260 images for validation (20%) and 260 images for testing (20%). Parts of the TrashNet dataset were also analyzed for this study (Thung & Yang, 2016).

The architecture used, YOLOv8, represents one of the new iterations of the YOLO series that brings significant improvements in real-time object detection (Jocher, 2023). The YOLOv8 architecture used includes backbone, neck, and head structures to efficiently extract the characteristics of waste types in the detection process. The YOLOv8 model introduces a neck structure that effectively connects the backbone area to the head that makes the prediction, using a PANet (Path Aggregation Network) module. It is used to combine various information from different abstraction levels of the network. Dynamic settings and anchors are attached to the head area of the architecture to make more accurate detections and to properly adapt to object sizes.

Benefiting from ongoing support and documentation, the YOLOv8 model has been implemented using the PyTorch framework and following the implementation details from the official developers' Github repo (Jocher, 2023).

As part of state-of-the-art deep learning solutions, YOLOv8 stands out for its architecture's ability to cover a wide range of tasks in the field of computer vision, tasks that include object detection, digital image classification and segmentation tasks. The YOLOv8 architecture proposes notable implementations that lean toward the development of network optimization and modification solutions, for better understanding and implementation of solutions. The YOLOv8 version is based on robust and efficient detection modules. Through its modular structure, the architecture can be modified both in width and in depth, being a critical step for implementing the model in various forms and hardware resources. At the same time, changing and optimizing the architecture is done without compromising accuracy and performance, proving scalability and flexibility to match. Like previous models, the YOLOv8 architecture is one-stage, making predictions on images in a single pass, and much more efficiently with the optimizations of this new iteration. In terms of speed and performance, the YOLOv8 architecture was built to improve the ability to detect objects in various lighting and partially visible contexts. At the same time, optimizations are added to this framework to give YOLOv8 the ability to detect objects at very high speeds, ideal for real-time applications.

All the architectures in the YOLOv8 family were implemented for the development of the present study, on the detection task.

In terms of hardware and software, the system on which the models and experiments of the present study were implemented included a custom system featuring a Win 10 Pro operating system, AMD Ryzen 9 5900HS CPU and a GeForce RTX 3060 6GB GPU. The chosen programming language was Python v3.9 and PyTorch as the reference framework.

RESULTS AND DISCUSSIONS

This part of the paper highlights the results obtained in the case of the present study, with notable performances of the detection models chosen and optimized for the present case of waste management and detection. Transfer learning and fine-tuning was used and the performances that were noted included metrics such as precision, recall, mAP@50, and mAP@50:95. Table 1 and Figures 2 to 6 show the values obtained for each model, after training and validation.

Table 1. Waste detection performances for YOLOv8 models on the validation set (All Class)

Model	Precision	Recall	mAP@50	mAP@50:95
YOLOv8n	0.949	0.926	0.979	0.821
YOLOv8s	0.957	0.920	0.987	0.818
YOLOv8m	0.914	0.968	0.982	0.822
YOLOv8l	0.931	0.885	0.964	0.801
YOLOv8x	0.948	0.913	0.973	0.815

The denoted “All” class represents an average of the results for the dataset classes, a common notation in the object detection area. It was observed that each model demonstrated state-of-the-art object detection performance, that aligns with the overall objective for waste detection systems.

Following this study, the processes attached to waste management using deep learning can present different challenges and limitations. Training models require large sets of labelled data that are often difficult to collect. Moreover, the diversity of the data is essential, as well as its quality, to ensure a high performance of the proposed model. In the same vein, generalization is another challenge resulting from the fact that deep learning models can be sensitive to variations in the input data and can perform poorly in identifying data outside the training process, using new data from real conditions.

The representative classes of the dataset are attached in the following figures, where they are illustrated using bar plots the evolution in the case of each class and metric. The metrics chosen to calculate model performance are global performance indicators that are oriented towards multi-point performance - overall detection, detection of objects of interest, the ability of the models to detect with different confidence thresholds the target objects, and the evolution of detections that deal with important all classes of the data set. Using these metrics provides an overview of each detection model implemented in this study and their ability to identify objects of interest under different conditions.

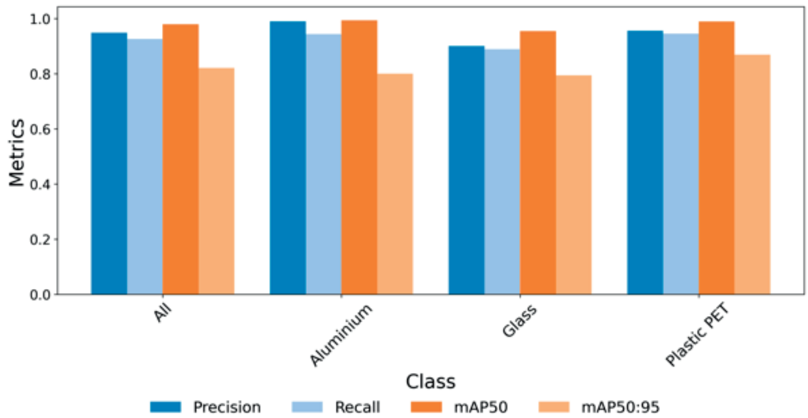

Figure 2. Performance metrics per class for YOLOv8n

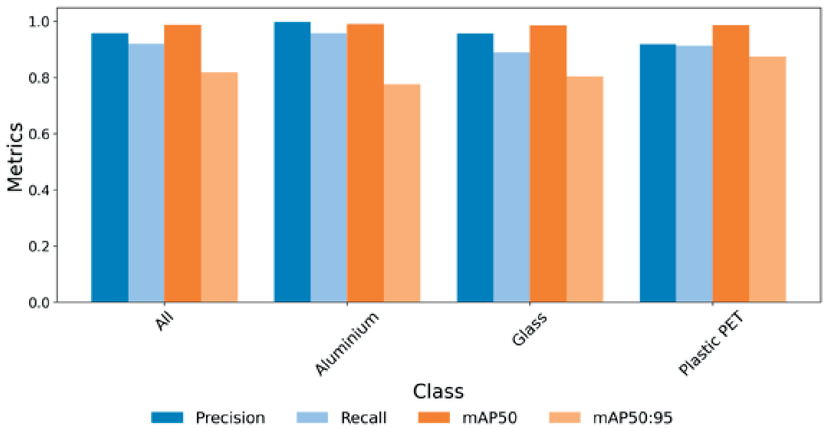

Figure 3. Performance metrics per class for YOLOv8s

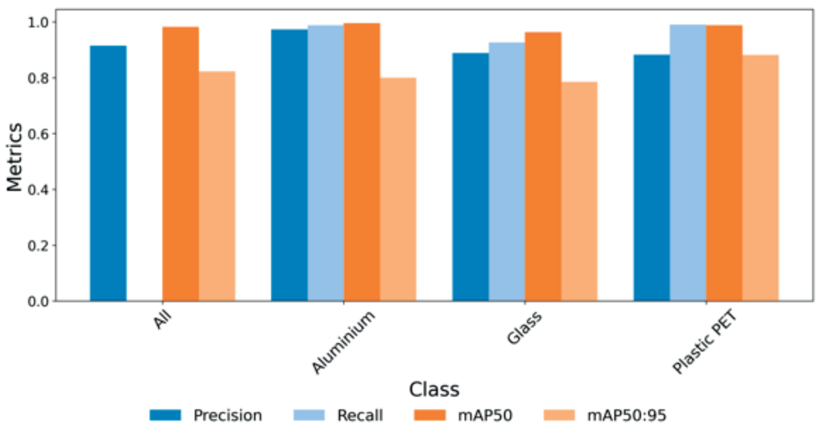

Figure 4. Performance metrics per class for YOLOv8m

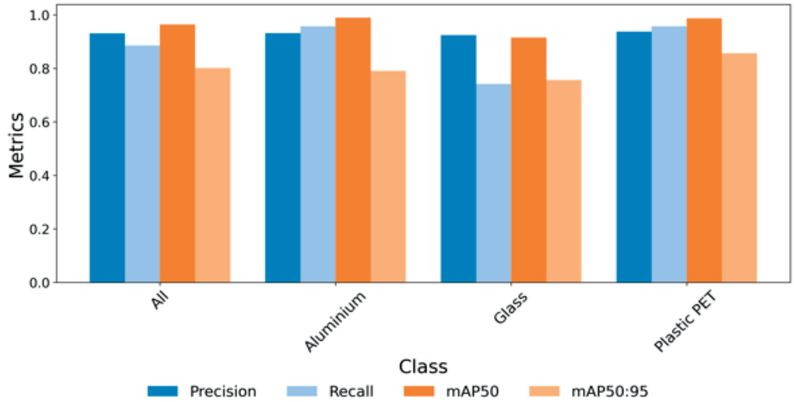

Figure 5. Performance metrics per class for YOLOv8l

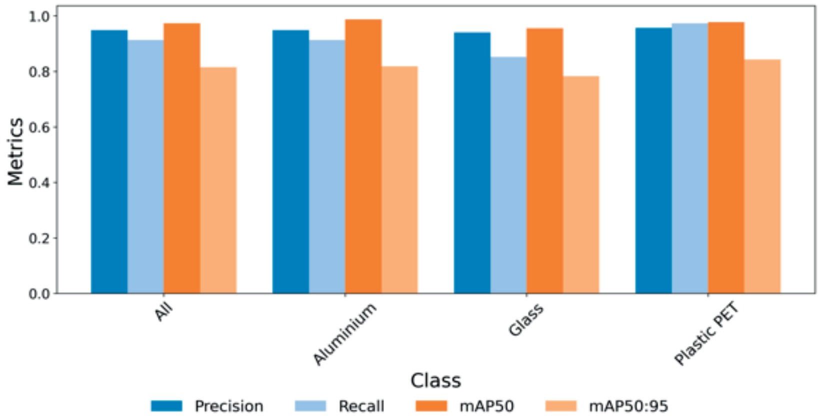

Figure 6. Performance metrics per class for YOLOv8x

Precision is an important indicator that measures the number of correct detections out of the total number of detections performed. A high precision indicates that the model makes few false detections, which is an important metric to isolate the false alarms of a detection model. On the other hand, Recall (sensitivity) measures the ability of the model to correctly identify true instances of a dataset, the reference objects. A high value of Recall describes the model's ability to correctly identify all objects, with as few missed objects as possible.
mAP@50 represents the average precision calculated at an IoU threshold of 50%. This Intersection over Union threshold calculates the overlap between the predicted and the actual bounding box. Typically, this indicator summarizes the model's detection capability in easy cases, with moderate overlap, bringing true detection confidence values above this 50% threshold. In another scenario, mAP@50:95 represents the average of the precision calculated at various thresholds, from 0.5 to 0.95 with a step of 0.05. This indicator presents a more rigorous assessment of detection models, analyzing their detection capability at stricter thresholds. A high mAP of this type indicates the model's true ability to detect instances of interest with high confidence and accuracy.
The models proposed for this study stand out as being balanced in terms of the results obtained, with a notable ratio between Precision and Recall, suitable for the proposed application on waste detection. YOLOv8n and YOLOv8s provided good performance for their low complexity, ideal for resource-constrained applications. On the other hand, great metrics are also noted for the medium and large models

of this family, but which come with commensurate complexity and processing power in their development, standing out with accurate detections.

CONCLUSIONS

In this paper, five detection models from the YOLOv8 architecture were presented to solve waste detection and management problems using deep learning. In this sense, the proposed models demonstrated very good performance in relation to the object detection task and the dataset used, observing the effectiveness of the methods, and noting opportunities for research and development for a critical task of modern society.

The obtained performances such as a mAP@50 and a Recall above 90% highlight the ability of the YOLOv8 models as part of automatic waste detection and to identify them with high accuracy in various environmental conditions. The study presented important metrics for the chosen object detection task and underlines the high capability and performance of the models in detecting the objects of interest with confidence. However, as in any other study in this field, limitations and opportunities for improvement were observed, describing a first step of automated waste detection using modern YOLO variants. The present work can be developed by implementing modules and architectures capable of extracting much better information and features in relation to waste detection, researching advanced models involving a larger data set, more classes, complex modified architectures, or a combination of models for a global decision (model ensemble).

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