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YOLO for Environmental Sustainability: An Examination of Deep Learning Methods for Intelligent Sorting of Garbage

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Abstract
Recycling and ecologically friendly waste management depend on the classification of waste. Conventional manual procedures are expensive, labour-intensive, and prone to mistakes. This can be resolved by using computer vision and deep learning methods to automatically recognize and categorize garbage.In this study, we investigate waste photo categorization using YOLOv8 (You Only Look Once, version 8), a single deep learning system that can specify and categorize items in real-time with a very high degree of accuracy.By training on a diverse dataset with six categories (cardboard, glass, metal, paper, plastic, and trash), the proposed YOLOv8-based method demonstrates significant improvements over conventional machine learning and earlier deep learning models.This approach promotes sustainable urban environments by ensuring reliable and efficient rubbish sorting.

Keywords: Computer vision, recycling, YOLOv8, deep learning, waste category, object detection, and sustainable disposal of Garbage.

1. Introduction

One of the biggest and urgent environmental problems the world is presently dealing with is waste creation, which is growing exponentially in the twenty-first century. Quick industrial growth and Growing cities , and shifting customer behaviour have led to a continuous rise in municipal solid waste (MSW) production worldwide (8). Improper waste handling not only contributes to environmental degradation but also poses considerable public health risks. Manual waste segregation—still prevalent in developing regions—is labour-intensive, time-consuming, inconsistent, and exposes workers to hazardous situations (9). Therefore, automation in waste sorting has become essential to improve efficiency, safety, and sustainability in modern waste management systemsThe fast development of artificial intelligence (AI), especially in visual processing and deep machine learning, has significantly increased the possibility for automated sorting of waste.. Among of the greatest approaches in this field is still Convolutional Neural Networks (CNNs), which are excellent at classifying images by automatically extracting multi-level spatial characteristics. (4). However, traditional CNN architectures like AlexNet, VGG, and ResNet primarily focus on image categories rather than real-time detection, limiting their practical application in dynamic waste sorting systems (2).Because they can perform object localization and classification

simultaneously in a single network run, frameworks such as YOLO have become crucial for overcoming these constraints. YOLO, developed by Redmon et al. (2016), revolutionized real-time object identification by providing an ideal balance between processing efficiency and accuracy.The subsequent iterations (YOLOv2–v9) have enhanced the initial model by introducing anchor boxes, multi-scale training, residual networks, decoupled heads, and anchor-free detection mechanisms (1,7). These advancements make YOLO models especially suitable for waste classification, where rapid and accurate identification of heterogeneous materials (plastic, paper, glass, metal, cardboard, etc.) is required. The potential of YOLO-based systems for trash management has been shown by recent studies. For example, Hossen et al. (2)created a strong deep learning model that achieved above95% accuracy in several categories for the efficient classification of recyclable garbage. Likewise, Sayem et al.
(6) introduced a dual-stream CNN for waste object recognition, demonstrating superior performance over conventional models. Furthermore, Li et al. (5) proposed improved YOLOv8 models integrating attention mechanisms and feature fusion for small-target detection, highlighting the flexibility of YOLO architectures for real-world applications. Despite these advancements, However, there are still issues that need to be addressed, such as class imbalance, small-object detection, diversity and quality variations in datasets, and the requirement for real-time inference on edge devices with constrained resources (3).In the context of automated trash classification, this survey seeks to offer a thorough comparative examination of the YOLO family of algorithms (v1–v9). It examines the architectural enhancements, performance trade-offs, and domain applicability of each version while pointing out significant drawbacks and unmet research needs. In order to promote sustainable growth through intelligent automation and effective recycling, the goal is to investigate how YOLO-based approaches might be optimized and successfully implemented in IoT-integrated smart waste management systems.

2. OVERVIEW OF LITERTUTRE REVIEW

The Voluntary Agreement (VA) for the collecting and recycling of plastic trash, which is scheduled to switch to an Extended Producer Responsibility (EPR) model in 2023, is examined by Do-Wan Kim [1], covers flooring materials and PVC profiles. This study attempts to evaluate the size of the recycling market and the average cost of recycling in order to develop the new system. A cost analysis was completed by seven flooring businesses (58% of all businesses) and eleven profile businesses (35% of all businesses) from the recycling companies who participated in the VA. As a result, it was found that recycling PVC profiles cost an average of 0.45 USD/kg, whereas recycling PVC flooring materials cost an average of 0.36 USD/kg.

In order to enhance the disposal of trash in urban areas, Abugaa Dominic [2] working on a real-time intelligent trash bin system. Conventional waste collecting systems frequently have drawbacks like low throughput, delayed bin emptying, and challenges in getting precise, real-time data. By continuously gathering and sending real-time data from smart trash cans placed across the city, the suggested method tackles these problems. The device successfully stops waste overflow and helps to preserve urban cleanliness by strategically placing these smart bins utilizing fuzzy logic.

AtmaneKhellal [3], For both visible and infrared object detection systems, Convolutional Neural Networks (CNNs), among the most well-liked and successful deep learning architectures, are used in the suggested method.However, the issue of overfitting causes poor performance in marine ship research because to a lack of training data. CNN is also trained via a very lengthy back-propagation process that necessitates extensive hyperparameter tuning. In order to get beyond these restrictions, we provide a novel method that uses Extreme Learning Machines (ELM) just to acquire practical CNN features and perform rapid and accurate classification,, which is appropriate for infrared-based identification systems.

Guanglong Chen [4] ,To learn more about MP contamination, the most recent studies on MPs in the Ocean ecosystems are compiled in this paper. This review is divided into three parts: (1) MP sources and outcomes in the marine environment; (2) MP effects on Ocean life; and (3)microorganisms that decompose marine MPs.The environmental issues brought on by microplastics need to be addressed with certain actions and initiatives. The findings in this assessment will serve as background for future research on marine microplastics and management plans.

Md. Nahiduzzaman [5], Waste classification methods have become widely used as a result of the increasing harm brought about by insufficient waste handling. Creating an automated categorization system with cutting-edge trash recognition technology is one practical strategy. This technique can reduce the amount of physical effort needed for recycling and waste separation tasks. A new three-stage trash classification system was suggested in this study. It integrates the concurrent lightweight depth-wise segmented convolutional neural networks (DP-CNN) with the ensemble extreme learning machine (En-ELM) classifier. First, there are two types of trash.

FaizulRakibSayem [6], Using 28 different recyclable categories of garbage photos, totaling 10,406 images, we offer robust deep learning models for waste image categorization and object recognition in this paper. Our special dual stream network fared better in the trash identification test than other cutting-edge models, with an overall classification accuracy of 83.11%.. For waste object recognition tasks, Additionally, we presented the generalized efficient layer aggregation network, or GELAN-E, model., which outperformed Previous cutting-edge detection models had a mean average precision (mAP50) of 63%.. These developments show a notable advancement in intelligent waste management and open the door to more workable and effective solutions.

Shoaib Uddin [7], The aim of this system is to automate the sorting process so that there is less human participation, accuracy in segregation, and increase in recycling activities. Integration of decision-making algorithms, IoT devices, and computer vision makes it possible to provide a Kansas solution for urban smart cities because of its scalability, adaptability, and low operational costs. It is expected that experimentally obtained results will provide accuracy of more than 90% which will aid in sustainable practices for waste management.

The suggested model RWC-Net is a deep learning framework that can correctly categorize six trash categories, according to Hossen [8]. It was trained and assessed on the TrashNet dataset, which consists of 2,527 annotated trash images.Our model's performance is rigorously assessed both quantitatively and qualitatively, and it is contrasted with many cutting-edge trash classification methods The suggested model outperformed several cutting-edge models, achieving an astounding overall accuracy rate of 95.01

percent.. Additionally, the F1-scores for the six categories of waste are high: 88.55% for trash, 97.14% for newspaper, 96.18% for glass, 94% for metal, 95.73% for paper, and 93.67% for plastic..

Md. FaysalAhamed [9], Waste classification methods have become widely used as a result of the increasing harm brought about by insufficient waste handling. Creating an automated categorization system with cutting-edge trash recognition technology is one practical strategy. This technique can reduce the amount of physical effort needed for recycling and waste separation tasks. A new three-stage trash classification system was suggested in this study. It integrates the concurrent lightweight level-wise separable convolutional neural network with the ensemble extreme learning machine (En-ELM) classifier.. First, waste materials fall into two primary categories: renewable and that which is not non -renewable.

Weipeng Li [10], In this paper, two improved YOLOv8models, IMCMD_YOLOv8_small and IMCMD_YOLOv8_large, are proposed to enhance small
target detection in drones by integrating attention mechanisms, feature fusion, and lightweight design, achieving higher accuracy and reduced parameters on the VisDrone2019 dataset

[11] Bo Ma, Ying Cai This research paper provides an overview of the You Only Look Once (YOLO) algorithm and its later, more advanced versions.. We depict a number of significant findings and perceptive conclusions from the investigation. The results unmistakably show how YOLO and conventional CNN designs differ and are similar, as well as how different YOLO versions function differently.
The primary insight is that there is still room for improvement in the YOLO algorithm. This article emphasizes offers literature support for specialized image information and feature extraction in the financial and other domains, as well as target identification and feature selection techniques.and provides a brief explanation of the YOLO algorithm's development process. This work also significantly adds to the body of knowledge on object detection and YOLO.

Julfikar Haider [12], The current research proposed a novel three-stage waste classification system It integrates the concurrent lightweight depth-wise separable convolutional neural network (DP-CNN) with the composition extreme learning machine (En-ELM) decoder.First, waste materials fall into two primary categories: renewable and non-recyclable. Based on the general characteristics of waste, the data set is separated into nine categories in the second stage.A higher level of information is required in the last stage of the categorization process since each image is assigned to one of 36 different classes.

Sanjay Kumar Ahuja [13], For efficient prediction, a deep learning approach is used in this work. The Residual U-Net is taken into account when the segmentation process is performed by the encoder and decoder. By examining a variety of images, the Bidirectional Conv-LSTM approach can then be modified to produce superior classification results. Furthermore, the values of its bytes are used to calculate the size of the pitting corrosion. Lastly, the MATLAB platform is used to implement the suggested job. Metrics used in performance analysis include F-measure, sensitivity, specificity, accuracy, and precision

Hosny, Khalid M. [14], We present an embedded Raspberry Pi Linux system for diagnosis in this work. First, the local binary pattern (LBP) technique is used to obtain certain properties. Second, multi-channel fractional-order Legendre-Fourier moments (MFrLFMs) are used to obtain the global features from the chest CT or X-ray images. Ultimately, the majority of important traits are chosen on a local and international level. The suggested system phases are combined to take into consideration the limited memory and processing capability of the embedded system.

XuePanpan [15], In order to We suggest an ideal few shot Thangka detection technique based on resnet and deformable convolution to address the issues of few finding, data deformable target sizes, and duplication among targets in the identification of headdresses and chairs in ThangkaYidam.First, the issue of a small number of.categories and compositivity in Thangka images is addressed by the optimized residual network.

TABLE I. LITERATURE REVIEW TABLE

Paper title	Dataset	Method / Model	Key Result	Observation
An automated waste classification system using deep learning techniques: Toward efficient waste recycling &environmental sustainability. 2025	TriCascade Waste Image (~35k images combined from multiple datasets)	Depthwise Separable CNN + Ensemble Extreme Learning Machine (DP-CNN + En-ELM) in parallel using XAI tools	Stage1: 96% Acc; Stage2: 91%; Stage3: 85.25%; very fast inference	1)This paper used 3 model – DP –CNN + En-ELM. 2)It has 96% accuracy and it is used for real-time waste sorting
AI-Powered Waste Segregation System (research proposal). 2025	Trash Net, Waste Net and others (planned)	CNN (Tensor Flow/Keras) + Raspberry Pi & servo-based IoT hardware	Target accuracy > 90% (proposed)	CNN + IoT-based waste segregation prototype using Raspberry Pi/Arduino for automatic sorting into biodegradable, recyclable, and hazardous bins.

A Reliable and Robust Deep Learning Model for Effective Recyclable Waste Classification (RWC-Net).2024	Trash Net (~2.5k images)	Custom CNN architecture (RWC-Net) with Score-CAM visualization	95.01% overall accuracy; class F1s up to 97%	1) hybrid DenseNet–Vision Transformer model and GELAN-E detector on the WaRP dataset (28 categories). 2Achieved 83.11% accuracy and 63% mAP@50, showing strong performance but requiring high computational power
Intelligent garbage classification system based on improved MobileNetV3-Large.2022	Large internal dataset (Baidu + web images; 4 categories, 158 subcategories)	Improved MobileNetV3-Large for images + LSTM for text, with WeChat applet & Raspberry Pi	81% image accuracy; 97.61% text accuracy	Presents a smart garbage classification model using CNN that improves waste sorting accuracy through automated image recognition, enhancing recycling efficiency and reducing human error.
Convolutional Neural Network Based on Extreme Learning Machine for	VAIS maritime IR ships dataset (small-scale)	ELM-CNN: unsupervised CNN + ELM ensemble classifier	~950× faster training; better accuracy on small data than BP-trained CNN	Presents an ELM-based CNN model that enhances feature

Maritime Ships Recognition in Infrared Images (ELM-CNN).2018				extraction speed and generalization for infrared ship recognition, achieving high accuracy with reduced training time.
Micro plastics in the Marine Environment: Sources, Fates, Impacts and Microbial Degradation (Review).2021	Literature review (meta-analysis)	Narrative review of prior studies	Synthesizes global evidence; shows severe ecological risk	Reviews the issue of marine microplastic pollution, discussing its sources, environmental impacts, and microbial degradation pathways to support mitigation strategies.
Feng et al., 2024 (*Improved YOLOv8 Algorithms for Small Object Detection in Aerial Imagery*, J. King Saud Univ. – CIS)2024	AI-TOD dataset (UAV/aerial images, small objects)	IMCMD_YOLOv8_small & large (C2f_CA attention, AMFF, Dynamic Head, removed P5 layer)	+7.7% and +10.8% mAP improvement; parameters reduced by 73% and 47%	High accuracy for small-object detection with reduced computation
Jiang et al., 2022 (*A Review of YOLO Algorithm Developments*, Procedia Comp. Sci.)2022	Survey of VOC, COCO, ImageNet, Open Images	Comparative review of YOLO architectures, features, loss functions	Summarized strengths/weaknesses of YOLO version	Comprehensive overview of YOLO's evolution
Redmon et al., 2016–2018 (*YOLOv1–YOLOv3*)	VOC 2007/2012, COCO	One-stage regression-based detection; YOLOv3 added multi-scale, anchors, residuals	Drastic speed boost; YOLOv3 balanced speed vs. accuracy	Fast, pioneering one-stage detector

2018				
Bochkovskiy et al., 2020 (*YOLOv4: Optimal Speed & Accuracy*) 2020	COCO 2017	CSPDarknet53 backbone, SPP, PANet	~43.5 mAP on COCO with high FPS	Excellent speed-accuracy balance
Jocher et al., 2020+ (*YOLOv5, Ultralytics*) 2020	COCO 2017 + custom datasets	PyTorch-based YOLOv5, auto-anchor, augmentations, modular design	Lightweight, fast training and deployment	Industry adoption, flexible, efficient
Sayem et al., 2025 (*Enhancing Waste Sorting & Recycling Efficiency*, Neural Computing and Applications)2025	WaRP dataset – 28 categories, 10,406 waste images	Dual-stream (DenseNet-201 + Vision Transformer) for classification; GELAN-E for detection	83.11% accuracy (classification), 63% mAP50 (detection)	Robust for complex industrial waste sorting
Nahiduzzaman et al., 2025 (*Automated Waste Classification Using Deep Learning*, Knowledge-Based Systems)2025	TriCascade WasteImage – 35,264 images, 2/9/36 class labels	Three-stage DP-CNN + Ensemble ELM	96% (binary), 91% (9-class), 85.25% (36-class); lightweight (1.09M params)	High accuracy; low computational cost
Kim et al., 2023 (*Calculation of the Standard Recycling Cost of PVC Waste in Korea*, Recycling – MDPI)2023	Industry survey data – 11 profile & 7 flooring companies, 2020	Economic/cost analysis of collection, sorting, recycling	Profiles: 0.45 USD/kg; Flooring: 0.36 USD/kg; Market size ~1135M USD	Provides baseline for policy & industry decision

3. METHODOLOGY

This survey paper's methodology is to thoroughly examine, evaluate, and contrast several YOLO-based deep
learning architectures used for trash classification problems. Data collection, literature analysis, model comparison, and performance parameter evaluation are all part of the methodical process.

A. Research Design

This effort attempts to locate, evaluate, and compile scholarly articles and technical papers on YOLO-based object recognition and trash classification that were published between 2018 and 2025 using a systematic literature review (SLR) methodology.
.Examining how many YOLO versions (v1–v9) have changed in terms of design, speed, accuracy, and real-world deployment potential for intelligent waste management is the primary goal.

B. Data Collection and Sources

Major scientific databases like IEEE Xplore, ScienceDirect, SpringerLink, MDPI, and Google Scholar were searched in order to obtain thorough and reliable information. The search was conducted using the following keywords: "YOLO waste classification," "deep learning for waste sorting," "real-time object detection," "YOLOv8 applications," and "recyclable waste recognition."The inclusion criteria were satisfied by papers that used YOLO (v1–v9) for waste classification or related computer vision tasks. Performance criteria like MAP, precision, recall, or F1-score were included in the study.Publications between 2018 and 2025. Research without sufficient experimental information was not included.
Non-peer-reviewed or copied works. Papers that only discuss conventional machine learning techniques.

C. Analytical Framework

The following framework was used to analyze search chosen study:
• Model Architecture: analyzing feature extraction modules, activation functions, backbone structure, and network depth.
• Dataset Characteristics: assessing the kind, size, diversity of
images, and labeling approach of the dataset (e.g., TrashNet, WasteNet, custom datasets).
Performance evaluation, which compares important parameters like inference time, accuracy, mAP, and F1-score.
• Implementation Environment: GPU usage, software frameworks (PyTorch, TensorFlow), and hardware configuration.
• Research gaps and limitations: pointing out unsolved problems with edge deployment, real-time inference, and scalability.
A clear picture of technological advancement and bottlenecks was made possible by the compilation of the comparison data into tables that summarized the advantages, disadvantages, and research gaps of each YOLO version.

D. Evaluation Parameters

The selected models were compared using standardized performance indicators: Accuracy (%) is the percentage of rubbish photographs that are successfully classified. MAP at fifty percent and between 50 and 95 determine the model's detection capability at various localization accuracy levels by calculating the mean average precision at specific IoU thresholds..Real-time capabilities is shown by the Inference Speed (FPS), which is the number of frames processed per second. Model Size (MB) is used to evaluate the viability of
deployment on embedded devices Model complexity is assessed using Computation Cost (GFLOPs).
The most recent model, YOLOv8, was examined in further detail, with particular attention paid to its

decoupled head, anchor-free detection, and Cross-Stage Partial (CSP) backbone, all of which enhance detection efficiency (Ultralytics, 2023).

E. Comparative Analysis Procedure

The following procedures were used to carry out the analysis:
1. Examine and extract YOLO versions v1–v9's architectural characteristics and performance statistics.
2. List their issues (overfitting, small-object detection) and advancements (speed, accuracy, loss function).
3. Determine trends and patterns in the evolution of the model.
4. Talk about potential future improvements including IoT integration, hybrid optimization, and lightweight deployment.

F. Outcome of Methodology

A thorough and objective comparison of YOLO algorithms was made possible by this methodological framework. The results demonstrate the quick development of YOLO designs from sophisticated anchor-free frameworks (YOLOv8 and YOLOv9) to coarse, grid-based detection (YOLOv1). Additionally, the methodical methodology guarantees reproducibility, offering a strong basis for upcoming studies on AI-powered intelligent waste management systems.

4. CONCLUSION

Automated trash classification system, this project tackles the growing challenge of efficient waste management. Traditional machine learning and manual methods are incorrect, time-consuming, and unsuited for practical use. The suggested YOLOv8-based method speeds up and improves the accuracy of waste recognition by combining feature extraction and classification into a single pipeline. Paper, plastic, glass, metal, cardboard, and litter are the six types it successfully separates. Because it guarantees real-time functioning, the technology is useful for recycling facilities and smart bins. The methodology boosts recycling efficiency and encourages sustainable environmental practices by reducing human effort and increasing accuracy.

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