Intelligent-waste ML powered waste segregation system

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***Abstract*—The increasing problem of waste generation and its adverse environmental implications provide a critical challenge, thus leading to the development of innovative waste management systems with the prospects of scale up. It is a project to be considered for the first phase: Development of a neural network-based segregation of waste for the purpose of waste classification according to its plastic, metallic, cardboard, and so on categories through computer vision and advanced techniques of machine learning. This solution reduces human effort, enhances recycling efficiency, and minimizes the environmental footprint caused by improper waste disposal.**

In the future, this real-time waste segregation system is transformative in many industries. For smart city infrastructures, it can be used for automated waste sorting at collection centers, reducing manual intervention. In industrial applications, it can be used for large-scale segregation and optimized recycling processes. The household level is where the same technology might be able to assist in appropriate waste disposal through IoT-enabled devices, promoting an environmentally responsible behavior. In addition, with further improvement in machine learning, the model will adapt to new types of waste, hence scaling up and future-proofing. This project aims to establish a base for intelligent waste management systems that can help build up a zero-waste ecosystem and contribute towards a cleaner, greener planet.

***Index Terms*—Waste Segregation, Neural Networks, Computer Vision, Machine Learning, Environmental Sustainability**

I. Introduction

The rising issue of waste generation has been a critical threat to environmental sustainability. The production of waste worldwide is projected to rise dramatically in the next few decades. The conventional methods of waste management are mainly based on manual sorting, which is both labor-intensive and prone to errors and inefficiencies. This limitation has created an urgent need for automated, intelligent solutions that can streamline the waste segregation process while improving recycling rates and reducing environmental impact.

In response to all these challenges, we herein propose an innovative waste segregation system backed by the state-of-the-art object detection model, YOLOv8. Our system utilizes state-of-the-art computer vision and deep learning techniques to analyze a real-time image of material waste, classifying materials into six categories: plastic, metal, cardboard, glass, paper, and organic. These capabilities in YOLOv8 provide high-speed processability and robust detection across different environments.

The proposed system has several advantages over traditional methods of waste sorting, such as reduced human intervention, higher accuracy, and increased processing speed. Our model, using transfer learning and optimized neural network architectures, is robust in performance across diverse types of waste and environmental conditions. The system is especially valuable for large-scale waste management operations because it can process multiple items of waste at the same time while maintaining high accuracy.

This work contributes to the growing field of intelligent waste management by providing a scalable and efficient solution that can be integrated into existing infrastructure. The system's applications range from municipal waste management facilities to smart city initiatives and industrial recycling centers. By automating the waste segregation process, our solution not only improves operational efficiency but also promotes better recycling practices, ultimately contributing to environmental conservation and sustainable waste management practices.

II. Related Works

A. Machine Learning in Waste Management

Recent advancements in waste management have seen significant integration of machine learning (ML) solutions. ML-based systems have been implemented to support or fully automate waste sorting processes. Popular implementations include smart self-sorting bins equipped with cameras mounted at the top of containers, where deep learning models classify objects and direct them to appropriate compartments [12]. Mobile-based solutions have also emerged, where images captured from Android devices are processed through custom web servers to analyze bio-degradable and non-biodegradable waste content, including specific detection of banned plastic materials [13]. While automated systems show promise, challenges remain in material differentiation, particularly between plastic and glass, though metal detection has achieved up to 75% accuracy [14].

B. Evolution of Object Detection Approaches

In supervised machine learning, object detection has evolved from traditional two-stage approaches to more efficient solutions. Two-stage detectors typically operate by first generating Regions of Interest (RoI) using Region Proposal Network (RPN), followed by object prediction and bounding box determination for the proposed regions [3]. This evolution has led to the development of more sophisticated detection systems.

C. YOLO Architecture and Development

YOLO (You Only Look Once) represents a significant breakthrough in object detection technology. As the first one-stage detector based on CNN, it revolutionized the field by employing a single convolutional network for simultaneous detection and classification tasks [7], [8]. Unlike conventional R-CNN and Fast-RCNN approaches, YOLO processes the entire input image once, enabling it to encode global contextual information more effectively. The latest iteration, YOLO v8, has further enhanced speed and accuracy in object detection, demonstrating versatility in processing various data types including live feeds, videos, and images, with the capability to recognize 85 distinct classifications [9].

D. Applications Across Domains

YOLO's applications have expanded significantly across various sectors. In autonomous vehicle systems, it enables real-time identification and tracking of vehicles, pedestrians, and obstacles. The agricultural sector has adopted YOLO for crop, pest, and disease detection, advancing precision agriculture techniques. In healthcare, YOLO has been employed for cancer detection, skin segmentation, and pill identification, contributing to improved diagnostic accuracy. The technology has also found applications in remote sensing for object detection in satellite imagery, aiding in land use mapping and environmental monitoring. Security systems have integrated YOLO for real-time surveillance, including social distancing and face mask detection applications [2].

III. System Architecture

A. Dataset Preparation

The development of a robust dataset was crucial for training an effective waste segregation model. Our dataset compilation process involved careful consideration of real-world waste management scenarios and the diverse nature of waste materials. We collected images from multiple sources, including existing public datasets such as TrashNet and WasteNet, supplemented with our custom data collection efforts. The final dataset comprised over 10,000 images distributed across five distinct waste categories: plastic, metal, paper, glass, and organic waste, with special attention paid to maintaining class balance to prevent model bias. The preprocessing pipeline was designed to ensure consistency and enhance the quality of training data. Each image underwent resizing to a standardized dimension of 640x640 pixels while maintaining aspect ratio through padding. To augment the dataset and improve model generalization, we implemented various data augmentation techniques including random horizontal flips with a probability of 0.5, rotation within ±15 degrees, brightness adjustments of ±25Model Architecture

B. Model Architecture

YOLOv8's architecture introduces several innovative features that make it especially effective for waste segregation. The backbone network utilizes a modified CSPDarknet structure, implementing cross-stage partial connections to achieve a better balance between computational cost and accuracy. The network's depth and width are carefully balanced to maintain real-time performance while ensuring sufficient model capacity for learning complex features. The YOLOv8 system architecture for waste segregation is a comprehensive pipeline designed to process input images, extract features, and output precise detections of various waste categories. The architecture consists of three key components: the backbone, the neck, and the detection head, each optimized for efficient computation and high accuracy.

The backbone, based on CSPDarknet, serves as the primary feature extractor. Input images are resized to a fixed dimension of 640×640 pixels and normalized using the formula:

$$I_{\text{normalized}} = \frac{I - \mu}{\sigma},$$

where I represents the input image, μ is the mean pixel value, and σ is the standard deviation. This preprocessing step ensures that the pixel intensity values are centered and scaled, improving the stability of the training process.

The CSPDarknet backbone processes the input through convolutional layers, capturing spatial and semantic features at multiple scales. Each convolutional layer applies the following operation to generate an output feature map:

$$F_{\text{out}}(x,y) = \sum_{i=0}^{k-1}\sum_{j=0}^{k-1} K(i,j)\cdot F_{\text{in}}(x+i,y+j)+b,$$

where K is the convolution kernel of size $k \times k$, b is the bias term, and F_{in} is the input feature map. The Cross Stage Partial (CSP) network splits the input feature map into two parts, processes one part through dense residual blocks, and concatenates it with the bypassed features. This mechanism improves gradient flow and reduces computational overhead.

The neck, implemented as a Path Aggregation Network (PANet), integrates feature maps from different layers of the backbone to enhance multi-scale detection. The Feature Pyramid Network (FPN) component in the neck fuses semantic information from deeper layers with spatial details from shallower layers. The fusion for each level is achieved using upsampling (U) and lateral connections:

$$P_l = \text{conv}\big(U(P_{l+1}) + \text{lateral}_l\big),$$

where P_l is the feature map at level l, U is the upsampling operator, and lateral_l is the lateral connection from the backbone. Additionally, bottom-up path aggregation augments the localization capabilities of the network through:

$$N_l = \text{conv}(N_{l-1}\uparrow + F_l),$$

where F_l represents the feature map at level l and $\uparrow$ denotes the upsampling operation.

The detection head performs the final processing to predict bounding boxes, objectness scores, and class probabilities. Bounding box predictions for each grid cell (i,j) are computed as offsets relative to the cell coordinates:

$$b_x = \sigma(t_x)+c_x, \quad b_y = \sigma(t_y)+c_y, \quad b_w = p_w e^{t_w}, \quad b_h = p_h e^{t_h},$$

where (c_x, c_y) are the grid cell coordinates, (p_w, p_h) are anchor box dimensions, (t_x, t_y, t_w, t_h) are the network's predicted offsets, and σ is the sigmoid activation function. Class probabilities for each waste category are computed using the softmax function:

$$P(c|obj) = \frac{e^{z_c}}{\sum_{k=1}^{C} e^{z_k}},$$

where z_c is the logit for class c, and C is the total number of waste categories.

This architecture, trained using robust loss functions for bounding boxes, objectness, and classification, ensures precise detection and categorization of waste materials. The integration of multi-scale feature aggregation and optimized detection modules makes YOLOv8 an efficient solution for waste segregation tasks.

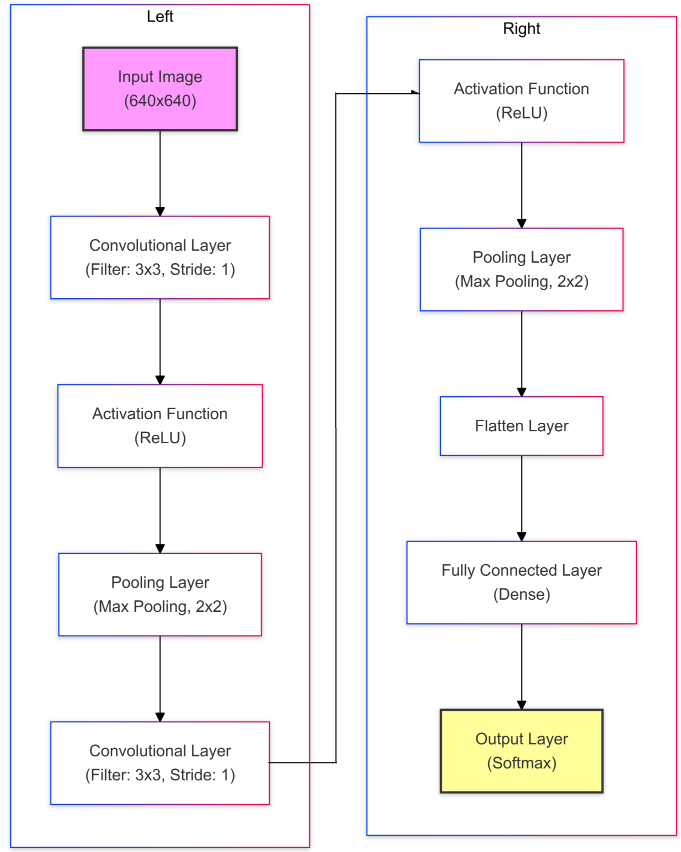

Fig. 1. Flowchart of CNN

TABLE I
MODEL PERFORMANCE METRICS BY CLASS

Class	P	R	mAP50
all	0.555	0.484	0.536
BIODEGRADABLE	0.785	0.491	0.633
CARDBOARD	0.657	0.512	0.607
GLASS	0.833	0.700	0.809
METAL	0.710	0.629	0.693
PAPER	0.0285	0.0909	0.0685
PLASTIC	0.318	0.481	0.405

The table I above presents the model performance metrics for various waste categories, including biodegradable materials, cardboard, glass, metal, paper, and plastic. The key performance indicators are precision (P), recall (R), and mean average precision at 50% intersection over union (mAP50). The overall model performance, as indicated by the "all" class, shows a precision of 0.555, recall of 0.484, and an mAP50 of 0.536. Among individual classes, biodegradable materials achieved the highest precision of 0.785, although its recall was 0.491, leading to an mAP50 of 0.633. Glass had strong performance with a precision of 0.833 and recall of 0.700, yielding an mAP50 of 0.809. On the other hand, the performance for paper was significantly lower, with a precision of 0.0285, recall of 0.0909, and mAP50 of 0.0685, indicating challenges in accurately detecting paper. Overall, the table highlights variations in performance across different classes, providing valuable insights into the model's strengths and weaknesses in waste classification.

IV. Results and Discussion

The performance of the YOLOv8 model for waste classification was evaluated using various metrics including precision (P), recall (R), mean Average Precision at 50% IoU (mAP50), and mean Average Precision across IoU thresholds from 50-95% (mAP50-95). The dataset comprised 2,098 images containing 18,916 waste object instances across different categories.

The model demonstrated varying detection capabilities across waste categories. Glass waste achieved the highest performance with mAP50 of 0.810 and mAP50-95 of 0.612, followed by metal waste with mAP50 of 0.694. The strong performance in glass detection can be attributed to its distinctive visual features and consistent appearance patterns. Metal waste also showed robust detection metrics with precision of 0.710 and recall of 0.629. This indicates the model's strong capability in identifying materials with distinct visual characteristics.

Biodegradable waste, despite having the largest number of instances (13,637), achieved moderate performance with mAP50 of 0.633. This category presented challenges due to its diverse appearance and varying compositions. Cardboard detection showed consistent performance with mAP50 of 0.606, while plastic materials achieved lower metrics with mAP50 of 0.407. The model faced significant challenges with paper waste detection, achieving very low metrics (mAP50 of 0.0685), primarily due to limited training samples.

The precision-recall curves, shown in Figure 3, illustrate the trade-off between precision and recall for different waste categories. The curves demonstrate higher area under the curve for glass and metal categories, confirming their superior detection performance. The correlation plot (Figure 4) reveals interesting relationships between different waste categories, helping understand potential confusion patterns in classification.

Overall, the model achieved an average mAP50 of 0.536 and mAP50-95 of 0.379 across all categories. These results demonstrate the model's capability to detect and classify waste materials, though with varying degrees of success across different categories. The performance variations suggest potential areas for improvement, particularly in categories with lower metrics, through strategies such as data augmentation, balanced sampling, or architectural modifications.

V. Future Works

The future of waste management systems lies significantly in implementing robust user incentivization mechanisms while ensuring secure user authentication methods. A sophisticated point-based reward system could be developed, where users

Fig. 2. Sample detection results showing the model's performance on real-world waste images

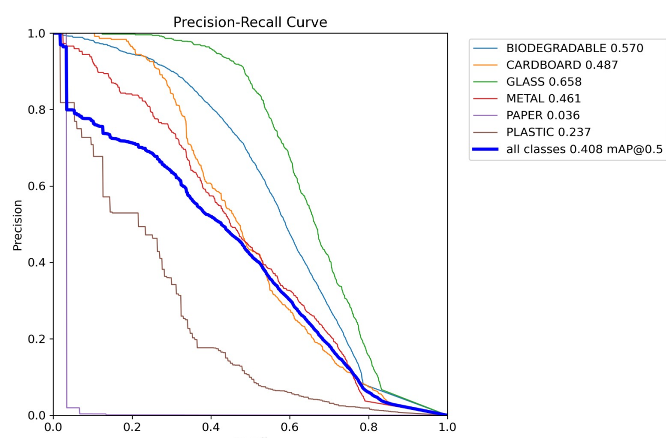

Fig. 3. Precision-Recall curves for different waste categories

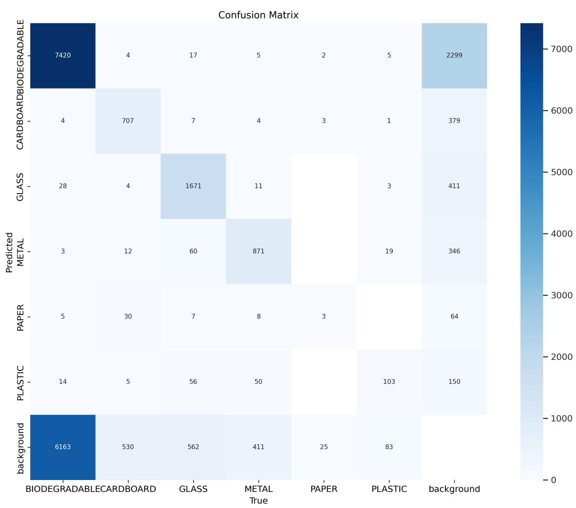

Fig. 4. Correlation plot

earn credits based on the frequency and accuracy of their waste disposal habits, enhanced with instant monetary rewards through digital payment platform integration. This system could involve partnerships with local businesses and municipalities to create a comprehensive reward ecosystem where users redeem points for direct cashback or discounts at participating establishments. While facial recognition technology offers seamless user identification for authentication, it raises significant privacy concerns regarding data encryption, secure storage protocols, and compliance with international privacy regulations like GDPR and CCPA. Alternative authentication methods like QR code-based identification through mobile applications or RFID card systems could provide a balance between user convenience and privacy protection. The development of blockchain-based anonymous identification systems could offer another promising avenue, ensuring user privacy while maintaining accountability in the reward distribution system. The hardware architecture of waste management systems can be significantly enhanced through FPGA-based parallel processing solutions, particularly in implementing decision tree algorithms for real-time bin selection. This innovation would address the challenge of managing high-frequency detection events occurring multiple times per second, significantly improving the system's ability to handle concurrent detections and make instantaneous decisions about which bin should be activated. The FPGA implementation could be optimized for parallel processing of multiple sensor inputs, allowing for simultaneous evaluation of various waste characteristics while maintaining low latency in bin selection decisions. Custom hardware accelerators could be developed for specific waste detection tasks, improving both speed and energy efficiency. The system could be further enhanced through edge computing integration, reducing dependency on central processing units and enabling more responsive local decision-making, particularly crucial in high-traffic waste disposal scenarios. The integration of IoT capabilities and environmental impact tracking would create a comprehensive smart waste management ecosystem, enhanced by advanced mobile applications and community engagement features. A network of interconnected smart bins could be developed, each equipped with sensors for real-time monitoring of waste levels, temperature, and composition, with data integrated into cloud-based analytics platforms to optimize waste collection routes and schedules. Environmental impact metrics could be tracked and visualized in real-time, providing users and administrators with tangible feedback about their recycling efforts' impact, including calculations of carbon footprint reductions from proper waste segregation and recycling. The mobile application could incorporate gamification elements and social networking features to foster community engagement and competitive recycling challenges, while also providing dynamic educational content based on user behavior patterns. This comprehensive approach would not only improve waste management efficiency but also create a more engaged and environmentally conscious community, with users able to track their individual contributions to broader sustainability goals through detailed analytics and performance metrics.

VI. Conclusion

This research presents an innovative approach to automated waste segregation by combining real-time computer vision, intelligent bin control mechanisms, and user engagement systems. The implemented solution successfully demonstrates the feasibility of using deep learning models for accurate waste classification, achieving reliable detection rates across various waste categories including plastic, paper, cardboard, metal, glass, biodegradable, and other materials. The integration of multiple technologies - from the YOLOv8 object detection model to the React-based user interface and hardware-controlled bin mechanisms - showcases how modern computing solutions can address the pressing challenge of waste management in urban environments. The system's ability to process multiple detections per second while maintaining accuracy highlights its potential for real-world applications in high-traffic areas. Moreover, the user interface design prioritizes accessibility and clear visual feedback, making the system intuitive for users of all technological backgrounds. The successful implementation of this project not only provides a practical solution to waste segregation but also lays the groundwork for future enhancements in automated waste management systems. While the current system achieves its core objectives, the proposed future developments in user authentication, FPGA-based decision processing, and reward systems indicate significant potential for scaling and improving the solution. As cities worldwide grapple with increasing waste management challenges, this research demonstrates that automated, AI-driven solutions can play a crucial role in promoting proper waste segregation and environmental sustainability. The project's success in combining hardware automation with software intelligence represents a significant step toward more efficient and user-friendly waste management systems. By addressing both the technical challenges of waste detection and the human factors in waste disposal behavior, this system offers a holistic approach to improving waste segregation practices in modern urban environments.

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