

## **SIMPLE ARTIFICIAL INTELLIGENCE APPLICATION FOR CLASSIFYING HOUSEHOLD WASTE AT THE NEIGHBORHOOD WASTE BANK**

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**Abstract**— Waste management remains a critical environmental issue globally, including in Indonesia, where increasing household waste generation creates significant environmental and social challenges, particularly at the neighborhood level. In community-based Waste Banks, manual sorting processes are often inconsistent due to limited human resources and varying levels of public understanding of waste categories. This study aims to develop and evaluate a lightweight, web-based real-time waste detection and classification system to support community-level waste management. The proposed system utilizes the YOLOv8 object detection architecture implemented through the Ultralytics framework with PyTorch as the deep learning backend, integrated with OpenCV for real-time video processing and Streamlit for web-based deployment. The dataset consists of approximately 9,200 annotated images across 24 waste categories, divided into training, validation, and testing sets, with data augmentation applied to improve robustness. Model performance was evaluated using precision, recall, and mean Average Precision at IoU 0.5 (mAP@0.5). The results demonstrate high detection performance, achieving 99.5% mAP@0.5, 99.4% precision, and 100.0% recall, while maintaining stable real-time detection under varying lighting conditions. However, these results are obtained under relatively controlled dataset conditions; therefore, further evaluation in more diverse real-world environments is necessary to ensure generalization capability. The system enables multi-object detection without requiring specialized hardware, making it accessible for neighborhood-level Waste Banks and providing a practical solution for community-based waste management.

**Keywords:** Artificial Intelligence, Community-Based Waste Management, Machine Learning, Real-Time Object Detection, Waste Classification.

**Intisari**— Pengelolaan sampah masih menjadi isu lingkungan yang kritis secara global, termasuk di Indonesia, di mana peningkatan produksi sampah rumah tangga menimbulkan tantangan lingkungan dan sosial, terutama di tingkat lingkungan. Pada Bank Sampah berbasis komunitas, proses penyortiran manual seringkali tidak konsisten akibat keterbatasan sumber daya manusia serta perbedaan pemahaman masyarakat terhadap kategori sampah. Penelitian ini bertujuan untuk mengembangkan dan mengevaluasi sistem deteksi dan klasifikasi sampah berbasis web yang ringan dan real-time guna mendukung pengelolaan sampah di tingkat komunitas. Sistem yang diusulkan menggunakan arsitektur YOLOv8 melalui framework Ultralytics dengan PyTorch sebagai backend, serta terintegrasi dengan OpenCV untuk pemrosesan video real-time dan Streamlit untuk deployment berbasis web. Dataset yang digunakan terdiri dari sekitar 9.200 citra beranotasi dengan 24 kategori sampah, yang dibagi menjadi data pelatihan, validasi, dan pengujian, serta dilengkapi dengan augmentasi data untuk meningkatkan ketahanan model. Evaluasi dilakukan menggunakan metrik precision, recall, dan mAP@0.5. Hasil penelitian menunjukkan performa deteksi yang sangat tinggi dengan nilai mAP@0.5 sebesar 99,5%, precision 99,4%, dan recall



100,0%, serta mampu mempertahankan deteksi real-time yang stabil pada berbagai kondisi pencahayaan. Namun, hasil ini diperoleh pada kondisi dataset yang relatif terkontrol, sehingga diperlukan pengujian lebih lanjut pada kondisi nyata yang lebih beragam. Sistem ini mampu mendeteksi banyak objek tanpa perangkat keras khusus, sehingga mudah diterapkan pada Bank Sampah tingkat lingkungan sebagai solusi praktis pengelolaan sampah berbasis komunitas.

**Kata Kunci:** Artificial Intelligence, Manajemen Sampah Berbasis Masyarakat, Machine Learning, Deteksi Objek Real-Time, Klasifikasi Sampah.

## INTRODUCTION

Waste management remains a major environmental issue at the global level, including in Indonesia. Human activities in daily life significantly contribute to the increasing volume of waste, which, if not properly managed, can lead to serious environmental and social impacts [1], [2]. At the national level, various studies have developed waste classification and detection systems based on Artificial Intelligence (AI) to support more effective sorting processes. Several studies have utilized Convolutional Neural Networks (CNN) to classify organic and inorganic waste with relatively high accuracy [3], [4], [5], [6]. However, these approaches are generally based on image classification methods that assume a single object per image, limiting their applicability in real-world conditions.

At the community level, such as neighborhood associations (RT), this issue becomes more prominent because household waste is the primary source of daily waste generation. Limited public awareness and understanding of waste sorting at the source often result in organic and inorganic waste being mixed. This condition reduces recycling effectiveness and increases the burden on waste transportation systems and final disposal sites. In addition, Waste Bank operations at this level still face technical challenges, including limited human resources, inconsistent manual classification, and varying levels of understanding regarding waste categories.

To address the limitations of image classification, several studies have implemented object detection approaches using the YOLO algorithm for real-time waste detection [7], [8], [9], [10]. This method enables the detection of multiple objects in a single frame, making it more suitable for real-world scenarios. Some studies have further integrated these systems with IoT devices and specialized hardware such as smart sensors to support smart waste management systems [11], [12]. However, such implementations often require additional

infrastructure and may not be practical for small-scale community use.

Despite these advancements, lightweight web-based implementations that are directly accessible and applicable at the neighborhood level remain limited. In particular, there is still a lack of research integrating real-time camera-based detection with systems that are easy to use, require minimal setup, and can be operated by small-scale Waste Bank communities.

Therefore, this study proposes the development of a web-based application using Streamlit, integrated with a device camera to perform real-time waste detection and classification using a YOLOv8 model implemented in PyTorch [10], [11], [12]. The system also utilizes OpenCV for real-time video processing, enabling direct detection through a web interface without requiring specialized hardware. Furthermore, the system is designed to handle real-world challenges, such as varying lighting conditions, object diversity, and multi-object detection scenarios.

The novelty of this research lies in the integration of high-performance real-time object detection with a lightweight and accessible web-based implementation tailored for community-level waste management. This study contributes by (1) providing an efficient real-time multi-object waste detection system and (2) demonstrating that deep learning technology can be implemented as an accessible tool to enhance community participation and awareness in sustainable waste management practices.

## MATERIALS AND METHODS

This research adopts a system development approach consisting of five main stages: Research & Planning, Design & Development, Testing, Launch, and Maintenance. These stages ensure that the proposed real-time waste detection system is systematically designed, implemented, evaluated, and sustained for neighborhood level Waste Bank operations.

**WEB DEVELOPMENT LIFE CYCLE**



Source: (Research Results, 2026)

Figure 1. Web Development

**Research & Planning**

This study applies a structured system development methodology consisting of Research and Planning, Design and Development, Testing, Launch, and Maintenance stages. The Research and Planning stage begins with identifying operational challenges at the neighborhood level Waste Bank, where waste sorting is still performed manually. Manual classification often results in inconsistencies due to differences in residents' understanding of waste categories and limited human resources.

Previous studies indicate that deep learning-based computer vision systems significantly improve the accuracy and efficiency of waste classification processes [13], [14], [15], [16], [10]. In particular, object detection methods such as YOLO have demonstrated strong performance in real-time recognition scenarios due to their ability to perform localization and classification simultaneously in a single forward pass [17], [18], [19], [20], [10], [11]. Based on these findings, this research proposes a real-time waste detection system using the YOLOv8 architecture to support community-based waste management. At this stage, system requirements, performance indicators (precision, recall, and mAP), hardware specifications, and software frameworks were defined to ensure feasibility at the neighborhood level.

**Design and Development**

The Design and Development stage focuses on dataset preparation, model training, and system architecture design. The dataset used in this study was obtained from the Roboflow Universe waste-detection dataset, which consists of approximately 9,200 annotated images covering 24 classes of household waste objects [19], [20]. Each image includes bounding box annotations compatible with the YOLO format,

enabling object localization and classification tasks [21], [22], [23]. The dataset reflects real-world environmental variations such as lighting conditions, background complexity, and multi-object scenarios, which are important for practical implementation at neighborhood level Waste Banks. The dataset was divided into training (70%), validation (20%), and testing (10%) subsets to ensure balanced model learning and unbiased performance evaluation. Data augmentation techniques such as horizontal flipping, rotation, and brightness adjustment were applied to improve model robustness against environmental variability [24], [25], [26].

The object detection model was developed using YOLOv8 under the Ultralytics framework with PyTorch as the backend deep learning engine. YOLOv8 was selected because of its efficiency in real-time object detection and its improved architectural optimization compared to earlier YOLO versions. The training process involves optimizing bounding box regression loss, classification loss, and objectness loss to ensure accurate localization and classification of waste objects [27].

The system architecture integrates OpenCV for real-time video frame capture, the trained YOLOv8 model for inference, and Streamlit as a lightweight web interface framework. This architecture enables users to activate a device camera directly through a browser and observe detection results in real-time without requiring complex installation or specialized hardware infrastructure. The training process was conducted using the YOLOv8 model variant YOLOv8n (nano version), which was selected due to its lightweight architecture and suitability for real-time applications on limited hardware resources. The model was trained for 100 epochs with a batch size of 16 and an input image size of 640 × 640 pixels. The optimization process



utilized the Stochastic Gradient Descent (SGD) optimizer with an initial learning rate of 0.01 and momentum of 0.937. Early stopping was applied to prevent overfitting based on validation performance [28], [29], [30]. The training process was executed on a system equipped with an NVIDIA MX350 with 2GB VRAM, 16GB RAM, and an Intel Core i5-10210U. This hardware configuration ensures that the model training and inference processes remain efficient while maintaining compatibility with low-cost deployment environments at the neighborhood level. These experimental settings were selected to balance computational efficiency and detection accuracy, ensuring the feasibility of real-time implementation.

### Testing

The Testing stage evaluates both model performance and functional system reliability. Model performance was measured using standard object detection metrics, including precision, recall, F1-score, and mean Average Precision (mAP@0.5), which are commonly used to evaluate deep learning-based detection systems [31], [32]. These metrics assess how accurately the model detects and classifies waste objects while minimizing false positives and false negatives. In addition to quantitative evaluation, functional testing was conducted using real-time camera input to assess system stability, multi-object detection capability, and inference speed under varying lighting conditions. The testing scenario simulates actual operational conditions at a neighborhood level Waste Bank to evaluate system practicality and usability.

### Launch

After successful validation, the system was deployed as a web based application using Streamlit. The deployment process ensures that the application can be accessed through a web browser, allowing users at the neighborhood level Waste Bank to operate the system without installing complex software packages. The launch phase also includes user interface optimization to ensure ease of use for community members who may not have technical backgrounds. The lightweight web based implementation addresses limitations identified in previous studies, where many AI based waste detection systems required specialized hardware or standalone desktop environments [33], [34]. By enabling browser based access, the proposed system enhances accessibility and scalability at the community level.

### Maintenance

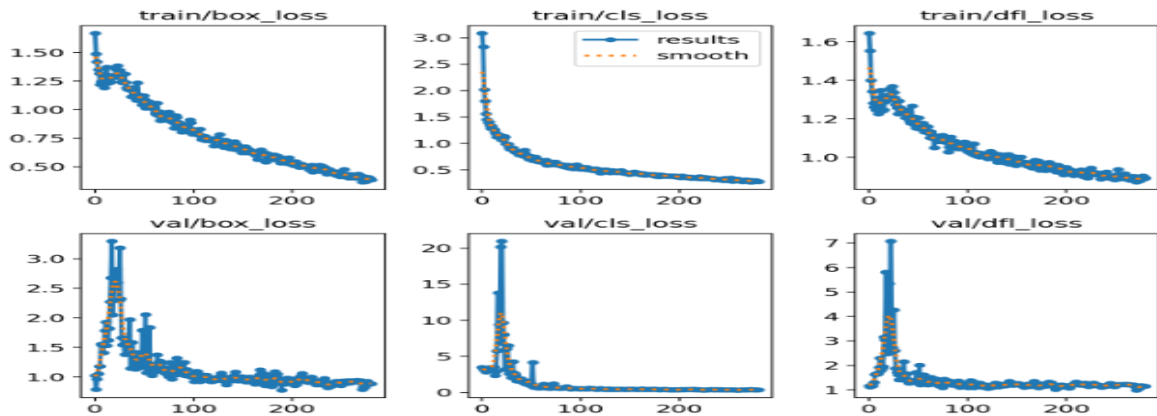
The Maintenance stage ensures long term system sustainability and adaptability. Periodic model retraining is conducted using newly collected waste images to improve detection accuracy and accommodate new waste object variations. Performance monitoring is performed to evaluate changes in precision and recall over time. Software dependencies are also updated to maintain compatibility with evolving deep learning libraries and deployment frameworks. Continuous dataset expansion and retraining are essential to maintain model generalization in dynamic real-world conditions, particularly in community-based waste management environments where object appearance may vary significantly [10], [29]. Through this maintenance strategy, the proposed system remains reliable, adaptable, and sustainable for long term implementation at the neighborhood level Waste Bank.

## RESULTS AND DISCUSSION

### Model Training Result

This section presents the experimental results obtained after training the proposed model. The analysis includes the evaluation of training and validation loss behavior, performance metric progression during training, and a summary of the final model performance. The results are illustrated through graphical representations and quantitative measurements to provide a comprehensive understanding of the model's effectiveness. To evaluate the learning behavior of the model during training, Figure 2 illustrates the training and validation loss curves, including box loss, classification loss, and Distribution Focal Loss (DFL).

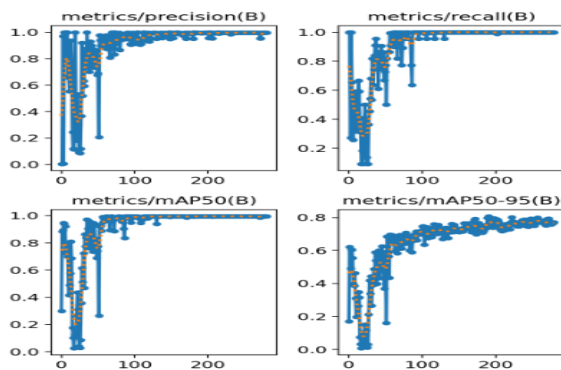
Throughout the training process, all loss components demonstrate a consistent decreasing trend across epochs. The box loss gradually declines, indicating improved object localization accuracy. Likewise, the classification loss decreases significantly, showing that the model becomes increasingly capable of distinguishing object classes. The DFL loss also stabilizes toward the final epochs, suggesting improved bounding box regression performance. Furthermore, the validation loss follows a similar downward pattern without significant divergence from the training loss, indicating that the model does not experience severe overfitting and maintains good generalization capability.



Source: (Research Results, 2026)

Figure 2. Training and Validation Loss Curves

Following the analysis of the loss behavior, the model performance is further evaluated using detection metrics, as shown in Figure 3. The precision and recall values increase rapidly during the initial training epochs and remain stable at high levels as training progresses. The recall reaching 100% indicates that the model successfully detects nearly all objects in the validation dataset. Additionally, the mAP@50 curve approaches 99.5%, demonstrating excellent detection performance at an Intersection over Union (IoU) threshold of 0.5. The mAP@50-95 also shows strong convergence, indicating consistent performance under stricter IoU thresholds. These results confirm the robustness and reliability of the trained model.



Source: (Research Results, 2026)

Figure 3. Precision, Recall, and mAP Curves

Table 1 presents the final evaluation results of the trained model, showing an mAP@50 of 99.5%, precision of 99.4%, and recall of 100.0%. While these values indicate excellent detection performance, a deeper analysis reveals several important aspects of the model behavior. The high precision value (99.4%) indicates that the model produces very few false positive detections,

meaning that most predicted waste objects are correctly classified. Meanwhile, the recall value reaching 100.0% suggests that the model is able to detect nearly all objects present in the dataset without missing significant instances. This balance between precision and recall demonstrates that the model achieves both accuracy and completeness in object detection tasks.

Furthermore, the mAP@50 value of 99.5% reflects the model's strong capability in localizing objects with a high degree of overlap between predicted and ground truth bounding boxes. This indicates that the model not only recognizes object classes correctly but also accurately identifies their spatial positions within the image. However, despite these strong results, it is important to consider that such high performance may be influenced by the characteristics of the dataset, including annotation quality and similarity between training and validation data. Therefore, while Table 1 confirms the effectiveness of the model under controlled conditions, additional evaluation using more diverse real-world data is necessary to fully validate its generalization capability.

Table 1. The Trained Model Result

No	Metrics	Value
1	mAP@50	99.5%
2	Precision	99.4%
3	Recall	100.0%

Source: (Research Results, 2026)

In addition, this study does not perform cross-validation or extensive comparative analysis with other object detection models such as Faster R-CNN, SSD, or earlier YOLO variants (e.g., YOLOv5). This limitation is due to the primary objective of the research, which is to develop a lightweight and practical real-time



detection system suitable for neighborhood-level Waste Bank implementation rather than benchmarking multiple models.

However, previous studies have shown that YOLO-based architectures generally outperform traditional two-stage detectors such as Faster R-CNN in real-time scenarios due to their single-stage detection mechanism and faster inference speed [11,] [12], [14], [15], [19]. Therefore, YOLOv8 was selected as a suitable approach to balance detection accuracy and computational efficiency. For future work, more comprehensive evaluation methods such as confusion matrix analysis, per-class precision-recall evaluation, and comparative benchmarking with other object detection models will be conducted to further validate the robustness and generalization capability of the proposed system. To further validate the practical applicability of the trained model, real-time testing was conducted using live camera input in a web-based environment.

#### Real-Time Detection Performance

The implemented system was tested using live camera input through the Streamlit based web interface. The detection results were displayed in real-time, with bounding boxes, class labels, and confidence scores overlaid on the video frames. The system demonstrated stable performance during continuous operation, successfully detecting multiple waste objects within a single frame under varying lighting conditions. The average inference speed was sufficient to maintain near real-time performance, ensuring that the system remains responsive for practical use at the neighborhood level Waste Bank. However, during testing under low light conditions, a slight delay in detection response was observed. This delay is primarily caused by reduced image clarity, which affects feature extraction quality and increases the computational effort required during preprocessing and inference stages. Low illumination can introduce noise and reduce contrast, thereby influencing the confidence score and detection speed of the model.

Despite this limitation, the model was still able to detect dominant object features with high accuracy, even when objects were partially occluded or overlapping. This behavior confirms that YOLOv8 is capable of handling complex detection environments, consistent with previous real-time detection studies [4], [10], [11], [12], [17]. The minor delay observed under suboptimal lighting conditions does not significantly affect system usability but indicates that adequate lighting is an important factor for optimal real-

time performance in community-based waste management environments.



Source: (Research Results, 2026)

Figure 4. Results from the Detection System

Figure 4 illustrates the real-time detection output generated by the system through the Streamlit interface. The system successfully identifies multiple waste objects simultaneously, displaying bounding boxes, class labels, and confidence scores in real-time. This visualization confirms that the model is capable of performing object detection not only in controlled datasets but also in dynamic environments. The detection results demonstrate that the system maintains consistency between training performance and real-world implementation.

#### Discussion

These findings are consistent with the quantitative results presented in Table 1 and the performance trends illustrated in Figures 2 and 3. The extremely high performance metrics (mAP@0.5 = 99.5%, precision = 99.4%, and recall = 100.0%) indicate that the model is well trained and highly optimized for the selected dataset. This performance is supported by the training behavior shown in Figure 2 and Figure 3, where loss values consistently decrease and evaluation metrics converge at high levels. Such convergence suggests that the model is able to effectively learn both object localization and classification features. However, from a critical perspective, these results may also be influenced by the characteristics of the dataset. The use of a well-annotated dataset with relatively consistent object representation and limited environmental variability can lead to higher evaluation scores. This implies that while the model performs exceptionally well under experimental conditions, its generalization capability in more complex real-world environments may still require further validation. Factors such as low lighting conditions, overlapping objects, and background clutter, as observed during real-time testing, can affect detection stability.

When compared with previous studies, the results of this research are consistent with findings that YOLO-based models provide high accuracy and fast inference for real-time object detection tasks [17] [18]. For instance, earlier implementations using Convolutional Neural Networks (CNN) for image classification typically achieve high accuracy but are limited to single-object detection scenarios [14], [19], [23]. In contrast, object detection approaches such as YOLO enable simultaneous localization and classification of multiple objects within a single frame, making them more suitable for real-world waste management applications. Additionally, compared to two-stage detectors such as Faster R-CNN, YOLO-based models offer significantly faster processing speed, which is essential for real-time systems [33].

The main contribution of this study lies in bridging the gap between high-performance object detection models and their practical implementation in community-level environments through a lightweight, web-based system. Unlike many previous works that focus primarily on model accuracy or require specialized hardware, this research emphasizes accessibility and usability at the community level. The system can be operated directly through a web browser using a standard device camera, making it more applicable for neighborhood-level Waste Bank operations with limited technical resources [33], [34]. Overall, the experimental findings demonstrate that the proposed system is not only technically reliable but also contextually relevant. This study bridges the gap between theoretical model performance and practical implementation, providing a scalable and user-friendly solution for community-based waste management. Future research should focus on expanding the dataset with real-world variations and conducting comparative evaluations with other detection models to further strengthen the system's robustness and generalization capability.

## CONCLUSION

This study presents the development and implementation of a real-time waste detection and classification system based on the YOLOv8 deep learning architecture, deployed through a lightweight Streamlit web application. The proposed system addresses practical challenges faced by neighborhood level Waste Banks, particularly inconsistencies in manual waste sorting, limited human resources, and variations in residents' understanding of waste categories.

The experimental results demonstrate exceptionally high performance, achieving a mAP@0.5 of 99.5%, precision of 99.4%, and recall of 100.0%. These findings confirm that the YOLOv8-based object detection model is highly effective in simultaneously localizing and classifying multiple waste objects within a single frame. Compared to conventional CNN based image classification approaches that focus on single object inputs, the proposed object detection approach offers greater adaptability to real-world operational conditions, including multi-object scenarios and varying environmental contexts.

The novelty of this research lies in the integration of real-time multi-object detection using YOLOv8 with a lightweight, web-based deployment via Streamlit that can be directly operated using standard device cameras without requiring additional hardware or complex infrastructure. Unlike previous studies that primarily focus on model accuracy or rely on IoT based systems with dedicated devices, this study emphasizes accessibility, usability, and direct applicability at the community level, particularly for small scale Waste Bank operations. This positions the proposed system as a practical implementation of human-centered AI tailored to grassroots environmental management. The integration of PyTorch, OpenCV, and Streamlit enables real-time detection directly through a device camera without requiring complex backend infrastructure or high end hardware acceleration. This lightweight deployment model enhances accessibility, scalability, and usability. In addition to functioning as an intelligent classification tool, the system also serves as a digital educational medium that promotes public awareness of waste sorting at the source.

Although the model achieved outstanding performance under experimental conditions, further validation in more diverse real-world environments is necessary to ensure robustness against extreme lighting variations, background complexity, and object occlusion. Future research can be directed toward several concrete developments, including: (1) expanding the dataset with more diverse waste categories and environmental conditions, (2) implementing model optimization techniques such as pruning or quantization to improve performance on low-spec devices, (3) integrating the system with cloud-based data storage for monitoring and analytics of waste collection, (4) developing a mobile-based application to increase user accessibility, and (5) incorporating user feedback mechanisms to improve system adaptability and classification



accuracy over time. In conclusion, this research demonstrates that advanced deep learning based object detection models can be effectively translated into practical, community oriented AI solutions. By explicitly bridging the gap between laboratory scale experimentation and real-world implementation, the proposed system contributes not only to the advancement of applied artificial intelligence but also to the development of accessible and sustainable waste management practices at the neighborhood level.

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