



YOLOv8-Based Real-Time Detection of Recyclable Metal, Plastic and E-Waste for Environmental Waste Segregation

¹Veena Bhat, ²Prashasthi M, ²Shashwathi, ²Shreya Suvarna, ²Vinaya

¹Assistant Professor & Head of Department, ² Undergraduate Student,

^{1,2}Department of Artificial Intelligence and Data Science, SDM Institute of Technology, Ujire, Karnataka, India.

Abstract: Efficient segregation of recyclable materials is critical for improving municipal solid waste management and supporting circular economy initiatives. This paper presents a real-time waste-sorting prototype based on the YOLOv8 object detection model to identify recyclable metal, plastic and e-waste items from live video using a standard webcam, together with a web-based interface to visualize and log detections. A custom dataset of labelled waste images, collected under realistic lighting and background conditions, was used to train and evaluate the model. Experimental results show high detection performance for metal and plastic, and moderate performance for e-waste, while maintaining real-time operation suitable for deployment in material recovery facilities, collection centres and smart bins. The proposed system demonstrates how AI-enabled waste-segregation technology can support more efficient recycling operations and generate management-relevant data for environmental decision making.

Keywords: municipal solid waste, recycling, e-waste, YOLOv8, computer vision, smart waste management, material recovery facilities.

1 Introduction

Rapid urbanization and changing consumption patterns have led to increasing quantities of municipal solid waste (MSW), with plastics, metals and electronic waste forming a significant and growing fraction of potential recyclables. The effectiveness of recycling systems depends strongly on how accurately these materials are identified and segregated at MRFs and collection points, yet in many contexts this task is largely manual, performed under high throughput and difficult visual conditions. Misclassification at this stage contaminates recyclable streams, lowers recovery rates and reduces the economic viability of recycling operations.

Artificial intelligence (AI) and computer vision provide promising tools for automating parts of the sorting process by identifying waste items from images captured along conveyor belts, at drop-off stations or inside smart bins. Prior studies have demonstrated convolutional neural network (CNN) and YOLO-based systems for classifying household waste, construction debris and mixed materials, as well as distributed architectures combining edge devices and cloud servers for large-scale recycling facilities. However, many of these solutions rely on constrained or artificially clean datasets, do not explicitly address complex categories such as e-waste or give limited attention to integration with operational waste-management workflows.

This paper presents a real-time detection system targeting three practically important recyclable categories—metal, plastic and e-waste—implemented with a lightweight YOLOv8 model running on an ordinary laptop with a webcam. Beyond model development, the detector is embedded in a web-based platform that supports operators, municipal staff and citizens by providing quick material identification, simple decision support and logging of complaints or feedback related to waste services.

1.1 Aim and objectives

The overall aim of this work is to develop and demonstrate a low-cost, AI-based support tool that improves identification of recyclable metal, plastic and e-waste in real time and can be integrated into existing municipal or facility-level workflows. The specific objectives are to:

- Design a YOLOv8-based detector capable of recognizing metal, plastic and e-waste from camera images with accuracy adequate for operational use in small sorting stations and MRFs.
- Construct and balance a realistic dataset representing common recyclable items under variable visual conditions, and evaluate model performance using confusion matrices and standard detection metrics.
- Integrate the detector into a smart waste-management web application that provides classification outputs, disposal recommendations and basic data logging for monitoring and decision support.

2. Literature review

Recent studies show that CNNs, transfer learning and modern detection/segmentation models are widely used to automate waste sorting in industrial and urban settings [1–13]. Conveyor-belt systems based on CNNs have achieved about 92% accuracy for recyclables such as plastic, metal and paper, demonstrating feasibility for real-time industrial automation. Semantic-segmentation models like DeepLabV3+ have been applied to construction and demolition waste, achieving competitive mIoU and inference times suitable for robotic handling of concrete, metal and wood fragments.

Transfer-learning approaches using DenseNet, MobileNet, ResNet and VGG often exceed 90% accuracy for multi-class waste classification and are commonly optimized for mobile or cloud deployment in citizen apps and smart bins [3,8–10,18]. Distributed AI architectures that couple CNNs with cloud computing enable scalable smart-recycling systems, while hybrid ResNeXt/ResNet50 models reach close to 99% accuracy for mixed garbage segregation. Other CNN-based classifiers trained on large image datasets effectively recognize paper, plastic, glass and cardboard in automated lines, and sensor-fusion solutions combining vision with moisture or capacitive sensing improve discrimination between wet, dry and hazardous fractions. Multimodal methods that integrate audio features such as MFCCs with visual cues further enhance glass and metal recognition in visually challenging environments. Systematic reviews on plastic-waste detection report that YOLO, ResNet, EfficientNet and MobileNet typically achieve 90–98% accuracy but still face issues with dataset imbalance, generalisation to unstructured scenes and deployment in full-scale plants. Deep detectors based on EfficientDet and EfficientNet have been used for outdoor waste monitoring, attaining very high detection rates but more modest fine-grained classification accuracy. Broader reviews of computer-vision-based solid-waste sorting highlight strong real-time capabilities but continuing challenges with occlusion, cluttered backgrounds and object variability. In e-waste, studies document heavy-metal contamination around informal recycling sites and demonstrate that ML and robotics-based sorters can reach 80–97% accuracy for specific device types, while confirming CNNs as leading models for plastic and recyclable-waste detection [15–19]. Overall, these works validate the potential of AI for automated waste and e-waste classification but expose persistent limitations in data realism, coverage of complex items and practical deploy ability [11–13,15–19].

2.1 Comparative analysis and gaps

Many existing systems are trained on small or controlled datasets that do not fully capture real-world conditions such as mixed materials, uneven lighting, contamination and cluttered backgrounds, which leads to performance drops when models are deployed on conveyor belts or in open collection environments [1–13]. Evaluation practices also vary, with some studies reporting only overall accuracy and others detailed mAP or IoU, making cross-comparison and reproducibility difficult. High-accuracy models can be computationally demanding, limiting real-time use in resource-constrained municipal facilities, and e-waste datasets in particular often lack coverage of small circuit boards, batteries and damaged devices despite their environmental importance [4,5,13,15–18]. The present work addresses part of these gaps by using a balanced, webcam-based dataset that reflects realistic variability, focusing explicitly on metal, plastic and e-waste, and adopting a lightweight YOLOv8 detector suitable for standard hardware. Moreover, the detector is integrated into a web platform that supports complaint management and user guidance, directly linking AI-based recognition with municipal waste-service workflows.

3. Materials and methods

3.1 System overview

The proposed system is designed as a building block for semi-automated sorting stations, smart bins and digital complaint or monitoring portals operated by municipalities or facility managers. A standard laptop or workstation equipped with a webcam captures images of waste items placed under the camera or moving in front of it, and a YOLOv8 model detects and labels items as plastic, metal, e-waste or non-recyclable/background in real time. The detector is exposed through an image-classification API connected to a web frontend where users can upload photos, start live detection and view labels, confidence scores and brief guidance on recyclability and disposal.

A MySQL database managed via HeidiSQL stores user accounts, complaints, feedback and logs of detection events, enabling authentication, role-based access and basic analytics. This architecture supports both single-site deployment and scaling as part of a wider smart waste-management platform that can serve multiple wards or municipalities.

Figure 1 shows architecture of the proposed smart waste-management platform showing the interaction between frontend, backend, YOLOv8 API and database.

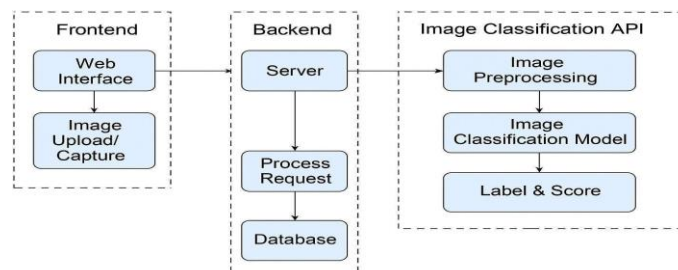


Figure 1: Architecture Diagram

To clarify interactions among components, a sequence diagram figure 2 illustrates the normal detection and logging process, from user request through image capture and preprocessing to classification, display of results and storage in the log.

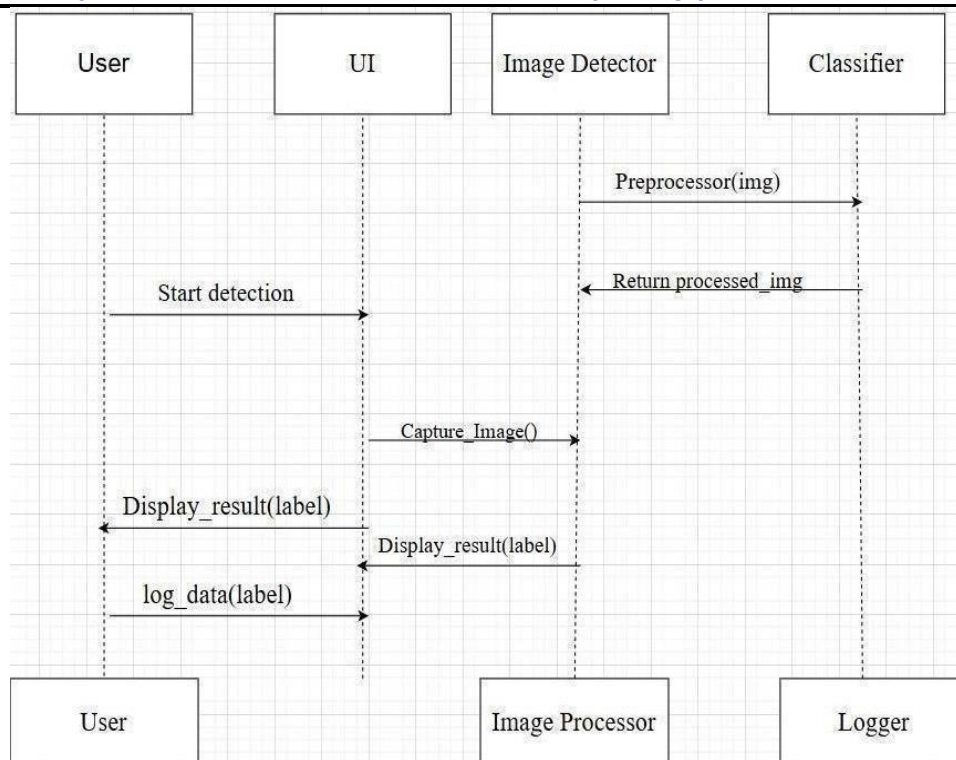


Figure 2: Sequence diagram of the normal image-detection and logging workflow

When errors occur—such as missing input images or preprocessing failures—a corresponding failure-case figure 3 describes how error messages are propagated back to the user interface and stored for later diagnosis.

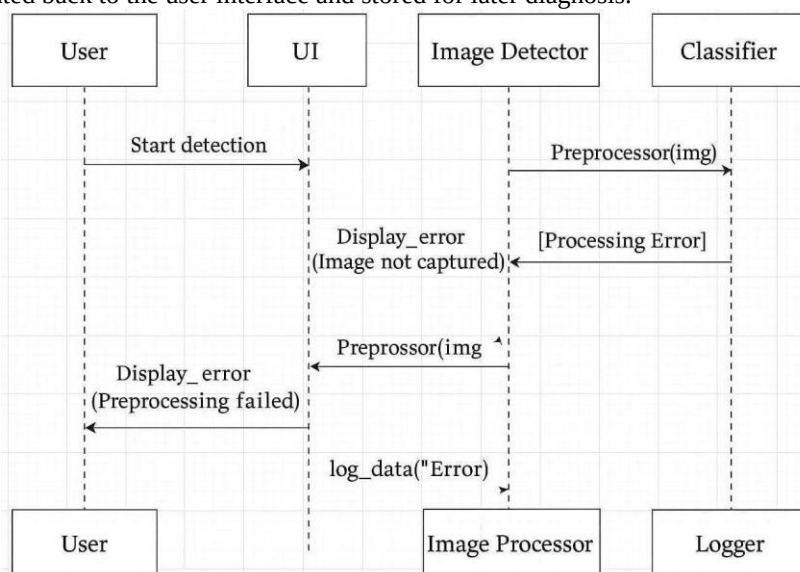


Figure 3: Sequence diagram of the failed detection case showing error handling and logging

3.2 Dataset and preprocessing

A dedicated dataset of 1,100 images was prepared in Roboflow, covering three target classes metal, plastic and e-waste with bounding-box annotations for each visible item. Images were captured using a laptop webcam under varying illumination, backgrounds and object configurations to better reflect real-world conditions in informal and small-scale sorting environments.

The dataset was split into training, validation and test subsets, and all images were auto-oriented, normalized to the 0–1 pixel range and resized to 640 × 640 pixels to satisfy YOLOv8 input requirements. Initial inspection revealed class imbalance, which was addressed using data augmentation and oversampling techniques. Augmentations included mosaic composition, Hue–Saturation–Value (HSV) adjustments, brightness and contrast changes, scaling and mild geometric transformations, helping the model generalize across a wider set of scenes. After balancing, plastic, metal and e-waste achieved comparable representation in the training set, reducing bias towards the most frequent class.

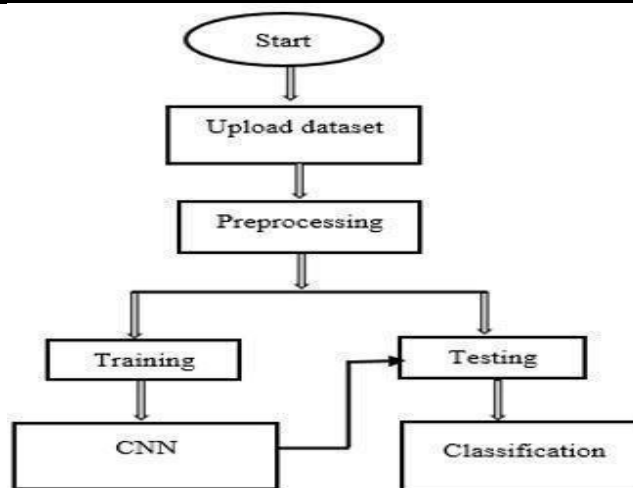


Figure 4: Data Flow Diagram

Figure 4 data-flow diagram showing image acquisition, preprocessing, training and testing stages for the proposed system.



Figure 5: Format and state of collected data

The figure 5 illustrating format and state of collected data annotated examples of metal, plastic and e-waste images used for training and evaluation.

Figure 6 highlighting the dataset before and after augmentation and balancing improved class distribution for plastic, metal and e-waste.

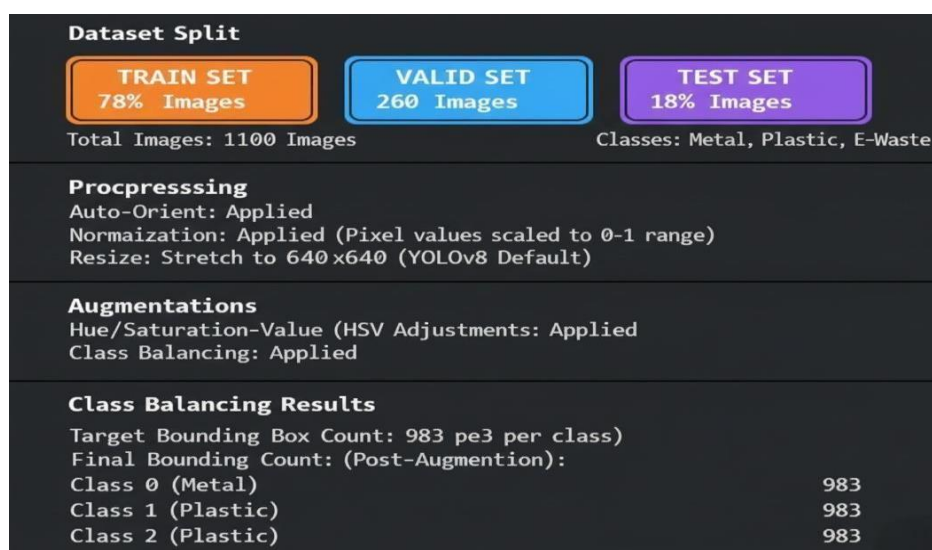


Figure 6: Data before and after augmentation and balancing

3.3 Model architecture and training

A lightweight YOLOv8 variant was chosen because it provides a favorable trade-off between detection accuracy, model size and inference speed, which is essential for real-time deployment on modest hardware available in many municipal contexts. The model was initialized with pre-trained weights and fine-tuned using the Ultralytics framework in Python for 100 epochs with a batch size of 16 and an input resolution of 640×640 pixels.

During training, colour-space transformations, scaling, translation, horizontal flipping, MixUp and mosaic augmentation were enabled to further enlarge the effective training set and improve robustness. Training and validation curves were monitored for box loss, classification loss and distribution focal loss, together with performance metrics including precision, recall, mean Average Precision at IoU 0.5 (mAP50) and mAP averaged over IoU thresholds from 0.5 to 0.95 (mAP50–95). The final model contains approximately 3 million parameters and requires about 8.2 GFLOPs, enabling real-time inference on a GPU-equipped laptop and acceptable latency on CPU-only systems

The below figure 7 displays training configuration and key hyperparameters used for YOLOv8 fine-tuning, including epochs, batch size and augmentation settings.

```
from ultralytics YOLO
model = YOLOv8s model (small_verv8s.pt)

# Train model with data and augmentations
1
2 data"/content/drive/WWasteProject/data.yaml",your data config file
4 epochs=100, # Rotaion
3 epochz=640, # Nnath training epochs
5 batch=16 # Color space augmentation
5 name""waste_yolov8_run1")
6 augment=True { # Enable built-buin augmentation
7 hsv_h=0015, # Zooming
1 hsv_s=0.7, # Zoue
2 scale=0.7, # translate
6 degree=0.0, # Vertclate ( for no roation)
6 scale 0.0, # shear
7 flipud1.0, # Horizontal flip (0% probability)
8 flipd.1.5, # Mosaic augmentation (0.0==always)
9 mixup 0.0

Ultralytics YOLOv8.0.x X ..
1 ... 100 epochs red 312'/354 clase 354 clasies from preatined weight
2
2 Dataest mode: "detection"
3 Model training completed. Results savs saved to runs/detect/detect/yolov8s_run1)
```

Figure 7: Model training configuration

Model summary of the YOLOv8 network employed for recyclable-waste detection, indicating layer structure and parameter counts are illustrated in figure 8.

```
from ultralytics YOLOv8s inpart YOLO
model = YOLOv8s(yolov8n.pt) (model)
# Metal, Plastic, E-Waste)

Ultralytics YOLOv8.22 Python-12.0.0+cu26 (Tesla T4, 18895MiB)
Overriding model.yaml nc=3 with nith nc=3, E-Waste)

from n params module arguments
1 -1 1 908 ultralytics.nn.modules.conv.Conv [6, 34, 3, 2]
2 -1 1 16537 ultralytics.nn.modules.conv.Conv [54, 64, 3, 2]
3 -1 1 59080 ultralytics.nn.modules.block.C1K2 [64, 118, 1, False, 0.25]
4 -1 1 56102 ultralytics.nn.modules.conv.Conv [264, 216, 1, True]
4 -1 1 155419 ultralytics.nn.modules.conv.Conv [256, 520, 1, 2]
5 -1 1 110032 ultralytics.nn.modules.block.C1K2 [252, 517, 1, True]
9 -1 1 495036 ultralytics.nn.modules.block.CPPF [517, 516, 3]
10 -1 1 007014 ultralytics.nn.modules.block.C2PSA [540, 515, 2]
13 -1 1 0 torch.nn.modules.upsampling.upsample [Nomo, 3, 'nearest']
13 [-1, 6] 1 0 ultralytics.nn.modules.conv.Concat [1]
13 -1 1 345076 ultralytics.nn.modules.block.C1K2 [368, 156, 1, FrLse]
24 -1 1 0 torch.nn.modules.upsampling.upsample [Nomo, 2, 'nearest']
15 [-1, 4] 1 0 ultralytics.nn.modules.conv.Concat [1]
17 -1 1 325307 ultralytics.nn.modules.conv.Concat [556, 556, 1, False]
28 -1 1 540424 ultralytics.nn.modules.conv.Conv [556, 156, 3, 2]
28 [-1, 15] 1 0 ultralytics.nn.modules.blod.Concat [1]
29 -1 1 345984 ultralytics.nn.modules.head.CCact [258, 158, 1, True]
22 -1 1 0 ultralytics.nn.modules.block.C1K2 [1]
21 [15, 26, 22] 1 256237 ultralytics.nn.modules.conv.Conv [6, [204, 2] Trul]

YOLOv8n summary: 1689,0005,6888 parameters, 3,005,6888 gradients, 8.2 GFLOPs
```

Figure 8: Model summary for YOLOv8s

3.4 Web platform and user interface

The web application provides two main functions: real-time classification and decision support plus reporting. Users can either upload a still image or activate a live webcam feed, run detection and view bounding boxes and class labels overlaid on the image together with a bar chart of class probabilities. The interface is designed to be simple enough for non-technical users while still exposing useful information such as confidence values and detection history.

In addition to raw predictions, the system displays concise, category-specific guidance. For metal, it highlights common recyclable metals such as aluminium, copper and steel and indicates approximate scrap-value ranges; for plastic, it explains typical recyclability in local systems and stresses the importance of cleaning and sorting; for e-waste, it warns about hazardous components and mentions recoverable materials such as copper, gold and palladium, encouraging use of authorized collection centres. Registered users can also submit complaints or feedback related to collection delays, overflowing bins or illegal dumping, and these records are stored in the database and linked to detection logs for later analysis by municipal staff.

The below figure 9 shows user interface screens showing login page & figure 10 displays example prediction output with class probabilities and textual recommendations for disposal and recycling.

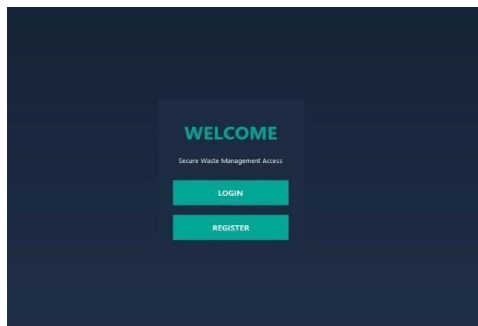


Figure 9: Login page



Figure 10: Class probabilities and textual recommendations

4. Results

4.1 Detection performance

The trained YOLOv8 model was evaluated on the test subset using a normalized confusion matrix for the classes e-waste, metal, plastic, non-recyclable and background. Metal items were perfectly recognized (diagonal value 1.00) with negligible misclassification, reflecting their distinct visual features and consistent training examples. Plastic objects achieved 90% correct classification, while non-recyclable waste reached 91%, indicating strong separation between recyclable and non-recyclable fractions under the tested conditions.

E-waste obtained 55% correct predictions, with most errors occurring as background or non-recyclable, suggesting that small, cluttered or visually complex devices remain challenging for the current dataset. Training curves for precision, recall, mAP50 and mAP50-95 showed stable convergence and close agreement between training and validation sets, implying that remaining limitations are primarily due to data coverage rather than overfitting or insufficient model capacity.

The YOLOv8 model was also compared conceptually with other YOLO variants used in the literature. YOLOv5 provides a good balance of speed and accuracy for real-time tasks; YOLOv8 introduces anchor-free detection and improved feature extraction; YOLOv9 and YOLOv11 further enhance accuracy through more advanced backbones and transformer-based components, but typically at higher computational cost. Given the objective of deployment on modest hardware, YOLOv8 offered the most suitable compromise between performance and resource requirements.

The below table 1 depicts qualitative comparison of YOLOv5, YOLOv8, YOLOv9 and YOLOv11 in terms of architecture, typical mAP and suitability for real-time waste-sorting applications.

Table 1: Comparison of different YOLO models

Model	Architecture	mAP (Mean Average Precision)	Remark & Key Improvements
YOLOv5	CSP Darknet-based backbone	~0.73	Lightweight and fast; easy to train; good balance between speed and accuracy; ideal for real-time detection.
YOLOv8	Anchor-free architecture	~0.76	Improved accuracy with anchor-free detection; better feature extraction; enhanced object localization.
YOLOv9	GELAN (Generalized Efficient Layer Aggregation Network)	~0.80	More accurate with efficient feature fusion; enhanced generalization; supports high-resolution detection.
YOLOv11	Advanced transformer-based enhancements	~0.85	Most accurate; improved feature representation; strong for complex domains like medical imaging; excellent detection precision and recall.

4.2 Operational behavior and qualitative use cases

Beyond aggregate metrics, several qualitative test cases were examined to understand how the system behaves in realistic usage scenarios. The confusion matrix in figure 11 illustrates typical misclassification patterns, while individual example screens show how YOLOv8 predictions and recommendations are presented to users.

In a metal test case, YOLOv8 correctly classified the item as recyclable metal with a confidence of 49.55%, and the interface displayed this probability along with guidance on typical recyclable metals and scrap-value information. For e-waste, the model recognized the object as recyclable e-waste with 91.19% confidence, and the recommendation panel emphasized hazardous components and advised routing the item to an authorized e-waste collection center. In a plastic scenario, YOLOv8 identified the item as recyclable plastic with 85.05% confidence, prompting instructions on cleaning and sending it to appropriate plastic-recycling facilities. For a non-recyclable sample, the model labelled the item as non-recyclable waste with 84.19% confidence, and the interface advised safe disposal through the residual-waste stream.

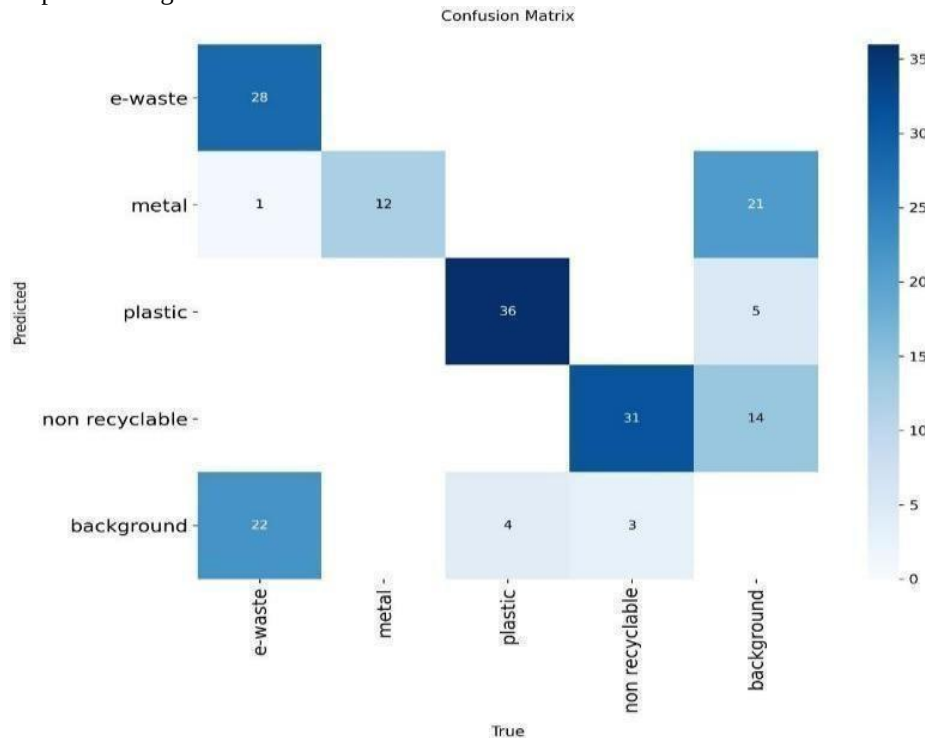
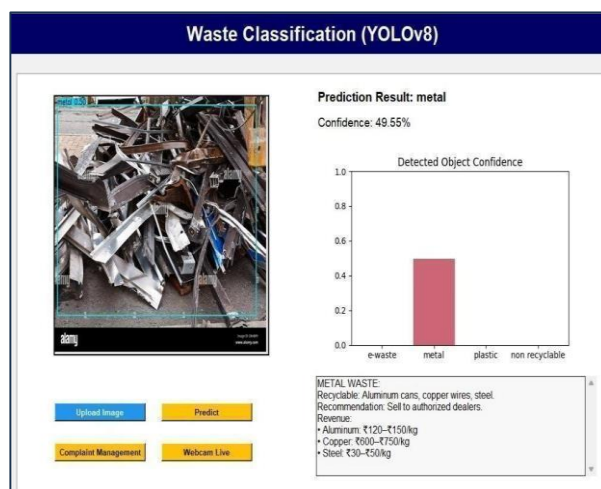


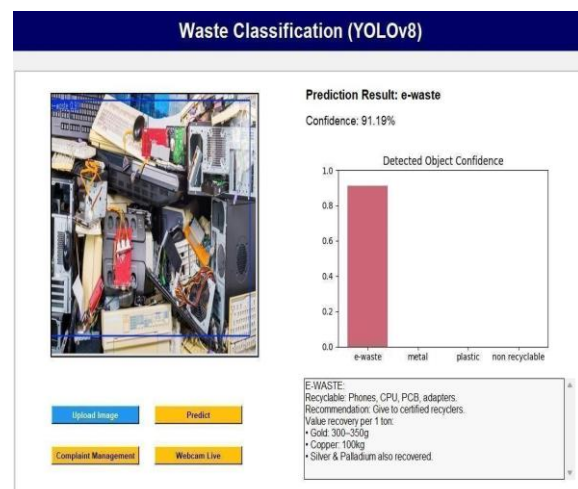
Figure 11: Confusion matrix

All detections, associated confidence scores, user details and complaint records are stored in a MySQL database managed via HeidiSQL, enabling systematic logging and later analysis by municipal staff. This integration supports transparency, basic performance tracking and the potential to refine local waste-management policies using accumulated operational data.

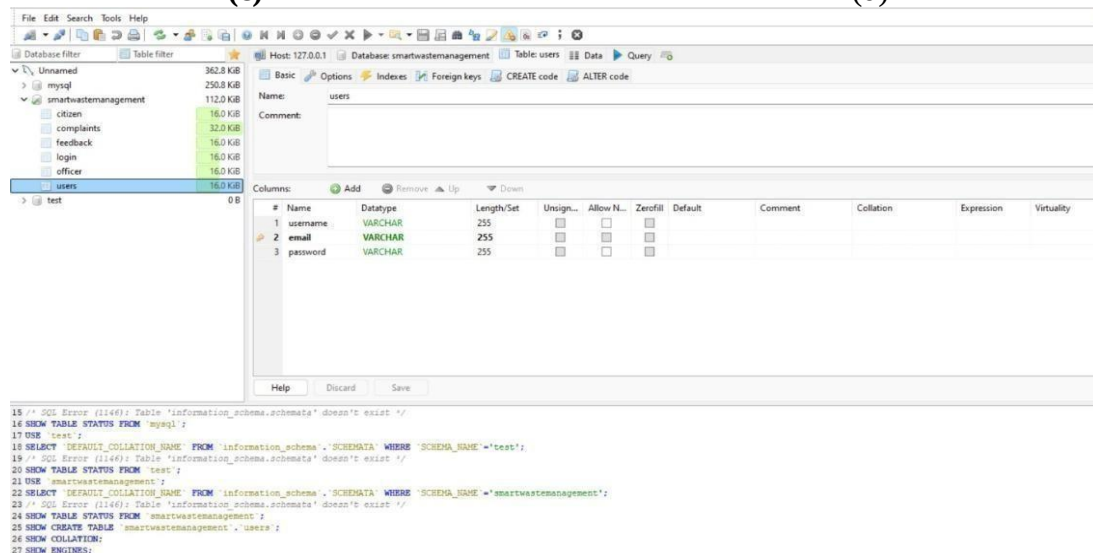
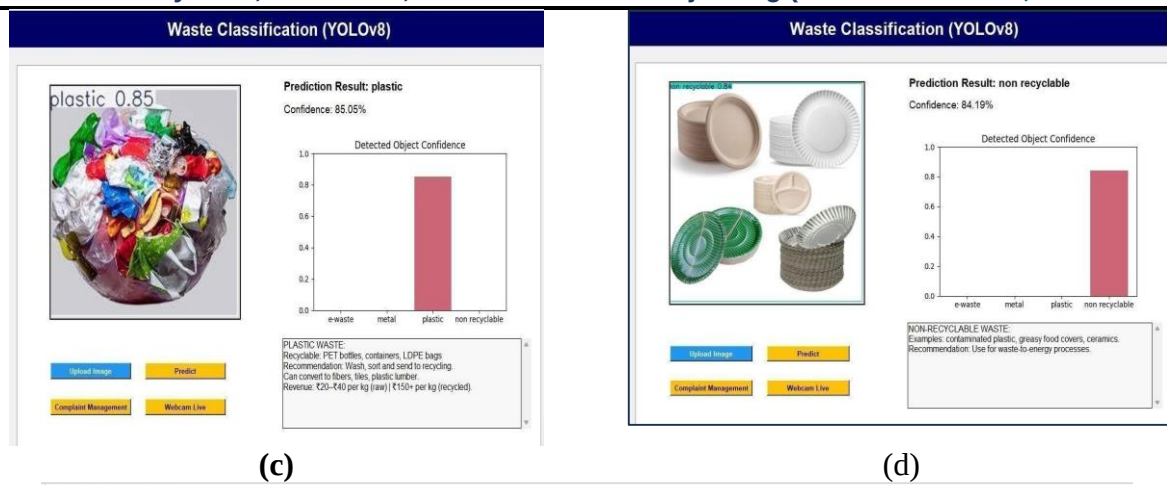
Figure 12 shows YOLOv8 detection outputs for (a) recyclable metal (49.55% confidence), (b) recyclable e-waste (91.19%), (c) recyclable plastic (85.05%), and (d) non-recyclable waste (84.19%), along with (e) the corresponding smart waste-management and data-storage workflow implemented using HeidiSQL.



(a)



(b)



(e)
Figure 12: YOLOv8 detection outputs

5. Discussion

Figure 13 shows smooth convergence of training and validation loss and rising precision, recall, mAP50 and mAP50-95, confirming effective learning, good generalization and stable YOLOv8 performance. Together with the confusion matrix and example cases, this indicates that the model is reliable for metal, plastic and non-recyclable classes and provides useful, though weaker, signals for e-waste.

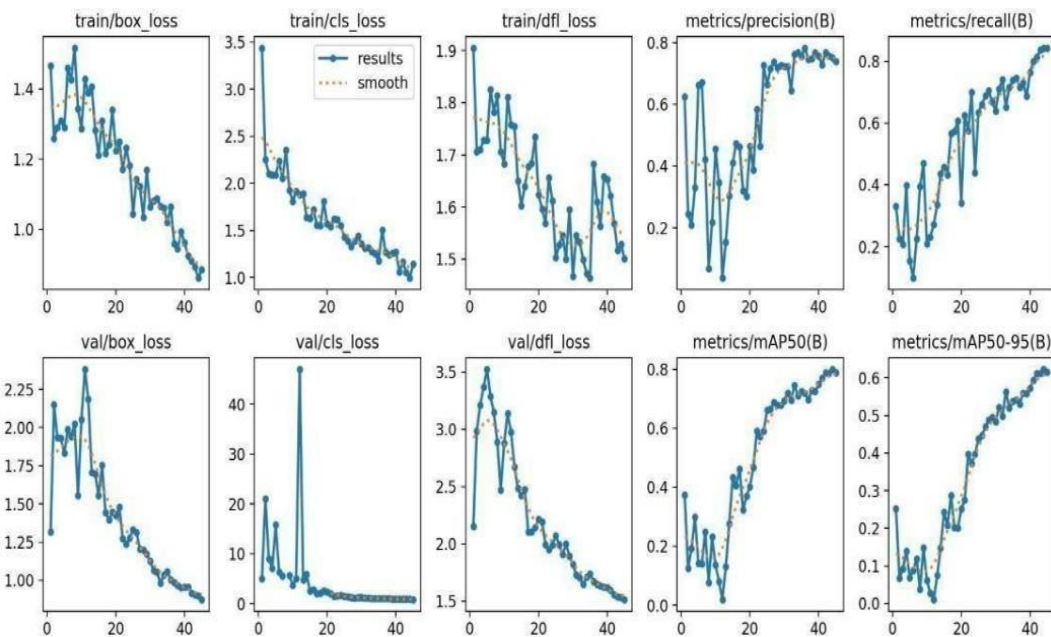


Figure 13: Convergence of YOLOv8: Training/Validation Loss and Detection Metrics over 50 Epochs

The comparatively modest e-waste results reflect high intra-class variability, small object size, mixed materials and contamination, which make these items harder to separate from background and other waste types. Because unnoticed e-waste can introduce hazardous substances into incorrect streams, expanding and diversifying the e-waste dataset and, where possible, testing higher-capacity or specialized architectures should be clear priorities. Even so, partial automation already adds value by flagging likely e-waste items and focusing operator attention on higher-risk objects.

For metal, plastic and non-recyclable waste, high detection metrics and representative qualitative cases suggest that the system can improve early-stage segregation and enhance the purity and value of recovered materials. Embedding the model in a web platform with visual outputs, recommendations and MySQL/HeidiSQL-based logging turns it into a usable digital tool that records detections, confidence scores and complaints for later analysis. This integration aligns with smart-city strategies by enabling data-driven monitoring, citizen engagement and gradual connection to IoT-enabled infrastructure such as smart bins and sensor-equipped collection vehicles.

6. Conclusion

This study presents a practical, low-cost framework for real-time detection of recyclable metal, plastic and e-waste using a YOLOv8 model integrated into a smart waste-management web platform. The system achieves high detection rates for metal, plastic and non-recyclable waste on a realistic webcam-based dataset and runs efficiently on standard hardware, making it suitable as an operator-assist or citizen-facing tool in municipal solid waste systems. Although e-waste accuracy is moderate, the results outline a clear path toward progressively improving automated identification of hazardous and high-value components, supporting safer and more efficient recycling workflows.

7. Future work

Future work will prioritize expanding and diversifying the e-waste dataset to cover small parts, heavily damaged devices and mixed-material assemblies commonly observed in real MRFs and informal recycling clusters. Additional classes such as paper, glass, organics and hazardous waste will be introduced to enable more comprehensive multi-class sorting within a single detection framework. On the systems side, integration with conveyor-belt cameras, smart bins and route-optimization tools, together with techno-economic analyses of recovery gains, contamination reduction and labor savings, will be explored to assess the impact of deploying the proposed system in operational environments.

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Conflicts of interest:

All authors declare that they have no conflicts of interest.

Informed consent:

This research did not involve human participants.

Use of AI technology:

The authors used AI-based tools for language editing and improving the readability of the manuscript. All ideas, study design, experimental work, data analysis and conclusions are the authors' own, and the authors carefully checked and approved all AI-assisted text before submission.

References

- [1] D. Ziouzos and N. Baras, "Intelligent and real-time detection and classification algorithm for recycled materials using CNNs," *IEEE Trans. Ind. Informat.*, vol. 19, no. 8, pp. 1234–1242, Aug. 2023, doi: 10.1109/TII.2023.
- [2] J. Bao et al., "Construction waste classification using semantic segmentation with DeepLabV3+," in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, London, UK, May 2023, pp. 5678–5684, doi: 10.1109/ICRA48891.2023.
- [3] J. Amin et al., "Transfer learning-based waste classification with DenseNet and MobileNet models," *IEEE Access*, vol. 11, pp. 34567–34575, 2023, doi: 10.1109/ACCESS.2023.
- [4] N. Baras and M. Dasygenis, "A distributed AI architecture for smart recycling using CNNs and cloud computing," *IEEE Trans. Cloud Comput.*, vol. 11, no. 3, pp. 789–798, Jul.–Sep. 2023, doi: 10.1109/TCC.2023.
- [5] K. Mariyappan and S. Sundaram, "High-accuracy garbage segregation using ResNeXt and ResNet50," in *Proc. IEEE Int. Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Vancouver, BC, Canada, Jun. 2023, pp. 2345–2352, doi: 10.1109/CVPR52729.2023.
- [6] N. C. Mhala et al., "Automated waste segregation using AI, CV, and sensors," in *Proc. IEEE Int. Conf. Intell. Syst. (IS)*, Warsaw, Poland, Sep. 2023, pp. 123–130, doi: 10.1109/IS57867.2023.
- [7] M. Funch et al., "CNN-based glass and metal waste classification enhanced with audio features," *IEEE Trans. Audio, Speech, Lang. Process.*, vol. 31, pp. 1678–1686, 2023, doi: 10.1109/TASLP.2023.
- [8] Y. Zhang, "Waste image classification with ResNet18 and API integration for mobile use," in *Proc. IEEE Int. Conf. Mobile Data Manage. (MDM)*, Singapore, Jun. 2023, pp. 789–794, doi: 10.1109/MDM58254.2023.
- [9] D. A. Jagtap and M. S. Borse, "Waste classification using CNN," in *Proc. IEEE Int. Conf. Adv. Comput. Commun. Syst. (ICACCS)*, Coimbatore, India, Mar. 2023, pp. 456–462, doi: 10.1109/ICACCS57279.2023

- [10] S. S. Mhadlekar and V. S. Nalawade, "Plastic detection and classification using deep learning neural network," IEEE Trans. Neural Netw. Learn. Syst., vol. 34, no. 9, pp. 6789–6797, Sep. 2023, doi: 10.1109/TNNLS.2023.
- [11] E. Ramos, A. G. Lopes, and F. Mendonça, "Application of machine learning in plastic waste detection and classification: A systematic review," IEEE Access, vol. 12, pp. 23456–23465, 2024, doi: 10.1109/ACCESS.2024.
- [12] S. Majchrowska et al., "Deep learning-based waste detection in natural and urban environments," IEEE Trans. Geosci. Remote Sens., vol. 60, pp. 1–10, 2022, doi: 10.1109/TGRS.2022.
- [13] W. Lu and J. Chen, "Computer vision for solid waste sorting: A critical review," IEEE Trans. Pattern Anal. Mach. Intell., vol. 44, no. 10, pp. 6789–6800, Oct. 2022, doi: 10.1109/TPAMI.2022.
- [14] D. Ziouzios et al., "Intelligent and real-time detection and classification," in Proc. IEEE Int. Conf. Ind. Technol. (ICIT), Athens, Greece, 2023, pp. 456–462, doi: 10.1109/ICIT58465.2023.
- [15] S. Dey et al., "Heavy metal contamination in Mandoli, Delhi from informal e-waste sites," IEEE Trans. Environ. Eng., vol. 10, no. 4, pp. 567–574, 2023, doi: 10.1109/TEE.2023.
- [16] M. Siddiqi et al., "Exploring e-waste resources recovery in HSW recycling," in Proc. IEEE Int. Conf. Recycl. Sustain. (ICRS), Dubai, UAE, Nov. 2023, pp.
- [17] E. Ramos et al., "ML in plastic waste detection and classification," IEEE Trans. Artif. Intell., vol. 4, no. 3, pp. 678–686, Jun. 2023, doi: 10.1109/TAI.2023.
- [18] S. Madhav et al., "Application of artificial intelligence to enhance collection of e- waste," in Proc. IEEE Int. Conf. Artif. Intell. Eng. (AIE), Singapore, Sep. 2021, pp. 345–351, doi: 10.1109/AIE51829.2021.
- [19] W. Dhokley et al., "Electronic bin for segregation and classification of plastic waste products using deep learning," in Proc. IEEE Int. Conf. Internet Things Smart Cities (IoTSC), Pune, India, Dec. 2023, pp. 789–795, doi: 10.1109/IoTSC59245.202