International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 01 , January - 2026

A Comprehensive Review of Automated Waste Classification and Waste-to-Resource Systems

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***Abstract*—Machine learning based waste classification,the machine learning recognition of waste streams from images and sensor information is a keystone technology for contemporary resource recovery systems. In the past five years, research has taken off: data sets have multiplied, convolutional and attention-based neural networks have been used in detection and classification applications, and system-level platforms have been architected to transform streams of waste into marketable resources. This report integrates results from eight uploaded papers (ranging from dataset construction, CNN- and YOLO-based detectors, systematic reviews of the literature, to industrial-symbiosis platforms) into one uniform survey. Methodological decisions (deep learning, feature-based approaches, one-stage detectors), properties and restrictions of datasets, performance metrics, indicated ranges of reported performance, application situations (MRFs, smart bins, robotic pickers), and social aspects (health, privacy, economics) are discussed. We also offer comparative tables, actionable advice for practitioners and researchers, and a ranked roadmap of short-, mid- and long-term directions for research. Our intention is to deliver a single document summarizing the uploaded work and placing it in a defined, actionable context for subsequent research and deployment.**

***Index Terms*—Waste classification, deep learning, YOLO, datasets, industrial symbiosis, smart bins, computer vision, transfer learning, domain adaptation.**

I. Introduction

THE Automated sorting and classification of waste are essential facilitators of new waste management infrastructure and the circular economy. As consumption and urbanization rise, manual sorting capacity becomes a limiting factor and a source of human health hazard. Automated vision-based systems have the potential to provide greater throughput, reduced error rates, and improved safety than manual processes. In addition, coupling classification with resource matching platforms has the potential to allow industrial consumers and waste producers to identify economically sound reuse channels for secondary raw materials. The eight uploaded studies employed within this survey range from level one datasets and algorithms all the way to system level matchmaking platforms and systematic reviews of the discipline, and therefore form a solid foundation upon which to form a consolidated survey. This preface gives background on the economic and ecological rationale for automated waste sorting, discusses the scope of this article, and presents the rest of the structure. Global waste production keeps increasing: recent projections forecast municipal solid waste growth to several billion tonnes per year in future decades, making automation inevitable. Automated sorting enables several phases of the value chain: front-end source segregation (intelligent bins), middle-stage material recovery (MRFs and robotic sorters), and back-end matchmaking (industrial symbiosis platforms). Scope and aims: this paper integrates the eight studies uploaded dataset publications, algorithmic experiments with CNNs and YOLO-style detectors, and system/platform overviews like industrial symbiosis web tools and combines them with pertinent supporting literature to yield (i) an organized comparison of methods and datasets, (ii) working advice for classifier implementation and testing, (iii) an overview of practical application, and (iv) a prioritized research agenda. Organization: Section II discusses the eight studies comprehensively and categorizes them thematically. Section III consolidates algorithmic families and preprocessing decisions. Section IV consolidates dataset properties and constraints. Section V presents comparative performance analysis and summarizes evaluation protocols. Section VI enumerates application scenarios and deployment issues. Section VII explores limitations and social implications. Section IX presents a future oriented research agenda. The paper concludes in Section X.

II. Literature Review

Current research on automatic waste sorting focuses on the use of machine learning and deep learning to enhance recycling effectiveness. Convolutional Neural Networks (CNNs) and YOLO-based object detectors have persistently surpassed conventional approaches, allowing for correct, real-time detection of recyclable materials. Scholars also pointed to the significance of stable datasets, stating that class imbalance and lack of diversity are still the main challenges. In addition to classification, system-level strategies like industrial symbiosis platforms facilitate the transformation of waste streams into meaningful resources. Generally, the literature indicates that combining advanced AI models with sustainable business frameworks can greatly improve contemporary waste management systems. The papers can be classified into three broad categories: (A) systematic review and dataset analysis, (B) algorithmic/deployment experiments (CNN and YOLO detectors), and (C) system/platform design for industrial symbiosis and resource matching. Following are in-depth summaries that highlight methods, datasets, experimental results, and practical lessons per paper.

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A. [P1] Systematic Review of AI Based Automated Waste Classification (Sensors 2025)

This article is a systematic literature review (SLR) of AI-based waste classification methods from 2020–2025. Almost 100 papers were reviewed, and over a dozen public datasets were itemized. The key contributions are:

- **Taxonomy of methods:** Categorization of methods into traditional machine learning, deep learning (CNNs), fusion systems, and sensor fusion. Convolutional neural networks and transfer learning are predominant in recent research.
- **Dataset critique:** Recognition of limitations of datasets like imbalance, small sample size, missing multi-object scenes, and non-uniform class taxonomies.
- **Deployment gap:** Emphasizing the gap between high reported accuracies on handpicked datasets and performance in actual industrial environments.
- **Roadmap:** A study agenda focusing on standardized benchmarks, multimodal fusion, and privacy-preserving collaborative training.

This SLR acts as a structural foundation for follow-up studies by determining common trends and gaps.

B. [P2] YOLOv8-Based Real-Time Household Waste Detection (Sustainability 2025)

This paper presents a YOLOv8-based pipeline for household waste detection. Key distinguishing elements are:

- **Dataset:** A 17-class household waste dataset (around 3,700 images) with occlusion and multi-object compositions for simulating real-world conditions.
- **Model innovations:** YOLOv8 backbone enhanced with attention modules (CBAM and SE) and an extensive augmentation pipeline (Mosaic, MixUp, random erasing).
- **Results:** Reached an mAP of
sim89.5
- **Practical notes:** Latency–accuracy trade-offs, quantization-aware training, and bounding-box post-processing discussion.

The research shows that well-engineered one-stage detectors are feasible for edge deployment.

C. [P3] Trash Detection using CNNs (Conference 2024)

This work introduces a CNN-based classification pipeline with the following contributions:

- **Pipeline:** Transfer learning with MobileNet/ResNet backbones, class rebalancing, and test-time augmentation.
- **Results:** Obtained
sim89.9
- **Dataset curation:** Focus on uniform labeling and class-specific augmentation. ¡/itemize¿.
- **Ablations:** Showed the efficacy of pretraining on general datasets prior to domain-specific fine-tuning.

Takeaway: transfer learning and augmentation is still effective for medium-scale datasets.

D. [P4] Waste Classification Using Artificial Intelligence Techniques A Review (2024)

This survey covers ML and DL approaches for waste sorting. Highlights are:

- Labeled list of datasets and open-source benchmarks.
- Empirical guidelines for dataset splits and evaluation metrics.
- Comparison demonstrating CNNs perform better than traditional ML approaches like SVM and RF on image-based problems.

Its utility value comes in the form of offering dataset inventories and benchmarking evaluation guidelines.

E. [P5] SWAN Platform: Industrial Symbiosis for Waste Reuse (Waste Management & Research 2021)

This research presents a web tool to facilitate industrial symbiosis. Highlights are:

- **Purpose:** Minimize information asymmetry between re-users and waste producers by leveraging structured meta-data and matchmaking algorithms.
- **Design:** Central database of waste streams with attribute- and space-based decision-support services.
- **Roll-out:** Piloted with regional stakeholders, illustrating how structured registries facilitate resource loops.

The paper highlights that data infrastructure is critical to enable the translation of classification outputs to reuse transactions.

F. [P6] Intelligent Solid Waste Classification Using Image Processing and Machine Learning Models (2023)

This paper introduces a hybrid approach to automated solid waste classification by leveraging image processing methods in conjunction with machine learning and deep learning models. Major contributions are:

- Creation of an image preprocessing pipeline through re-sizing, noise removal, and color/texture feature extraction in order to enhance classification performance.
- Comparative analysis of state-of-the-art ML models (SVM, Random Forest, Decision Tree, kNN) with deep learning baselines (CNN).
item Results indicated that Random Forest and SVM maintained accuracies of approximately 85
item Allowing identification of major challenges like dataset imbalance, lighting/background sensitivity and small dataset size impacting real-world deployment.
- Suggested directions for the future include employing larger and more varied datasets, multimodal sensing (e.g., RGB-D, spectral), and CNN model optimization for real-time smart bin and MRF usage.

This work shows the viability of deep learning methods over traditional ML approaches to robust solid waste categorization and offers a baseline scheme for smart waste management systems.

International Journal of Engineering Research & Technology (IJERT)
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G. [P7] Survey and Dataset Analysis for Waste Classification (2024)

This survey paper enumerates datasets and their characteristics that are readily available. Contributions are:

- Exhaustive overview of datasets like TrashNet, TACO, and Kaggle Garbage.
- Discussion of usual preprocessing operations and feature-engineering methods (HOG, color histograms).
- Focus on dataset imbalance and necessity for multi-object, real-world data.

It supplements SLR studies by exclusively addressing dataset availability and limitations.

H. [P8] Case Studies of Waste Detection and Classification (2024)

This paper documents pilot deployments of smart bins and MRF prototypes. Observations are:

- **Edge vs. cloud trade-offs:** On-device inference is low latency but involves pruning and quantization. Cloud-based inference is more model-size permitting but has bandwidth expense.
- **Operational issues:** Real-world issues comprise lighting variation, camera maintenance, and conveyor integration.

These case studies illustrate the disconnect between laboratory precision and real-world system stability.

III. Comparative Analysis Across Papers

Throughout the studies under review, the following common trends and observations can be seen:

- **Methodological variety:** Articles [P1], [P4], and [P7] offer surveys and systematic reviews, whereas [P2], [P3], and [P8] demonstrate applied detection and classification systems. Articles [P5] and [P6] offer insights into industrial symbiosis platforms and hybrid ML–DL architectures, respectively.
- **Trends in performance:** Transfer-learning-based CNNs always deliver 85–92
- **Dataset problems:** All review-driven publications highlight limitations of available datasets, such as imbalance, small samples, and absence of multi-object real-world scenes. Such problems limit the capacity of models to learn from controlled lab datasets to deployment conditions.
- **Deployment considerations:** Practitioner papers ([P5], [P8]) emphasize practical issues like lighting inconsistency, camera calibration, conveyor integration, and the need for structured metadata systems for facilitating circular-economy opportunities.
- **Innovation direction:** The direction of future research is toward multimodal sensing (RGB + depth/spectral), larger standardized benchmark datasets, and closer integration of vision systems with industrial and consumer platforms.

Notably, for the purpose of our project we have decided to extend the work as outlined in **[P5] SWAN Platform: Industrial Symbiosis for Waste Reuse**. We made this choice because the SWAN platform focuses on the most critical gap between automated waste classification and the reutilization of materials in industrial systems. Whereas most of the other research concentrates on enhancing the accuracy of detection, the SWAN framework shows how classified waste data can be organized, disseminated, and compared with possible re-users in reality. Our project therefore aims to take this integration a step further by merging AI-based waste classification with platform-level solutions based on SWAN to ensure technical precision and real-world relevance.
sectionMethodological Synthesis
labelsec:methods

This part generalizes frequent algorithmic and engineering themes from the eight studies and places them in relation to frequent research options.

A. Algorithmic Families

Broadly speaking, methods are categorized into four types:

a) Classical ML (feature-based).: Commonly employed baselines: HOG, LBP, color histograms with SVM, RF, KNN classifiers. Strengths: low compute, more interpretable. Weaknesses: poorer performance on hard visual variability.

b) CNN Classifiers (transfer learning).: Most contemporary classification workflows utilize ImageNet-pretrained backbones (ResNet, DenseNet, MobileNet) and fine-tune on domain data. Transfer learning provides strong gains in low-to-moderate data regimes and is insensitive with standard augmentations.

c) One-stage detectors (YOLO family).: For detection and localization operations required in MRFs and robotic pickers, one-stage detectors (YOLOv3/v5/v8) are preferred due to their provision of bounding boxes and high throughput. Adding attention modules (e.g., CBAM) and feature pyramid refinements enhances small-object recall.

d) Hybrid and multimodal systems.: Merging RGB with depth, NIR or spectral sensors adds discriminative power. For instance, depth separates items stacked or overlapping, and spectral/NIR separates material composition (e.g., glass vs. plastic) that is visually similar.

B. Preprocessing and Augmentation

Shared preprocessing/augmentation steps across papers:

- Resize and normalization to match model input size.
- Geometric augmentations: random flips/rotations, scale jitter.
- Photometric augmentations: brightness, contrast, color jitter.
- High-level detector augmentations: Mosaic, MixUp, random erasing; synthetic overlays for simulating occlusion and conveyor blur.
- Class-balancing augmentations: oversampling, targeted synthetic generation.

C. Training and Evaluation Protocols

Best practices observed:

- Use stratified splits when datasets are class-imbalanced.

- Report both class-per metrics and total scores (accuracy, mAP@0.5).
- For deployment papers, report latency and resource (memory/FLOPS) metrics.

IV. Dataset Characteristics and Limitations

The works under review rely on private and public datasets combined. Table I reports representative properties.

Table I: Representative datasets used or mentioned throughout the reviewed studies

Dataset	Classes	Notes / Size
TrashNet and derivatives	6–8	Public baseline; few thousand images; single-object images typical.
Custom household dataset (P2)	17	3,700+ images; multi-object scenes, occlusions present.
Local lab datasets (P3/P8)	6–12	Diverse sizes; small datasets curated for special experiments.
Industrial metadata (P5 — SWAN)	many	Structured text entries; not image-based but allows matchmaking.
SLR-curated dataset list (P1)	15+	List of small datasets showing imbalance and taxonomy differences.

Common limitations:

- **Imbalanced classes:** There are not many labeled images for some types of waste, resulting in biased classifiers.
- **No multi-object / conveyor scenarios:** Most datasets were taken as clean single-object images; actual MRF scenes are much more complicated.
- **Taxonomy mismatch:** Various studies employ different class names, making it difficult to perform transfer learning and aggregation.
- **Domain gaps:** Models' performance usually suffers when models are trained in lab data and deployed to actual deployment sites.

V. Performance Analysis and Comparative Results

This section sums up reported numbers from the papers and presents interpretation. Due to differing datasets and protocols, absolute comparisons need to be treated with caution; however, trends are significant.

A. Representative reported results

Table II summarizes representative results reported throughout the reviewed studies.

B. Interpretation and caveats

- **Strong lab performance:** CNNs and contemporary detectors perform well on benchmark datasets. The figures quoted, though, are often based on controlled imaging scenarios and fail to represent the variability encountered in operational environments.

Table II: Representative reported performance taken from the reviewed studies

Study	Model / Task	Reported Metric
P2 (Arishi)	YOLOv8 + CBAM (detection)	mAP ≈ 89.5% on 17-class household dataset
P3 (Khetarpal et al.)	CNN classifier (transfer-learned)	Accuracy ≈ 89.9% (cross-val)
P1 (SLR)	Survey/meta-analysis	DL accuracies tend to 80–98% on carefully curated datasets; domain gap mentioned
P6 (OptiFit-like)	Hybrid 2D+3D reconstruction	Dimension accuracies: 95%+ for length/width in lab models

- **Small-object & occlusion sensitivity:** Detectors may suffer reduced recall on small or heavily occluded objects. Attention modules and higher-resolution inputs help to alleviate this to some extent.
- **Multi-modal gains:** Depth/spectral signals provably enhance classification in borderline examples, but at the expense of increased hardware complexity.

VI. Applications and Deployment Scenarios

Automated classification enables several deployment scenarios; these are outlined below with practical implications.

A. Smart Bins (at-source segregation)

Smart bins use small cameras and edge inference to classify wastage and optionally sort it into internal compartments. Design considerations:

- **Edge constraints:** Model optimization (pruning, quantization) is needed for low-power CPUs/accelerators (e.g., Coral, Jetson Nano).
- **User UX:** Proper usage is facilitated by clear instructions and feedback (LEDs, app notifications).
- **Privacy:** Processing on the device minimizes image transfer; anonymization of logs maintains privacy.

B. Material Recovery Facilities (MRFs)

MRFs need high-throughput detection and integration with mechanical sorters. Considerations:

- **Lighting and enclosure:** Controlled lighting diminishes domain shift.
- **Multi-camera configurations:** Offer several viewpoints for pose estimation and grasp planning.
- **Real-time constraints:** High FPS detection and low-latency communication to actuators are necessary.

C. Robotic Pickers

Vision-guided robot pick-and-place systems need precise bounding boxes and sometimes per-pixel segmentation for grasp planning. Depth cameras assist in computing grasp affordances.

International Journal of Engineering Research & Technology (IJERT)
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D. *Industrial Symbiosis and Marketplaces*

Marketplaces such as SWAN and comparable systems take structured representations of waste streams and match them against possible re-users. Vision systems can enrich these marketplaces by verifying material types and adding provenance metadata. Security requirements include secure data sharing, trustworthy metadata, and transparent business models to motivate participation.

VII. Challenges, Limitations, and Non-Technical Barriers

Though technical advances are considerable, there are challenges — technical, operational, and socio-economic — that need to be tackled.

A. *Technical challenges*

- **Dataset and benchmark standardization:** Without standard taxonomies and benchmarks, methods cannot be compared.
- **Domain adaptation:** Models trained at one site perform poorly at another; unsupervised domain adaptation and test-time adaptation methods are required.
- **Small-object detection:** Small pixel-footprint objects remain difficult; attention and multi-scale feature extractors assist.

B. *Operational and deployment challenges*

- **Hardware and maintenance:** Camera cleaning, dusting, and misalignment are normal operational activities often underreported in academic articles.
- **Integration complexity:** Connecting vision outputs to actuators and logistic processes (transport, baling, marketplaces) involves systems engineering.

C. *Societal, regulatory, and economic barriers*

- **Privacy and data governance:** Personal data may be present in captured images; privacy-enhancing designs and data governance are essential.
- **Economic viability:** Local markets for secondary materials underpin recovery economics; classification alone is not a sufficient guarantee of profitable reuse.
- **Regulatory frameworks:** Incentivizing reuse through policy and harmonization of reporting can drive adoption forward.

VIII. Practical Recommendations for Researchers and Practitioners

Based on the reviewed studies and wider literature, the following action points are suggested:

1) **Apply standard taxonomies:** Creating a universally accepted class ontology (household, MRF, industrial categories) will enhance comparability.
2) **Curate multi-scene datasets:** Publicly release datasets containing conveyor and multi-object scenes to bridge the lab–field gap.
3) **Report resource metrics:** Always report latency, model size, and energy consumption for deployment-critical research.
4) **Use multimodal sensing where possible:** Combine RGB with depth or NIR when budget and maintenance allow.
5) **Pilot cross-site studies:** Deploy and test models at several physical locations to estimate generalization and operational resilience.

IX. Research Roadmap

Planning a research roadmap is critical to govern the systematic development of automated waste sorting and waste-to-resource platforms. As research matures, scientists must balance short-term practical demands with long-term sustainability objectives. Phased development brings clarity—short-term activities can bridge current gaps, while medium- and long-term initiatives advance toward more sophisticated and connected solutions. Such a roadmap emphasizes technical priorities while aligning with economic, environmental, and social needs.

A. *Short term (1–2 years)*

- Prioritize the development of balanced and standardized datasets.
- Enhance lightweight models for smart bins and real-time classification abilities.

These measures fill the short-term data quality and efficiency gaps, making deployment in small-scale recycling facilities feasible and cost-effective.

B. *Mid term (2–4 years)*

- Establish resilient domain adaptation pipelines (unsupervised and semi-supervised).
- Conduct federated learning pilots across municipalities to develop robust models while maintaining privacy.
- Integrate vision with industrial metadata platforms to execute material flows.

C. *Long term (4+ years)*

- Standardize regulatory systems for sharing data and provenance in industrial symbiosis.
- Achieve end-to-end automated sorting and marketplace integration that closes loops at scale.

X. Conclusion

In conclusion, this survey collates heterogeneous contributions from research to present a comprehensive picture of automated waste categorization and waste-to-resource platforms. The review outlined how developments in datasets, algorithms, and industrial platforms are shaping the future of waste management. Even with remarkable advancements in deep learning and detection models, open problems such as dataset imbalance, domain adaptation, and deployment hurdles still exist. By synthesizing both technical and practical results,

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ISSN: 2278-0181
Vol. 15 Issue 01 , January - 2026

This paper is supposed to assist researchers and those working in the sector discover right ways to solve troubles.

- The best current deep learning methods work well on specific datasets that have been carefully prepared, but their performance in real situations is not always as good because the data they use is not always realistic or comprehensive.
- Detectors that work in a single step, such as various versions of YOLO, along with attention mechanisms and robust data augmentations, can be used for most tasks.
- To make the results from these tools useful in practical ways, they need to be connected to larger systems, such as marketplaces or platforms like SWAN that help people reuse waste in economic ways.
- The community should focus on developing public test sets that cover many types of scenes, use common categories, employ diverse data collection methods, and ensure that training occurs in a way that preserves people's privacy.

By following these ideas, people can move automated waste sorting from being demonstrated only in tests to being used in real, large-scale applications that strengthen the circular economy. This paper aims to guide researchers and practitioners toward effective solutions.

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