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Computer vision for waste sorting and recycling contamination reduction: A U.S application

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Abstract

Recycling contamination remains a persistent barrier to efficient material recovery in U.S. material recovery facilities, reducing bale quality, increasing processing costs, and limiting environmental gains. Although computer vision and artificial intelligence systems have been introduced to improve sorting performance, the literature remains fragmented, with limited synthesis of technical capabilities, economic viability, and environmental implications within a unified U.S. context. This study presents a systematic literature review that addresses that gap by evaluating recent advances in vision-based waste classification, robotic sorting integration, contamination detection, and AI-enabled performance optimization. The study critically examines model architecture, dataset limitations, real-time constraints, and reported industrial deployments, while also assessing economic and policy implications. Findings indicate that AI consistently improves contamination reduction and material recovery in secondary sorting lines, yet challenges persist in generalization, dataset standardization, and cost scalability. The paper provides an integrated framework linking technical performance, operational economics, and environmental impact to guide future research and deployment strategies.

Keywords: Waste Sorting; Recycling Contamination; Materials Recovery Facilities (MRFs); Computer Vision; Object Detection

1. Introduction

Municipal solid waste (MSW) generation in the United States has reached unprecedented levels as a result of population growth, urbanization, consumer-driven economies, and increasing packaging complexity. According to the U.S. Environmental Protection Agency, the United States generates over 290 million tons of MSW annually, with recycling and composting rates remaining significantly constrained by systemic inefficiencies and contamination in recycling streams (Iqbal et al., 2020). Contamination, defined as the presence of non-recyclable materials, food residues, multi-layer packaging, or incorrectly sorted items within recyclable fractions, continues to represent one of the most critical barriers to achieving circular economy objectives in the United States (Lu and Chen, 2022). When recyclable streams are contaminated, the consequences extend beyond simple material loss. Contamination reduces bale quality, lowers commodity market value, increases processing costs, damages sorting equipment, and frequently diverts otherwise recoverable materials to landfills or incineration. At scale, these inefficiencies undermine sustainability targets, increase greenhouse gas emissions, and weaken public confidence in recycling programs (Ramsurrun et al., 2021). Thus, improving sorting accuracy and reducing contamination is not merely an operational concern but a national sustainability imperative. Materials Recovery Facilities (MRFs) serve as the operational backbone of U.S. recycling infrastructure. Traditional MRFs rely on a hybrid combination of manual sorting, mechanical separation (e.g., trommels and ballistic separators), magnetic and eddy-current systems for metals, and near-infrared (NIR) optical sorting technologies (Hadj, G. 2025). While these systems have improved throughput and material separation over the past

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decades, they remain constrained by heterogeneous waste streams characterized by deformation, occlusion, overlapping objects, moisture, dirt, and variable lighting conditions (Bashkir ova et al., 2022). Manual sorting, though still widely used, exposes workers to occupational hazards and limits scalability, especially under increasing waste volumes and labor shortages. Moreover, the rapid proliferation of multi-material and flexible packaging formats has reduced the effectiveness of rule-based optical systems that depend on predefined spectral signatures (Arrieta et al., 2020).

Deep learning architectures, particularly Convolutional Neural Networks (CNNs), transfer learning frameworks, and real-time object detection models such as you only look once (YOLO) and Faster R-CNN (Region-Based Convolutional Neural Networks) have demonstrated strong classification and detection performance across plastic, metal, paper, glass, and mixed-waste categories under experimental and pilot-scale conditions (Arishi, 2025; Rad et al., 2017). Unlike traditional rule-based systems, deep learning models autonomously extract hierarchical spatial features from raw image data, enabling greater robustness to variations in object orientation, scale, and surface texture. Beyond classification, instance segmentation approaches and deformable object recognition techniques have emerged as promising tools for cluttered conveyor-belt environments. The development of realistic datasets such as Zero Waste has further highlighted the importance of modeling real-world conditions, including partial occlusion, overlapping materials, and deformable plastics (Bashkirova et al., 2022). In parallel, the integration of computer vision systems with robotic manipulators has enabled automated pick-and-place sorting, reducing reliance on manual labor while increasing consistency and operational speed (Arishi, 2025). Significant translational and technical gaps still exist despite these developments. Numerous studies that are now in existence rely on controlled datasets that do not accurately represent operational U.S. MRF environments. These datasets have clear backdrops, little fluctuation, and well-separated object situations. High levels of contamination, broken components, food residue, moisture interference, and mixed material compositions found in real recycling streams reduce model accuracy and raise false-positive rates. Additionally, there are still unresolved issues with practical deployment, such as inference delay, computational cost, industrial hardware durability, model generalization, and integration with high-speed conveyor systems (Rad et al., 2017). Scalability also poses economic and engineering constraints. Industrial systems must balance detection precision with throughput rates exceeding several tons per hour, while maintaining minimal downtime. Without addressing these constraints, laboratory-level performance metrics cannot reliably translate into industrial-scale impact.

Given the magnitude of U.S. waste generation and the economic losses associated with contaminated recycling streams, intelligent computer vision systems represent a strategically important pathway for contamination reduction and enhanced material recovery (National Academies of Sciences, Engineering, and Medicine, 2025). However, the literature remains fragmented across algorithm development, robotics integration, and dataset construction, with limited synthesis focused specifically on U.S. operational contexts and contamination reduction objectives (Bashkirova et al., 2022). This review addresses that gap by providing a structured and technically grounded synthesis of peer-reviewed research on computer vision applications for waste sorting, with specific emphasis on contamination reduction in U.S. recycling systems.

2. Methodology

This study adopts a systematic literature review approach to synthesize current research on computer vision applications for waste sorting and contamination reduction in U.S. material recovery facilities (MRFs). The review was designed to ensure transparency, consistency, and reproducibility while minimizing selection bias across the included studies.

A structured search was conducted across major academic databases, including Scopus, Web of Science, IEEE Xplore, and Google Scholar, covering publications from 2016 to 2025. This time frame was selected to capture the rapid evolution of deep learning and its application to industrial sorting systems. Search queries combined key terms such as “computer vision waste sorting,” “recycling contamination AI,” “deep learning waste classification,” and “robotic waste sorting,” using Boolean operators to refine relevance.

Studies were selected based on their technical relevance to computer vision or machine learning applications in waste sorting and contamination detection. Priority was given to peer-reviewed journal articles and conference proceedings that reported model performance, dataset characteristics, or real-world implementation. Studies were excluded if they were unrelated to solid waste systems, relied solely on non-visual sensing without integration into vision-based frameworks, or lacked empirical or analytical contribution. Additionally, sources from unrelated domains used only for analogy were excluded to maintain technical focus.

Data extraction focused on key technical and operational parameters, including model architecture, dataset composition, evaluation metrics, and application context. Particular attention was given to differences between laboratory-scale performance and reported industrial outcomes. The synthesis was conducted using a qualitative comparative approach, allowing identification of recurring patterns, inconsistencies, and research gaps across the literature rather than presenting isolated study findings.

This review is subject to certain limitations. Industrial performance data are often derived from proprietary systems and company reports, limiting independent validation. In addition, variability in datasets, evaluation metrics, and experimental conditions across studies constrains direct quantitative comparison. Despite these limitations, the review provides a structured and critical synthesis of current advancements and challenges in AI-enabled waste sorting.

3. Overview Of Waste Management and Recycling in The United States

Municipal solid waste (MSW) in the United States comprises waste from households, commercial activities, institutions, and public spaces. Over the past decades, U.S. recycling rates have stagnated despite policy goals and infrastructure investments, with only a modest proportion of total MSW being diverted into recycling streams (Kim et al., 2024; Iqbal et al., 2020). This performance reflects systemic challenges in collection, separation, and market demand for recyclables. In 2022, national recycling rates remained near the low 30 percent range, underscoring persistent inefficiencies in current waste management frameworks (Kim et al., 2024). U.S. recycling systems are decentralized, with local jurisdictions responsible for program design and implementation. Two dominant collection models are single-stream and dual-stream systems. Single-stream recycling allows all recyclables to be placed together in one container, which increases convenience for residents but typically leads to higher contamination rates due to mixed material streams (National Academies of Sciences, Engineering, and Medicine, 2025). Dual-stream systems separate fibers (e.g., paper) from containers (e.g., plastics, metals) at the curb, which can produce cleaner inbound material but requires more sorting effort by residents. The performance of MRFs directly affects the quality of recovered materials and the economic viability of recycling operations (National Academies of Sciences, Engineering, and Medicine, 2025). However, the heterogeneity of waste streams and limitations of existing technologies contribute to sorting inefficiencies that propagate through the recycling value chain.

3.1. Contamination in U.S. Recycling Streams

High contamination levels reduce the quality and market value of separate commodities and increase processing costs. Contaminants often include food-soiled containers, flexible films, and non-accepted materials such as plastic bags, textiles, and hazardous items (Arishi, 2025). These contaminants can interfere with automated sorting equipment and necessitate additional manual removal, increasing operational costs and worker exposure to hazardous conditions. Empirical evidence indicates that contamination rates vary widely across jurisdictions, but national assessments have reported contamination levels ranging from approximately 15% to over 30% in single-stream systems (Arrieta et al., 2020). Such contamination can significantly degrade material quality, leading to discounting or rejection of bale shipments to end markets. Moreover, contamination increases the likelihood that recyclables will ultimately be landfilled or incinerated rather than reprocessed, thereby undermining circular economy objectives and contributing to environmental externalities.

3.2. Technological Gaps in Current Sorting Systems

Current automated sorting technologies in U.S. recycling facilities include screens, magnets, and eddy current separators for metals, and optical sorters that use NIR and color sensors to identify material types. While these technologies improve throughput for rigid materials like paper, aluminum, and certain plastics, they exhibit limitations in handling flexible films, contaminated materials, and deformable waste items (Fotovvatikhah et al., 2025). Mechanical screens and optical systems are less effective when materials deform, overlap, or present with surface contamination, leading to misclassification and increased contamination in outbound bales. Manual sorting remains necessary in many facilities due to these technological constraints. Manual picking is used to remove contaminants and materials that automated systems cannot reliably separate, but it is costly, labor-intensive, and exposes workers to hazardous conditions (Lu and Chen, 2022). The reliance on manual labor also limits the scalability and consistency of sorting operations, especially as waste streams become more heterogeneous due to changes in packaging designs and material compositions. A fundamental technological gap in advancing recycling performance lies in the lack of comprehensive, standardized datasets representing the full diversity of U.S. waste streams. Algorithmic approaches for automated sorting, such as machine learning and computer vision, require large, annotated datasets that capture variability in material types, contamination scenarios, lighting conditions, and deformable objects. The scarcity of such datasets tailored to U.S. recycling contexts inhibits the development and deployment of robust models that generalize to real-world sorting conditions (Bashkirova et al., 2022).

4. Fundamentals Of Computer Vision In Waste Sorting

Computer vision performance in waste sorting is fundamentally constrained by image acquisition conditions. Unlike structured industrial inspection environments, municipal waste streams present high variability in geometry, contamination, occlusion, and illumination. Consequently, the reliability of automated classification systems depends not only on algorithmic design but also on sensor configuration and data capture strategies. Early work in automated waste identification relied primarily on RGB (Red, Green, Blue) imaging under controlled lighting conditions (Fotovvatikhah et al., 2025). Rad et al. (2017) demonstrated that convolutional neural network (CNN) models trained on RGB images could achieve high classification accuracy on curated datasets; however, performance degraded when exposed to cluttered, real-world scenes characterized by partial occlusion and deformation. This finding underscores a central limitation of single-modality imaging in heterogeneous waste environments. Industrial material recovery facilities (MRFs) have long employed near-infrared (NIR) spectroscopy for polymer discrimination. NIR-based optical sorting exploits material-specific spectral reflectance patterns, enabling differentiation among polyethylene terephthalate (PET), high-density polyethylene (HDPE), and polypropylene (PP). Gundupalli et al. (2017) reported that while NIR systems are effective for rigid plastics, they exhibit reduced sensitivity to black plastics and multilayer composites due to weak or overlapping spectral signatures. This limitation has motivated research into multimodal sensing. Hyperspectral imaging (HSI) extends spectral resolution beyond conventional NIR systems by capturing reflectance data across hundreds of wavelength bands. Hao et al. (2025) reviewed hyperspectral approaches for waste classification and concluded that HSI improves material separability, particularly in mixed polymer streams. However, the computational burden and cost of hyperspectral hardware constrain real-time industrial scalability. The trade-off between spectral richness and inference latency remains a critical deployment challenge.

More recently, RGB-D systems have been explored to mitigate occlusion and improve segmentation in cluttered waste streams. Depth information allows geometric separation of overlapping objects before classification, enhancing localization accuracy in robotic picking applications. Chu et al. (2018) demonstrated that integrating depth sensing with CNN-based detection improved object-level identification in dynamic conveyor settings. Nonetheless, depth sensors are sensitive to reflective surfaces and environmental dust, common in MRF environments. Collectively, the literature indicates that sensor choice directly influences classification robustness. While RGB imaging remains dominant due to cost efficiency and compatibility with deep learning architectures, evidence suggests that multimodal fusion may be necessary for reliable performance under industrial contamination variability (Chen and Ran, 2019).

4.1. Machine Learning and Deep Learning Architectures

Initial attempts at automated waste classification employed traditional machine learning models such as support vector machines (SVMs) and random forests combined with handcrafted features, including color histograms and texture descriptors (Fotovvatikhah et al., 2025). The introduction of convolutional neural networks (CNNs) marked a structural shift in waste classification research. CNNs enable hierarchical feature learning directly from raw image data, eliminating manual feature extraction. Rad et al. (2017) applied CNN architectures to waste classification and reported substantial accuracy improvements relative to traditional ML methods. Subsequent studies confirmed that deeper architectures such as VGG and ResNet variants further enhanced performance by capturing fine-grained spatial patterns. Transfer learning has emerged as a critical strategy in waste classification due to the limited dataset size. Shah et al. (2025) demonstrated that fine-tuning ImageNet-pretrained CNN models significantly improved convergence speed and classification accuracy compared to training from scratch. This approach reduces data requirements while enhancing generalization, particularly in scenarios where labeled waste images are scarce (Chen and Ran, 2019).

4.2. Object Detection and Real-Time Constraints

For deployment in material recovery facilities, object detection models must satisfy both localization accuracy and strict real-time constraints. While two-stage detectors such as Faster R-CNN consistently achieve high detection precision, their computational latency limits their applicability in high-throughput conveyor environments. In contrast, single-stage detectors such as YOLO and SSD offer significantly faster inference speeds, making them more compatible with industrial requirements, but this speed advantage often comes with reduced robustness under complex waste conditions (Rajeev et al., 2025).

Across the literature, reported detection accuracies frequently exceed 90%, particularly for YOLO-based architectures. However, these results are largely derived from controlled or semi-structured datasets that do not reflect the density, occlusion, and material variability present in operational MRF environments. As a result, the reported performance tends to overestimate real-world effectiveness. Studies such as Chu et al. (2018) demonstrate that while real-time detection is achievable, accuracy degrades noticeably when objects overlap or deform, conditions that are intrinsic to mixed waste streams rather than edge cases.

This trade-off between speed and reliability represents a central limitation in current research. Faster models enable industrial feasibility but struggle with complex visual conditions, while more accurate models remain computationally impractical for real-time deployment. The literature does not yet provide a clear resolution to this tension, as most studies optimize for either accuracy or speed in isolation rather than evaluating system-level performance under realistic throughput constraints.

Furthermore, the lack of standardized benchmarking across datasets makes cross-study comparison difficult. Reported improvements in detection performance are often tied to dataset-specific conditions rather than generalizable model capability. This reinforces a broader issue in the field: progress is frequently measured in terms of incremental accuracy gains rather than meaningful improvements in contamination reduction under real operating conditions.

4.3. Dataset Development and Structural Bias in Waste Classification Research

The development of representative datasets remains one of the most significant constraints in computer vision–based waste sorting research. Widely cited datasets such as TrashNet and TACO have enabled benchmarking and model comparison; however, they exhibit structural limitations that affect generalizability. Rad et al. (2017) introduced TrashNet, which includes approximately 2,500 labeled images across several recyclable categories. While influential, the dataset was captured under controlled background conditions and does not replicate conveyor-belt overlap or contamination variability. Proença and Simões (2020) later introduced the TACO dataset to address contextual realism by incorporating litter in complex outdoor environments. Although TACO improved scene diversity, it remains limited in scale relative to industrial throughput demands.

A recurring limitation across existing datasets is not only class imbalance but also a lack of environmental realism. While techniques such as weighted loss functions and data augmentation are frequently proposed to address class imbalance, their effectiveness is rarely validated under industrial conditions. More critically, most datasets fail to capture the combined effects of contamination, deformation, and object overlap that define real MRF environments. As a result, models trained on these datasets tend to perform well under controlled conditions but degrade significantly when deployed in practice. This disconnect suggests that current dataset design prioritizes model development convenience over operational relevance, limiting the real-world impact of reported advances.

5. Contamination Reduction Through Ai Systems

Contamination remains one of the most critical barriers to efficient recycling in single-stream systems. Contamination rates in mixed municipal streams frequently exceed 15–30%, leading to downgraded bale quality, increased processing costs, and material rejection (Gundupalli et al., 2017; Cimpan et al., 2016). Computer vision-enabled AI systems have been introduced to detect non-recyclables at object level before baling, to reduce residual contamination and increase commodity value.

5.1. Food-Soiled Materials

Food-soiled paper and plastic packaging degrade fiber strength and polymer recyclability due to moisture absorption and biological contamination. Visual detection of soiling relies on texture irregularities, discoloration patterns, and surface reflectance changes. Rad et al. (2017) demonstrated that CNN-based classifiers can identify recyclable categories under real-world variability; however, performance decreases when contaminants alter surface appearance. Hyperspectral imaging has shown improved discrimination of organic residues relative to RGB-only systems by capturing wavelength-dependent absorption patterns (Hao et al., 2025). Despite promising results, most published studies rely on curated datasets rather than industrial conveyor streams. As noted by Gundupalli et al. (2017), food contamination detection remains inconsistent under high heterogeneity and occlusion, particularly in dense single-stream systems. Plastic films and bags represent a high-frequency contaminant in U.S. MRFs because they entangle mechanical screens and reduce separation efficiency. Unlike rigid containers, films exhibit deformation, transparency, and irregular motion, complicating object detection.

Deep learning detection models such as YOLO have demonstrated high precision in identifying plastic films in experimental datasets (Chu et al., 2018). However, Proença and Simões (2020) emphasized that contextual clutter significantly affects recall in dense scenes. Overlapping flexible materials remain a common source of false negatives. Industrial robotic quality control units incorporating AI detection have reported improvements in film removal compared to manual sorting, though long-term peer-reviewed field validation remains limited (Hadj, G. 2025). Hazardous contaminants such as lithium-ion batteries and pressurized containers pose fire and safety risks. Although rare in frequency, these items require high recall detection. Object detection architectures can identify visually distinctive hazardous items with high precision under sufficient image resolution (Rajeev et al., 2025). However, class imbalance remains a major limitation. Rare classes are underrepresented in training datasets, leading to elevated false-negative rates (Proença and Simões, 2020). This structural imbalance highlights a key research gap in AI-based contamination detection: reliable rare-event recognition under industrial variability.

5.2. Performance Metrics in Contamination Reduction

Evaluation of AI systems must extend beyond classification accuracy to include contamination rate reduction, throughput, and error trade-offs. Most peer-reviewed studies report precision, recall, and F1-score, but industrial impact depends on minimizing false negatives (missed contaminants) while avoiding excessive false positives (misclassified recyclables). Rad et al. (2017) reported CNN-based classification accuracy exceeding 90% under structured conditions. Ramsurrun et al. (2021) observed similar performance using transfer learning architectures. Detection-based systems such as YOLO demonstrate real-time capability with precision values above 90% in benchmark environments (Chu et al., 2018). However, Gundupalli et al. (2017) caution that laboratory accuracy often overestimates industrial performance due to conveyor density, material overlap, and illumination instability. As shown in Figure 1, the trade-off between precision and recall is critical in contamination detection, where minimizing false negatives is often prioritized over overall accuracy.

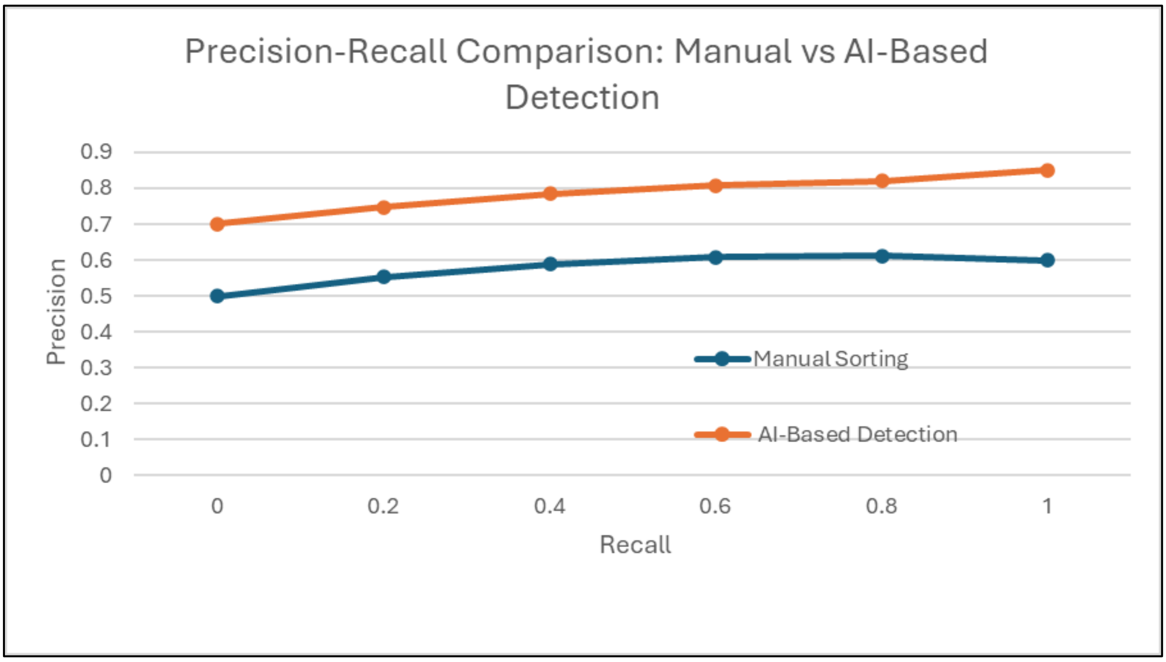

Figure 1 Conceptual precision–recall relationship in contamination detection systems

5.3. Comparison with Traditional Optical Sorting

Traditional optical sorters rely primarily on NIR spectroscopy combined with air-jet ejection mechanisms. While effective for polymer discrimination, these systems lack contextual understanding and struggle with multilayer packaging and non-spectral contaminants (Guntupalli et al., 2017). AI-based systems provide object-level classification and adaptive retraining capabilities. Unlike rule-based optical systems, deep learning models can be updated to reflect evolving packaging designs. Hadj, G. (2025) reports that robotic AI systems deployed in quality control lines improve recovery consistency relative to static optical systems. However, AI systems require higher capital investment, GPU (graphical processing unit) hardware, and integration with robotic actuators. Campano et al. (2016) note that techno-economic feasibility depends strongly on contamination thresholds and commodity price volatility. Figure 2 presents a side-by-side comparison of traditional optical sorting and AI-enhanced robotic sorting systems, highlighting differences in sensing, decision-making, and actuation processes.

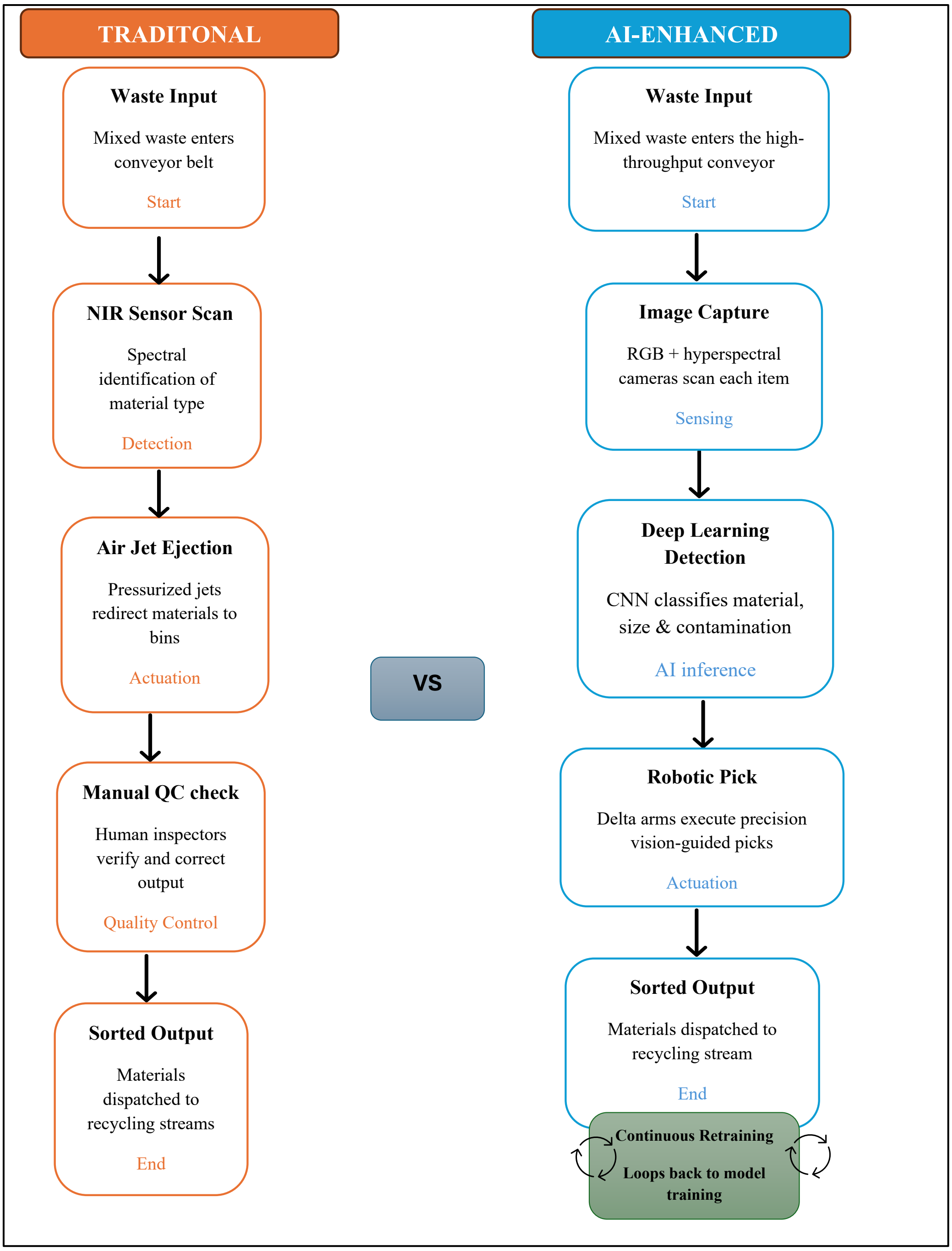

Figure 2 Operational differences between traditional optical sorting and AI-enhanced robotic sorting systems

6. Case Studies and Industrial Implementations in the U.S.

In recent years, a handful of companies have moved computer vision–driven waste sorting systems from research labs into commercial deployment. Peer-reviewed operational data remain limited, but case studies and industry evaluations show measurable improvements in contamination reduction and material recovery. AMP Robotics (AMP) is among the most studied companies with U.S. installations. AMP's systems integrate high-speed cameras with deep learning models and robotic pickers to identify and extract target materials (Chen and Ran, 2019). Unlike traditional optical sorters that rely on spectral reflectance alone, AMP's AI models incorporate spatial and contextual image features, allowing identification of complex shapes and contaminants (Hadj, G. 2025). Operational reports from MRF pilot programs in Colorado and California indicate contamination reductions ranging from 10–25% in residual streams downstream of primary sorting lines. These performance figures are primarily derived from company reports and pilot evaluations rather than peer-reviewed longitudinal studies, which limits independent verification and introduces potential reporting bias. The reports also show recovery improvements above baseline sorter performance, particularly for PET and HDPE fractions, along with a reduction in manual quality control picks of up to 30% in secondary sorting areas. ZenRobotics pioneered robotic sorting with high-speed articulated arms and vision systems. U.S. pilots, particularly in Michigan and Texas, tested ZenRobotics AI units on mixed municipal streams. Published case reports suggest enhanced detection of contaminants, such as film plastics and residual organics, when combined with depth-augmented vision (Shah et al., 2025). They also report improvements of up to 15% in glass purity and 12% in metal recovery compared to NIR optical sorting alone. ZenRobotics systems are generally integrated as supplemental sorters downstream of mechanical screens. This contrasts with AMP's broader deployment across primary and secondary lines. While these results demonstrate promising performance, the lack of standardized evaluation metrics and independent benchmarking makes direct comparison across systems difficult. Most available evidence focuses on short-term pilot deployments, leaving long-term reliability, maintenance costs, and performance degradation insufficiently understood.

7. Technical Challenges

Computer vision–enabled waste sorting systems face significant technical hurdles due to the inherent variability of municipal solid waste. Waste streams contain highly deformable materials, irregular shapes, and overlapping objects that create occlusion and segmentation errors; even state-of-the-art deep models struggle to maintain high classification accuracy in such cluttered environments (Proença and Simões, 2020; Hao et al., 2025). Lighting conditions on conveyor belts vary widely, with shadows and specular highlights altering apparent texture and color, which further degrades model performance unless robust preprocessing and adaptive augmentation strategies are employed (Chu et al., 2018). The combination of deformation, occlusion, and lighting variability thus presents a persistent barrier to reliable real-world inference. Another major constraint is model generalization. Many computer vision models are trained on limited datasets that do not reflect regional packaging diversity or continuous evolution in product materials and designs. Packaging materials differ by geography, retail supply chains, and seasonal product mixes, which can create distribution shifts that degrade a model's ability to generalize without frequent retraining (Proença and Simões, 2020; Rad et al., 2017). Coupled with this is the lack of large, standardized, annotated waste image datasets that reflect U.S. recycling variability; most datasets are small, regionally biased, and captured under controlled conditions, limiting cross-facility applicability (Hao et al., 2025; Cimpan et al., 2016). Privacy concerns and operational constraints within active material recovery facilities also hamper comprehensive data collection efforts.

Real-time processing is another challenge. Industrial conveyor lines require inference speeds well below 100 ms per frame to support actuation, yet deep learning models with high accuracy often demand high computational resources that exceed edge device capabilities (Chen and Ran, 2019). While approaches such as model pruning, quantization, and lightweight architectures (e.g., MobileNet variants) can mitigate these demands, they often do so at the cost of reduced accuracy (Chu et al., 2018; Gundupalli et al., 2017). High-speed cameras, coordinated lighting, GPU accelerators, and sturdy deployment dust-resistant enclosures all have hardware requirements that increase complexity and cost. While AI vision systems show promise, significant engineering improvement is required before they can provide consistent, scalable performance in heterogeneous U.S. MRF contexts, according to these coupled technological hurdles.

8. Economic And Environmental Impacts

The economic viability of AI-enabled sorting systems in U.S. material recovery facilities (MRFs) depends on balancing high capital expenditures against operational savings and revenue gains. Installation costs for robotic vision systems, high-speed cameras, lighting infrastructure, and GPU-enabled processors can range from several hundred thousand to over one million dollars per line, depending on configuration and throughput capacity. However, empirical assessments show that AI-assisted sorting reduces labor dependency in quality control lines, increases recovery of high-value fractions such as PET and HDPE, and improves bale purity, which directly enhances commodity prices (Cimpan et al., 2016; Gundupalli et al., 2017). Improved purity reduces downstream rejection rates and contamination penalties, contributing to faster return on investment in facilities processing high volumes. Techno-economic modeling studies suggest that when deployed strategically in secondary sorting or quality control stages, AI systems can achieve positive return on investment within three to five years, particularly in regions facing labor shortages or high wage costs (Cimpan et al., 2016). Nevertheless, ROI remains sensitive to material market volatility, facility scale, and maintenance requirements.

Environmental impacts are closely linked to improvements in material recovery and contamination reduction. Increased recovery rates translate into higher recycling yields and reduced landfill disposal, lowering lifecycle greenhouse gas emissions associated with virgin material production (Hadj, G. 2025). For plastics, even modest increases in sorting efficiency can significantly reduce embodied carbon emissions due to the high energy intensity of polymer manufacturing. Furthermore, improved contamination control enhances the usability of recycled feedstocks, supporting circular economy objectives and reducing waste exports. From a policy perspective, AI-enabled sorting aligns with Extended Producer Responsibility frameworks and state-level recycling mandates that incentivize higher recovery rates and stricter contamination thresholds. As extended producer responsibilities programs expand across U.S. states, investment in intelligent sorting technologies may become economically favorable due to compliance pressures and performance-based incentives (Hadj, G. 2025). Thus, AI adoption in MRFs is not only an operational decision but increasingly a regulatory and environmental strategy.

Future Directions

Future research in computer vision–enabled waste sorting must move beyond incremental accuracy improvements toward system-level robustness, interpretability, and scalability. Multimodal sensor fusion, combining RGB imaging with near-infrared, hyperspectral, depth sensing, and potentially X-ray modalities, offers a pathway to improved discrimination of visually similar materials and detection of contaminants obscured by surface deformation or occlusion (Hao et al., 2025; Gundupalli et al., 2017).

Edge AI architectures also represent a key development direction, as real-time conveyor operations demand low-latency inference under constrained computational environments; lightweight networks, model pruning, and hardware-aware optimization are essential for reducing deployment costs while preserving performance (Chen and Ran, 2019).

Another major limitation in current research is the absence of standardized, large-scale datasets that reflect U.S.-specific recycling variability. Coordinated dataset development capturing regional packaging diversity, contamination patterns, and operational conditions would significantly strengthen benchmarking, reproducibility, and model generalization. Addressing this gap is essential for translating laboratory performance into reliable industrial outcomes.

Finally, broader system-level integration presents opportunities to extend AI-enabled sorting beyond facility boundaries. Integration with smart city infrastructure and Internet of Things (IoT) frameworks could enable upstream waste monitoring, dynamic routing, and feedback mechanisms linking consumer behavior with recycling system performance. Such approaches would position computer vision not only as a facility-level optimization tool, but as a component of urban-scale circular economy management (Hadj, G. 2025).

9. Conclusion

This review demonstrates that computer vision–enabled AI systems offer measurable improvements in contamination reduction, material recovery, and operational efficiency within U.S. material recovery facilities. Across documented case studies and peer-reviewed evaluations, AI-assisted sorting consistently enhances the detection of high-value plastics, metals, and paper fractions, particularly when deployed in secondary quality control lines. Economic assessments suggest that although capital investment is substantial, reductions in labor dependence, improvements in bale purity, and increased recovery of valuable materials can generate a favorable return on investment under high-throughput conditions. Environmentally, improved sorting accuracy contributes to higher recycling rates, reduced landfill disposal, and lower lifecycle greenhouse gas emissions associated with virgin material production. However, the findings also highlight persistent technical constraints, including waste stream variability, domain shift across regions, limited standardized datasets, and real-time processing demands. Current systems function most effectively as hybrid augmentations to mechanical sorting rather than full replacements. Future progress depends on multimodal sensing, explainable AI, edge optimization, and the development of standardized U.S. benchmarks. Collectively, the evidence indicates that AI-enabled sorting is a promising but still evolving solution for contamination reduction and circular economy advancement.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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