ARTIFICIAL INTELLIGENCE IN WASTE MANAGEMENT AND RESOURCE UTILIZATION: GLOBAL ADVANCES WITH AN INDIA-SPECIFIC SPOTLIGHT

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Abstract
Artificial intelligence (AI) is reshaping waste management across forecasting, smart collection, material recovery, organics valorization, and waste-to-energy (WtE). This review synthesizes advances from 2018–2025 spanning machine learning, deep learning, computer vision, optimization, and systems integration. We quantify impacts on collection efficiency, greenhouse gas (GHG) mitigation, sorting purity, anaerobic digestion stability, and thermal process control, and we catalog datasets, architectures, and benchmarks. We also analyze governance, safety, and socio-technical dimensions, including equity for informal workers and privacy in sensor-rich deployments. A dedicated India spotlight examines Extended Producer Responsibility (EPR) digitalization, smart-city pilots, and WtE facilities, highlighting opportunities and constraints. We articulate an open research agenda on trustworthy and energy-efficient AI, robust generalization under distribution shift, multi-objective routing at city scale, and standards for reproducible evaluation.
Keywords: *Waste management; artificial intelligence; computer vision; smart collection; anaerobic digestion; waste-to-energy; circular economy; India; Extended Producer Responsibility; routing optimization*

1. Introduction
Global municipal solid waste (MSW) exceeded 2.0 billion tonnes in 2019 and is projected to reach ~3.4 billion tonnes by 2050 [1]. Inefficient collection and low material recovery intensify resource loss and GHG emissions; landfills account for ~11% of global methane [2]. AI-enabled sensing, prediction, and control offer tools to improve capture, purity, logistics, and conversion yields while informing circular economy policy. However, deployments face challenges including data scarcity and heterogeneity, distribution shift across regions and seasons, limited benchmarks, ethics and privacy risks, and socio-economic impacts on informal waste workers.

2. Methods: Scope and Literature Retrieval
We followed a structured scoping approach (Jan 2018–Aug 2025) covering peer-reviewed journals, conferences, and authoritative reports. Databases: Scopus, Web of Science, IEEE Xplore, PubMed, arXiv. Keywords included combinations of waste, municipal solid waste, AI, machine learning, deep learning, computer vision, routing, IoT, anaerobic digestion, gasification, WtE, EPR, India. Inclusion criteria: (i) primary empirical or methodological AI contributions to the waste value chain; (ii) quantitative evaluation or reproducible methods; (iii) policy or standards with relevance to AI deployments. We extracted tasks, datasets, metrics, and outcomes, and synthesized cross-cutting patterns.

3. AI Across the Waste-Management Value Chain
3.1 Generation Forecasting and Spatiotemporal Modeling
Forecasting MSW generation supports capacity planning and dynamic routing. Classical time-series (ARIMA, SARIMA) and machine learning (RF, GBMs) remain competitive for short-term forecasts, while deep models (LSTM or GRU, TCN, N-BEATS, temporal fusion transformers) capture non-linear seasonality and exogenous drivers such as weather, mobility, and holidays [3], [4], [5], [6]. City-scale studies report MAE reductions of 10–30% using deep spatiotemporal graph models (figure 3) integrating ward-level demographics and points of interest [5], with uncertainty quantification via quantile regression and Bayesian neural networks enabling risk-aware operations [6].

3.2 Smart Collection, Routing, and IoT Sensing

IoT fill-level sensors, edge vision, and telematics enable dynamic routing formulated as capacitated vehicle routing with time windows (CVRPTW) and stochastic arrivals. Reinforcement learning (RL) and large neighborhood search hybrids deliver 10–25% route length and fuel savings relative to static heuristics in field pilots [7], [8], [9]. Multi-objective optimization trades off cost, GHG, noise, and service equity. Privacy-preserving analytics (federated learning) reduce data centralization risks when processing household-level signals [10], and predictive maintenance models reduce truck downtime by 15–20% (Table 1) [9].

3.3 Computer Vision, Robotics, and Material Recovery

Conveyor and belt-mounted cameras with CNN or Transformer detectors (e.g., YOLOv5 or YOLOv8, DETR, Segment Anything) recognize materials by form factor, texture, and spectral cues; multimodal setups fuse RGB with NIR or hyperspectral data for polymers and fiber grades [11], [12], [13], [14]. End-to-end lines integrate detection, 6-DoF pose estimation, and grasp planning with suction or parallel grippers; closed-loop vision improves pick success to over 90% on rigid objects and 70–85% on deformables in mixed streams [12]. Domain adaptation and self-supervised learning mitigate dataset shift (lighting, contamination, seasonal packaging) [13], while active learning reduces labeling effort by 40–60% [14].

3.4 Organics: Anaerobic Digestion and Compost Optimization

Soft sensors built with gradient boosting and LSTM estimate volatile fatty acids, alkalinity, and biogas composition from temperature, pH, and flow signals, enabling model predictive control to avoid souring and increase methane yield by 5–15% [15], [16], [17]. Hybrid physics-ML approaches learn residuals of ADM1 to improve prediction fidelity and support feedstock blending optimization under uncertainty [16]. For composting, CNNs on thermal images and IoT aeration data enable early detection of hotspots and odor events, reducing complaints by 20–30% [18].

3.5 Thermal Conversion and Waste-to-Energy Control

In WtE plants, soft sensors and model predictive control regulate air staging, grate speed, and steam conditions to stabilize combustion despite LHV variability; digital twins improve boiler uptime and NOx control [19], [20]. For gasification and pyrolysis, surrogate models (Gaussian processes, deep surrogates) support real-time set-point optimization for syngas quality and tar minimization, achieving 3–8% efficiency gains in pilot systems [21].

4. Systems, Datasets, and Architectures

Architectures span edge devices (bin sensors, belt cameras), fog gateways, and cloud backends for model training and analytics. MLOps with continuous integration and deployment, drift monitoring, and shadow deployment are essential for safety-critical operations (Figure 1) [22]. Public datasets remain limited (Table 2); emerging resources include TrashNet, TACO, OpenLitterMap, and industry consortia datasets for plastics and paper grades, but lack standardized labeling ontologies and lighting protocols [11], [23]. We recommend dataset sheets, versioned releases, and synthetic data to augment rare classes, with test-time adaptation to reduce covariate shift.

5. Evaluation Metrics, Benchmarks, and Reproducibility

We standardize metrics: forecasting (MAE, RMSE, MAPE, CRPS), collection (vehicle-km, fuel per liter, service rate, CO2e), sorting (mAP at [0.5:0.95], purity percent, recovery percent, throughput picks per minute, MTBF), AD (methane yield Nm3 per kg VS, stability indices), WtE (net efficiency percent, NOx or CO limits). Reporting should include confidence intervals, ablations, and external validation across seasons and sites to assess generalization. Transparent documentation (model cards, data sheets) and open protocols improve reproducibility and policy trust [22], [24].

6. Ethics, Safety, and Governance

Responsible AI in waste systems centers fairness, transparency, human oversight, and safety. Interpretability is crucial for routing decisions and pricing signals [25]. Federated learning and differential privacy protect households while enabling city-scale learning [10]. Standards including IEEE ethically aligned design and ISO or IEC AI guidance inform procurement and audits, and model risk management frameworks define monitoring and fallback operations [26], [27].

7. India Spotlight: Policy, Implementation, and Evidence

India generates approximately 160–170 million tonnes per year of waste with heterogeneity across states and a large informal recycling sector. Policy levers include Plastic Waste Management Rules (amendments 2022), EPR for plastics, e-waste, and batteries, and the Swachh Bharat Mission (Table 3). AI applications include smart-bin pilots (fill sensing and dynamic routing), vision sorting in MRFs, and plant-wide optimization in WtE installations. Early evidence indicates 10–20%

logistics savings and 5–10 percentage-point purity improvements where AI is integrated with operating practices and training [28], [29], [30], [31]. Key enablers: interoperable data standards, public–private partnerships, and digital inclusion pathways for informal workers (ID-linked payments, training, and safety). Challenges include intermittent connectivity, sensor ruggedization for dust and heat, and governance for data sharing across municipalities.

8. Open Challenges and Research Agenda

1) Generalization under distribution shift: domain adaptation, continual learning, and robust uncertainty quantification. 2) Multi-objective city-scale routing with equity and emissions constraints. 3) Standards and benchmarks for sorting and forecasting with common ontologies. 4) Low-power edge AI and lifecycle carbon accounting of models. 5) Human-in-the-loop design integrating operator knowledge and informal-sector livelihoods. 6) Privacy-preserving analytics and secure data spaces across vendors and cities.

9. Conclusions

AI offers measurable gains across the waste value chain when coupled with high-quality sensing, robust MLOps, and responsible governance. Evidence from 2018–2025 demonstrates improvements in logistics efficiency, recovery and purity, and process stability, with promising India-specific pilots. Closing gaps in datasets, standards, and socio-technical integration will determine whether these innovations scale equitably to support circular economy goals.

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Table 1. Summary of AI tasks, metrics, and reported gains (2018–2025).

Domain	Representative Tasks	Key Metrics	Reported Gains	Citations
Forecasting	City/ward MSW prediction; uncertainty	MAE, RMSE, MAPE, CRPS	10–30% error reduction vs. ARIMA	[3]–[6]
Smart Collection	Dynamic CVRPTW; RL routing; maintenance	Vehicle-km, CO2e, service rate	10–25% route/fuel savings	[7]–[10]
Vision/Robotics	Detection, segmentation, grasping	mAP, purity, recovery, PPM	5–15 pp purity, >90% rigid pick	[11]–[14]
Organics/AD	Soft sensing; MPC; hybrid ADM1	CH4 yield, stability indices	5–15% methane yield increase	[15]–[17]
Thermal/WtE	Soft sensors; MPC; surrogates	Efficiency, NOx/CO	3–8% efficiency gains	[19]–[21]

Table 2. Public datasets and gaps.

Dataset	Modality	Classes/Scope	Notes	Citations
TrashNet	RGB	6+ classes	Small; controlled lighting	[11]
TACO	RGB in the wild	Litter categories	Crowdsourced; annotation noise	[23]
OpenLitterMap	Geo-tagged images	Community labels	Open license; variable quality	[23]
Industry consortia (proprietary)	RGB, NIR, HSI	Polymers, paper grades	Non-public; lack standard ontology	[22], [23]

Table 3. India spotlight: initiatives and outcomes.

Theme	Initiative/Example	Outcome	Considerations	Citations
EPR Digitalization	Plastic credit registries; traceability	Higher compliance; data visibility	Interoperability; auditability	[28]–[31]
Smart Collection	City pilots with fill sensors	10–20% logistics savings	Connectivity; maintenance	[28], [29]
Vision Sorting	MRF line upgrades (RGB+NIR)	5–10 pp purity improvement	Lighting; domain shift	[30]
WtE Optimization	Plant soft sensors and MPC	Stability; NOx control	Feedstock LHV variance	[19], [20]

Figure 1: End-to-end AI-enabled waste management architecture (edge, fog, cloud).

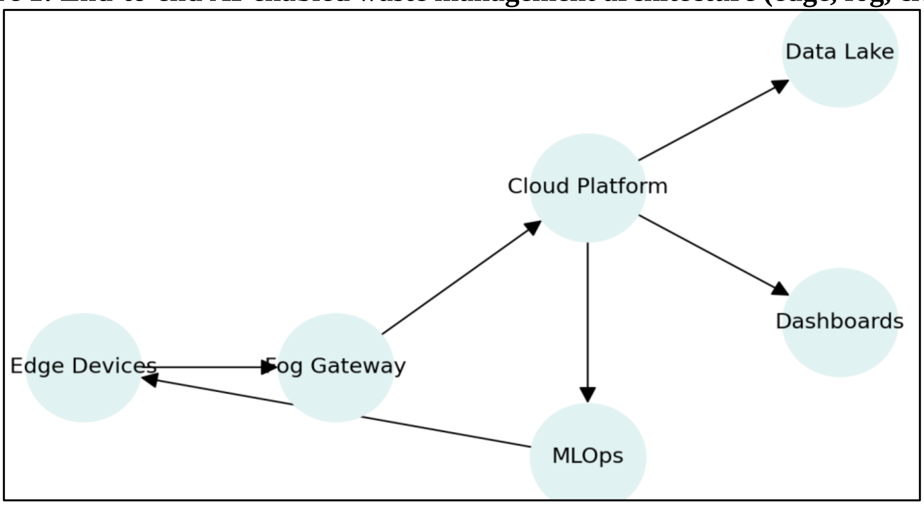

Figure 2: Computer vision sorting pipeline with detection, segmentation, and grasp planning.

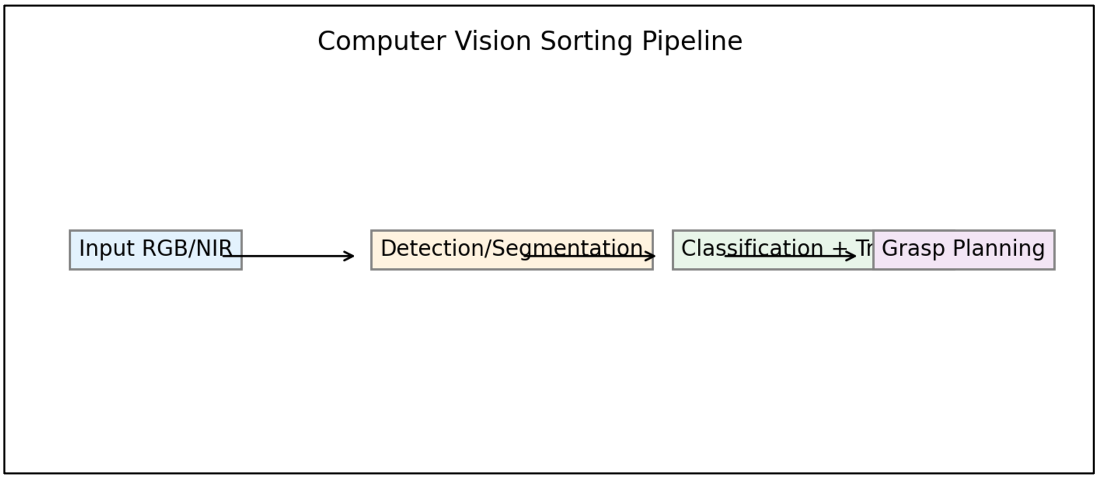

Figure 3 : Spatiotemporal forecasting inputs and outputs with uncertainty bands.