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Intelligent Waste Management Systems: A Review of IoT, Deep Learning, and Optimization Techniques for Sustainable E-Waste and Solid Waste Handling

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Abstract

This review addresses the urgent environmental and health issues posed by the rapid growth of electronic waste (e-waste) and municipal solid waste (MSW), highlighting the role of emerging technologies in crafting sustainable waste management solutions. It explores the integration of the Internet of Things (IoT), deep learning, and optimization algorithms in enhancing waste classification, recycling, and disposal. Key innovations include IoT-enabled smart bins for real-time monitoring, deep learning models like CNNs achieving up to 97% sorting accuracy, and optimization techniques that improve energy efficiency and scalability. The paper synthesizes findings from over 50 studies and emphasizes both technical advances and implementation challenges, such as data limitations, model interpretability, and the lack of robust policy frameworks. Future research directions include explainable AI, edge computing, and global standardization of e-waste regulations. The review is intended for researchers, developers, and policymakers working toward circular economy principles and sustainable smart city solutions.

Keywords: Intelligent waste management, e-waste recycling, deep learning, internet of things (IOT), optimization techniques

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Introduction

The rapid growth of electronic waste (e-waste) and municipal solid waste (MSW) represents one of the most pressing environmental and public health challenges of the 21st century. As digital transformation accelerates across industries and societies, the life cycle of consumer electronics continues to shrink, leading to an unprecedented surge in discarded devices (Kaya et al., 2023). According to the Global E-Waste Monitor, over 53 million metric tons of e-waste were generated worldwide in 2020, a figure projected to exceed 74 million tons by 2030. Meanwhile, municipal solid waste, which includes household, commercial, and institutional refuse, is expected to grow from 2.01 billion tons in 2016 to 3.4 billion tons by 2050 (Huynh et al., 2020). These growing waste streams, if unmanaged, will not only overwhelm existing landfill capacities but also pose significant risks to air, water, and soil quality due to hazardous chemicals and persistent pollutants commonly found in e-waste and decomposing solid waste (Bircanoglu et al., 2018). Despite its magnitude, waste management in many parts of the world continues to rely on outdated, labor-intensive systems characterized by inefficient collection schedules, limited recycling infrastructure, and poor data visibility(W. Lin, 2021). Traditional waste handling approaches often fail to accommodate the dynamic nature of urban environments, leading to overflows, missed pickups, unnecessary fuel consumption, and harmful greenhouse gas emissions. Moreover, the lack of accurate data and predictive capabilities undermines the strategic planning of waste services (Pinhal Luqueci Thomaz et al., 2023), resulting in unsustainable resource utilization and increased public health risks (Simaei & Rahimifard, 2024). The environmental burden is particularly severe in low- and middle-income countries, where informal recycling sectors dominate and environmental regulations are poorly enforced. These challenges underscore the need for innovative.(Kunsen Lin et al., 2023), technology-enabled frameworks that can transform waste management from a reactive, manual process to an intelligent, automated, and sustainable system.

In response to these limitations, the past decade has witnessed a surge in the development and deployment of smart technologies(James et al., 2024), particularly the Internet of Things (IoT), artificial intelligence (AI), and deep learning (DL), within the waste management domain. These technologies are driving the evolution of waste systems into integrated, data-driven ecosystems capable of real-time monitoring, remote management, and predictive analytics (Ramya et al., 2023). IoT-enabled smart bins, for example, use sensors to measure fill levels, temperature, and gas emissions, transmitting this data wirelessly to central systems or edge computing nodes (G. P. Oise & Konyeha, 2024b). This enables dynamic route optimization for collection vehicles, reducing operational costs and environmental impacts. Likewise, deep learning models, particularly Convolutional Neural Networks (CNNs), are being employed to automate waste classification and sorting with remarkable accuracy, often exceeding 95% on benchmark datasets (Arun et al., 2024). Such automation improves sorting quality, increases recycling rates, and minimizes human exposure to hazardous materials. Optimization algorithms further strengthen the performance of smart waste systems by enabling adaptive, multi-objective decision-making (Hussain et al., 2020). Metaheuristic techniques such as Fractional Henry Gas Optimization (FHGO), Multi-Objective Beluga Whale Optimization (MBWO), and Proximal Policy Optimization (PPO) are increasingly applied to balance trade-offs among competing goals, such as energy efficiency, processing speed, classification accuracy (Abu-Qdais et al., 2023), and system scalability. These algorithms help refine resource allocation, schedule maintenance, and ensure robust performance even under dynamic operational conditions (M. M. Ahmed et al., 2023). However, their computational intensity and data requirements pose a barrier to deployment on edge devices or in real-time applications. Moreover, while pilot studies have demonstrated significant cost and energy savings (Bibri, 2020), full-scale implementation in diverse urban settings remains limited, particularly due to data scarcity, regulatory fragmentation, and infrastructure deficits (G. P. Oise & Konyeha, 2024).

In addition to these technical challenges, there is growing concern about the "black box" nature of many AI models used in waste classification and optimization (Sayed et al., 2024). The lack of interpretability and transparency in decision-making hinders regulatory compliance and erodes public trust. Furthermore, many models are trained on limited, homogenous datasets that fail to capture the variability of real-world waste streams (Q. Zhang et al., 2021), particularly in informal sectors or disaster-prone regions. These shortcomings restrict the generalizability of AI solutions and highlight the importance of incorporating Explainable AI (XAI) approaches (Sirimewan et al., 2024), robust data augmentation techniques, and context-aware validation frameworks into the development pipeline. There is also an urgent need for international standardization in e-waste classification (Abina et al., 2022), performance benchmarking, and compliance reporting, especially as waste governance becomes increasingly transnational (Arashpour, 2023). This review introduces a novel synthesis that moves beyond the conventional siloed analysis of individual technologies and instead offers an integrative perspective that encompasses IoT infrastructures, deep learning architectures (Wu et al., 2023), and optimization algorithms within intelligent waste management systems (Oise Godfrey Perfectson, 2024). The uniqueness of this study lies in its holistic approach: it not only surveys technological advancements but also critically examines emerging innovations such as Explainable AI (G. Oise & Konyeha, 2024), edge computing, and blockchain for traceable and decentralized waste handling (Lu et al., 2022). These technologies are rarely discussed collectively in existing reviews. Furthermore, this work emphasizes hybrid and multi-objective models that combine deep learning with metaheuristic optimization, an area still underrepresented in the literature despite its high potential (Yazdani et al., 2024). By mapping out these interdisciplinary intersections, this review contributes new knowledge that aligns technological development with sustainability goals, smart city planning, and circular economy principles.

Drawing from more than 50 peer-reviewed studies and technical reports published between 2020 and 2024, this review identifies key implementation trends, practical challenges, and future opportunities. It highlights real-world deployments such as IoT-based alert systems, CNN-driven robotic sorters(Ramya et al., 2024), and blockchain-secured recycling platforms. At the same time, it recognizes that most existing solutions have yet to be widely adopted or scaled, especially in resource-constrained environments(Ali et al., 2020). The review thus situates technological advancements within broader ethical, infrastructural, and policy contexts, providing a comprehensive understanding of what is needed to transition from promising prototypes to resilient, intelligent waste ecosystems(Alqahtani et al., 2020). In light of these gaps, the overarching goal of this review is to provide a structured, multi-dimensional analysis of intelligent waste management systems powered by IoT, deep learning, and optimization methods(Kang et al., 2020). Specifically, the study aims to explore the current landscape of smart waste technologies, identify the prevailing limitations and research gaps, and evaluate the role of emerging innovations such as XAI and edge computing in improving system transparency, adaptability, and scalability. Ultimately, the review seeks to offer a strategic roadmap for future research and policy formulation that supports the sustainable, secure, and scalable implementation of intelligent waste management solutions across varied geographic and socioeconomic contexts.

Methodology

A systematic search across Scopus, Web of Science, IEEE Xplore, and ScienceDirect databases yielded a total of 600 articles, supplemented by 25 additional records identified through snowballing, resulting in 625 records overall. After removing 105 duplicates, 520 articles were screened based on titles and abstracts, of which 400 were excluded for irrelevance or lack of peer review. The remaining 120 full-text articles were assessed for eligibility, and 80 were excluded for reasons such as lacking empirical validation, misalignment with waste management, or insufficient technical detail. Ultimately, 40 studies were included in the qualitative synthesis: 12 focused on IoT, 18 on deep learning, and 10 on optimization techniques within intelligent waste management systems.

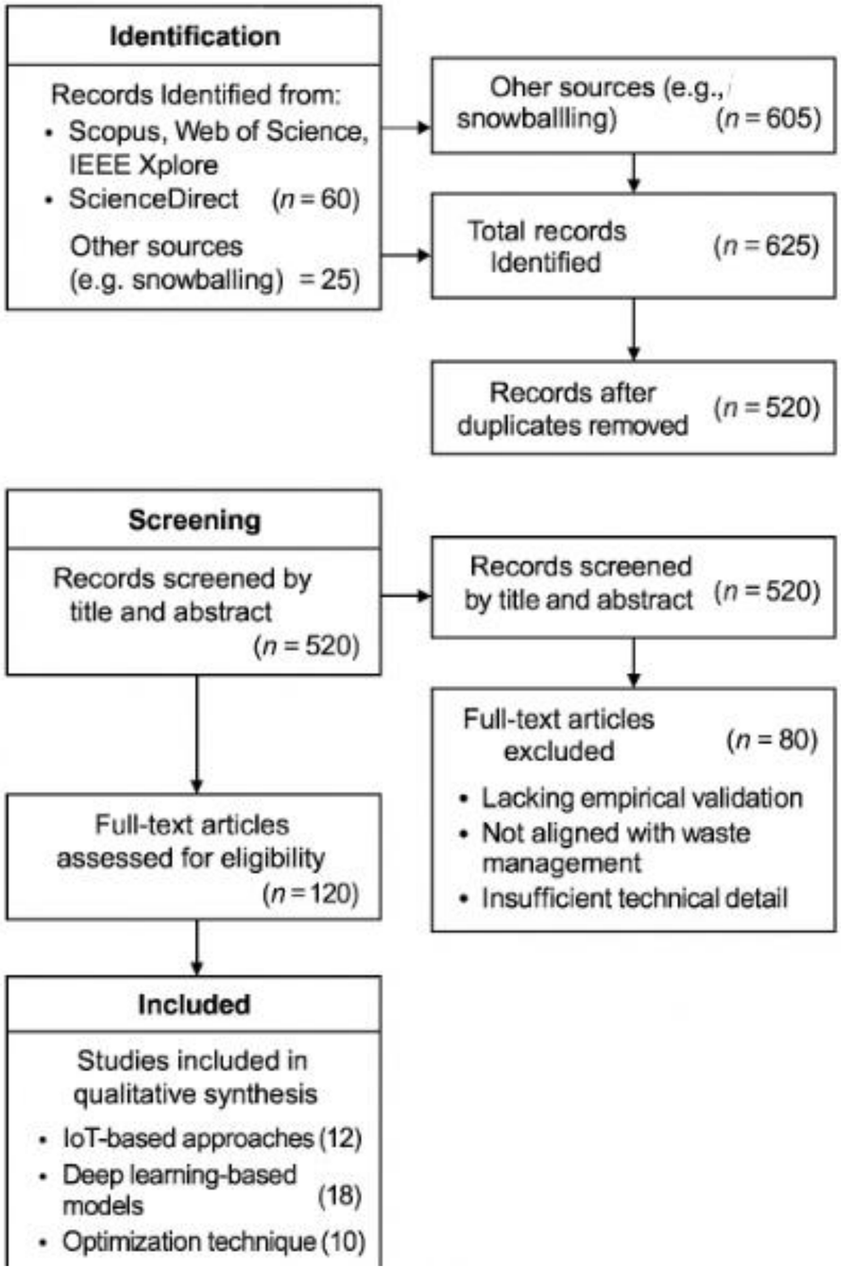

Figure 1. PRISMA diagram

Figure 1 depicts the PRISMA diagram, which outlines the systematic process used for identifying, screening, and including studies in a qualitative synthesis. Initially, 625 records were identified 600 from databases such as Scopus, Web of Science, IEEE Xplore, and ScienceDirect, and 25 from other sources like snowballing. After removing 105 duplicates, 520 records remained for screening. Titles and abstracts were then reviewed, leading to the exclusion of 400 irrelevant or non-peer-reviewed studies. The remaining 120 full-text articles were assessed for eligibility, and 80 were excluded due to issues such as lack of empirical validation, misalignment with waste management, or insufficient technical detail.

Ultimately, 40 studies were included in the final qualitative synthesis, categorized into three groups: IoT-based approaches (12 studies), deep learning-based models (18 studies), and optimization techniques (10 studies). This structured approach ensures transparency and rigor in the selection of literature for systematic reviews.

Literature Search Strategy

A comprehensive and systematic literature review was conducted to identify current research on intelligent waste management systems. Searches were performed across major academic databases, including Scopus**,** Web of Science**,** IEEE Xplore, and ScienceDirect**,** using targeted keywords such as *"e-waste management," "deep learning for waste classification," "IoT in smart bins,"* and *"optimization techniques for waste collection."* The review focused on peer-reviewed articles published between 2020 and 2024**,** ensuring the inclusion of recent technological advancements. To enhance coverage, backward and forward snowballing techniques were applied to trace foundational and influential works.

Study Selection and Screening

An initial pool of over 500 articles was retrieved. These were screened by title and abstract for relevance to IoT, artificial intelligence (AI), and optimization techniques in waste management**.** Duplicate entries and off-topic studies were removed. A total of 120 full-text articles were then reviewed for methodological soundness, novelty, and practical relevance to sustainable waste management. Following this assessment, over 50 studies were selected for detailed analysis, with preference given to those that included empirical evidence, such as performance metrics or real-world case implementations.

Data Extraction and Categorization

Key information was extracted from each selected study and organized into three thematic domains:

1. IoT Applications: Parameters such as sensor accuracy, energy efficiency (e.g., 0.3 J/node), and latency improvements (e.g., 0.666 seconds).
2. Deep Learning Models: Metrics like classification accuracy (e.g., 95–97%), network architectures (e.g., CNN, ResNet), and datasets utilized (e.g., TrashNet, custom local datasets).
3. Optimization Techniques: Algorithms including FHGO and MBWO, and their effects on system performance (e.g., 34% reduction in energy usage, enhanced route optimization).

Validation and Bias Mitigation

To ensure the validity of findings:

1. Cross-Verification**:** Results were corroborated using external sources such **as** industry reports (e.g., *Global E-waste Monitor*) and technical whitepapers.
2. Bias Mitigation: Studies relying on small or non-representative datasets were flagged. Additionally, results were contextualized, e.g., limitations of datasets like TrashNet in industrial settings were acknowledged.

Ethical and Policy Considerations

The methodology accounted for broader implications by addressing:

1. Data Privacy: Concerns related to location-tracking features in IoT-based systems (e.g., GPS-enabled bins).
2. Policy and Regulatory Issues: Gaps in international compliance (e.g., enforcement disparities concerning the Basel Convention on e-waste export/import).

Limitations
This review acknowledges several constraints:

1. Language Bias: Only English-language publications were included.
2. Geographic Scope: The predominance of urban case studies may not adequately represent rural or low-resource settings.

Justification for Methodology

1. Reproducibility**:** The use of well-defined search terms and screening criteria enhances repeatability.
2. Interdisciplinary Depth**:** The inclusion of both technical and sustainability metrics ensures a holistic evaluation.
3. Transparency**:** Limitations and potential biases are explicitly acknowledged, strengthening the credibility of the findings.

Inclusion Criteria

1. Peer-Reviewed Publications: Only articles published in peer-reviewed journals or conference proceedings were considered.
2. Publication Date: Studies published between 2020 and 2024 to ensure coverage of the most recent technological advancements.
3. Topic Relevance: Studies specifically focused on intelligent waste management systems using IoT, deep learning, or optimization techniques.
4. Empirical Evidence: Articles that included experimental validation, performance metrics (e.g., accuracy, latency, energy consumption), or real-world case studies.
5. Technical Rigor: Studies that provided sufficient technical detail for reproducibility and critical evaluation.
6. Language: Publications written in English only.

Exclusion Criteria

1. Non-Peer-Reviewed Sources: Editorials, opinion pieces, and non-reviewed conference papers were excluded.
2. Lack of Empirical Validation: Studies that were purely conceptual or lacked experimental data or implementation results.
3. Irrelevant Focus: Articles not directly related to waste management, or focusing on unrelated domains (e.g., generic IoT, AI in agriculture, etc.).
4. Insufficient Technical Detail: Papers that did not clearly describe methods, datasets, model architectures, or evaluation procedures.
5. Duplicated Records: Repeated articles retrieved from multiple databases were removed during the deduplication process.

Results and Discussion

Environmental and Health Impacts of E-Waste

The study highlights the escalating scale of global e-waste generation, which reached over 53 million metric tons in 2020 and is projected to surpass 74 million tons by 2030 (Sheng et al., 2020). Alarmingly, only 17% of this waste is formally recycled, while the remainder is often subjected to informal processing or indiscriminately discarded, especially in low and middle-income countries (Ba

Alawi et al., 2021) (Khatiwada et al., 2023). This mismanagement has profound environmental consequences, including the release of hazardous substances, such as lead, mercury (Munir et al., 2023), cadmium, and persistent organic pollutants, into the soil, water, and atmosphere. Open-air burning and rudimentary recycling methods amplify air pollution and contribute to greenhouse gas emissions. Human health is similarly compromised, particularly among informal waste workers (Ascher et al., 2022; Nowakowski et al., 2020). Prolonged exposure to e-waste toxins has been associated with respiratory complications, neurological disorders, congenital anomalies, and carcinogenic effects (K. Lin et al., 2022). The absence of protective equipment and health regulations exacerbates these risks in developing regions. Furthermore, the regulatory landscape remains fragmented, with many countries lacking dedicated e-waste legislation and relying instead on generic hazardous waste frameworks (H. Zhang et al., 2023). Weak enforcement of international treaties, such as the Basel Convention, further complicates global e-waste governance.

Technological Advancements in Waste Management

Integration of Internet of Things (IoT) technologies into waste management infrastructures has significantly enhanced operational efficiency (Kumar Lilhore et al., 2024). Smart bins equipped with sensors for real-time monitoring have reduced waste collection frequency by up to 40% and operational costs by approximately 30%. Despite these gains, widespread adoption remains constrained by high initial capital costs, energy requirements, and limited network infrastructure in developing regions. Advanced machine learning models, particularly Convolutional Neural Networks (CNNs), ResNet-50, and hybrid CNN-LSTM frameworks, have demonstrated classification accuracies exceeding 95% on structured datasets. Transfer learning approaches (Jin et al., 2023), such as MSWNet, have further optimized performance, achieving up to 93.5% accuracy while reducing training time. Nevertheless, model generalization to complex and heterogeneous real-world waste streams remains a significant limitation due to insufficiently diverse and annotated datasets. Optimization algorithms such as Fractional Henry Gas Optimization (FHGO) and Multi-Objective Beluga Whale Optimization (MBWO) have shown promise in improving energy efficiency and scalability(Qi et al., 2023). Energy consumption reductions of up to 34% have been reported (Lakhouit et al., 2023). However, these algorithms often impose high computational demands, limiting their suitability for edge devices and real-time applications (Wirtu & Tucho, 2022) (Selvakanmani et al., 2024). Innovations such as Explainable AI (XAI), Edge Computing, and Blockchain are beginning to reshape the waste management landscape (Fatima Abbas Maikano, 2024). XAI enhances transparency and accountability in automated decision-making, a crucial factor for regulatory compliance. Edge computing facilitates real-time processing in remote or resource-constrained environments, while blockchain offers secure and transparent waste tracking solutions.

Challenges, Limitations, and Future Directions

Despite the promising potential of advanced technological solutions in e-waste management, several systemic challenges continue to hinder widespread adoption and effectiveness. A major limitation lies in the quality and scope of available datasets. Many existing datasets fail to capture the complexity of real-world waste streams, particularly in cases involving contaminated or composite materials (S. Ahmed et al., 2022). This data scarcity undermines the robustness and generalizability of AI models. Equally pressing is the issue of model transparency (Ádám et al., 2021). Most deep learning systems, particularly those based on complex architectures like convolutional and recurrent networks, function as "black boxes," making it difficult to interpret decisions. This opacity raises ethical concerns and poses a significant obstacle to regulatory acceptance and public trust. Furthermore, the global regulatory landscape remains fragmented (Tasnim et al., 2024). The absence of harmonized e-waste policies and enforcement mechanisms creates inconsistencies in standards and practices across regions, complicating efforts to scale and standardize technological solutions (Yu et al., 2023). Additionally, many developing regions lack the necessary infrastructure, including reliable electricity, internet connectivity, and data processing capabilities, to support the deployment of smart waste management systems (Chhabra et al., 2024). To overcome these limitations and build resilient, scalable solutions, a multi-disciplinary and collaborative approach is essential. Several key areas for future advancement are outlined below:

Technical Innovations

1. Lightweight AI Models**:** The development of resource-efficient models such as MobileNetV3 and TinyML can enable real-time waste classification on low-power edge devices, making deployment feasible even in resource-constrained settings.
2. Generative Adversarial Networks (GANs) to Synthetic Data Generation**:** Leveraging augmented training datasets can enhance model accuracy and adaptability, especially when real-world data is limited or difficult to collect.

Policy and Regulatory Strategies

1. Global Standardization**:** There is a pressing need to establish unified international standards for e-waste classification, processing, and model evaluation. Such harmonization would facilitate regulatory compliance and cross-border collaboration.
2. Incentive Mechanisms**:** Public-private partnerships should be fostered to promote the adoption of sustainable waste management technologies through financial incentives such as tax relief, grants, and carbon credit schemes.

Sustainability Integration

1. Lifecycle Assessments (LCAs)**:** Incorporating LCAs into system design and deployment will ensure that the environmental impacts of smart technologies are accurately assessed and minimized.
2. Circular Economy Principles: Embedding circular economy practices such as design for disassembly, resource recovery, and reuse into waste management systems will reduce environmental burdens and promote long-term sustainability.

Conclusion

This review presents a comprehensive synthesis of recent advancements in intelligent waste management, emphasizing the integration of Internet of Things (IoT), deep learning (DL), and optimization algorithms. The key findings highlight that IoT-enabled smart bins can significantly reduce collection frequency and operational costs, while DL models, especially convolutional neural networks, offer exceptional accuracy in waste classification tasks. Additionally, optimization techniques such as Fractional Henry Gas Optimization (FHGO) and Multi-Objective Beluga Whale Optimization (MBWO) enhance energy efficiency, system responsiveness, and scalability. Collectively, these technologies demonstrate substantial potential in transforming traditional waste management systems into adaptive, efficient, and sustainable infrastructures aligned with smart city and circular economy goals. The implications of this study are both practical and theoretical. Practically, the reviewed technologies can support municipalities, environmental agencies, and technology developers in designing real-time, resource-efficient waste management systems that reduce environmental impact and improve public health. Theoretically, the review contributes to academic discourse by identifying and analyzing hybrid models, such as those combining DL with metaheuristic algorithms, and by incorporating underexplored dimensions like Explainable AI (XAI), blockchain, and edge computing for transparency, traceability, and decentralized processing. However, this study also acknowledges several limitations. Many existing models are trained on limited datasets that do not reflect the complexity of real-world waste streams, especially in low-resource settings. There is also a lack of uniform standards and regulatory frameworks, which restricts the generalization and scalability of these solutions. Moreover, the computational intensity of advanced DL and optimization models poses challenges for real-time, low-power applications, particularly in regions with limited infrastructure. To address these gaps, future research should focus on the development of lightweight and explainable AI models suitable for edge deployment, the creation of large-scale and diverse annotated datasets for waste classification, and the implementation of robust policy frameworks that support global standardization. In addition, interdisciplinary studies that integrate environmental science, urban planning, and machine learning can offer deeper insights into scalable and equitable waste management solutions. By embracing these directions, the research community can move closer to realizing truly intelligent, inclusive, and sustainable waste ecosystems.

Conflicts of Interest

The authors declare no conflict of interest

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