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A Systematic Literature Review of YOLO and IoT Applications in Smart Waste Management

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ABSTRACT: The increase in urbanization and global population expansion resulted in increased garbage production, causing considerable environmental and public health issues that exceeded traditional waste management approaches. To tackle these challenges, automated waste detection and analysis integrated computer vision, especially deep learning, with the Internet of Things (IoT) in intelligent waste management applications. This comprehensive literature review investigated a wide range of You Only Look Once (YOLO) applications in IoT-based waste detection and management, demonstrating its efficacy in addressing global waste issues. Employing specific keywords and Boolean operators, the review followed a rigorous methodology to explore reputable electronic databases for peer-reviewed articles published from 2019 to 2025. The primary findings indicated that different iterations of YOLO (v3 to v12) were integrated with diverse IoT devices and computing setups, including edge and centralized systems. These integrations facilitated four crucial applications: hazardous waste management, monitoring of smart bins, classification of waste types, and detection of litter in public spaces. This integration enhanced sustainability through improved waste management practices, increased efficiency in waste processes, and reduced manual labor requirements. Challenges included precise waste identification in complex scenarios, adaptation to fluctuating environmental conditions, and ensuring dependable, low-power operation of IoT devices. To sum up, the integration of YOLO and IoT established a robust basis for intelligent waste management, transforming reactive approaches into proactive strategies. Moving forward, research should prioritize enhancing the integration and power management of IoT sensors, optimizing edge deployment, and developing more resilient YOLO models.

KEYWORDS: IoT; object detection; SLR; waste management; YOLO

1. Introduction

The global population expanded rapidly, and an increasing number of individuals relocated to urban areas. These resulted in a substantial increase in waste production, which harmed public health and the environment [1, 2]. Numerous conventional waste management systems employed manual processes, which were prone to errors and inefficiencies in sorting and required significant time and effort [3, 4]. To address these issues, the integration of computer vision technology with the Internet of Things (IoT) emerged as a critical method for the automatic detection and analysis of waste [5, 6]. While advanced solutions offered promising opportunities, their implementation in complex, real-world waste environments presented unique challenges and limitations that required thorough analysis.

The primary features of these computer vision applications were derived from deep learning, a form of artificial intelligence [7]. YOLO was regarded as a leading object detection algorithm for smart waste management systems due to its real-time processing, high accuracy, and speed [8, 9]. YOLO variants, including YOLOv3, YOLOv4, YOLOv5, YOLOv7, YOLOv8, YOLOv9, YOLOv10, and YOLOv12, were applied in various environments such as cities, waterways, and even underwater to perform tasks like trash sorting [10], plastic detection [11, 12], and the identification of illegal dumping [13–15].

To develop intelligent and comprehensive waste management solutions, collaboration between YOLO and IoT was essential. IoT enabled data collection and communication, while YOLO provided smart visual analysis [3]. IoT-equipped smart bins gathered raw data using ultrasonic, force, temperature, gas, and GPS sensors [1, 16]. This integration offered several advantages: for example, smart bins could detect their fill levels [17], and advanced tracking systems could optimize collection routes [18]. This shift from reactive to proactive, data-driven strategies transformed waste management. YOLO utilized this visual data to extract meaningful information about the waste, its quantity, type, and location [19]. Neither technology alone was sufficient; IoT enabled real-time sensing and connectivity, while YOLO delivered the intelligence required for object detection and classification. Together, they supported the creation of cleaner, healthier, and more sustainable environments through intelligent and self-sufficient waste management systems [20].

This systematic literature review was meant to investigate the diverse applications of YOLO in IoT-based waste detection and management. It highlighted the effectiveness of these combined technologies in addressing global waste challenges and identified the limitations, research gaps, and future challenges in current implementations. The review was guided by the following research questions:

– What are the primary uses of YOLO in IoT-based waste management systems?
– What types of IoT devices and architectures are most commonly used with YOLO for waste detection?
– How do various real-world waste management systems address YOLO's key limitations?

2. Materials and Methods

A systematic and objective methodology was employed to conduct this literature review. This approach ensured the identification, selection, and synthesis of the most relevant studies on the application of YOLO and IoT in waste management. Adherence to established systematic review protocols enhanced the reliability and reproducibility of the findings.

2.1. Search strategy.

To discover relevant studies, a thorough literature search was conducted across a number of well-known electronic databases. IEEE Xplore, ScienceDirect, Springer, ACM Digital Library, Wiley Online Library, MDPI, and Garuda Kemdikbud were some of the databases used. These platforms were selected for their extensive literature on computer science, engineering, and environmental science. This approach allowed for a detailed overview of the academic field.

Targeted keywords and Boolean operators were carefully employed to obtain the most pertinent and precise search results. The primary keywords included "YOLO," "waste detection," "garbage detection," "trash detection," "waste management," "smart waste," "IoT," and "Internet of Things." Boolean operators such as "AND" and "OR" were used to combine these phrases and enhance the specificity of the search strings. An example of a search string utilized was '(YOLO) AND ("waste management" OR "trash detection") AND (IoT OR "Internet of Things")'. Carefully constructing these search strings was vital, as they directly impacted the comprehensiveness and relevance of the retrieved material. A vague string might have produced excessive irrelevant results or excluded significant studies, thereby diminishing the quality of the review.

To ensure the relevance and consistency of the findings, the search was limited to articles published within a specific timeframe, from 2019 to 2025. Furthermore, the search was restricted to articles published in the English language to maintain uniformity and facilitate analysis. The search encompassed exclusively peer-reviewed journal papers and conference proceedings. This criterion was carefully implemented to guarantee the high quality and academic validity of the chosen papers, a crucial element for demonstrating the legitimacy of the review's results.

2.2. Study selection criteria.

Clear criteria were carefully defined for the inclusion and exclusion of studies to ensure that the selected studies were directly relevant to the research questions and to maintain the overall quality of the review at a high level. Studies were included if they were specifically about using YOLO algorithms with IoT technology to manage waste. These studies utilized real-world evaluations, case studies, or experimental results to demonstrate the practical application and effectiveness of these technologies. In contrast, studies that solely discussed YOLO algorithms or IoT technology in general without relating them to waste management were not considered. Furthermore, this review did not include sources like conference abstracts, editorials, or non-academic reports to ensure the information was reliable and accurate. This intentional choice of method placed more weight on direct applicability and empirical evidence than on theoretical breadth. This ensured that the review's results were based on strong scientific contributions.

The entire process of selecting studies for inclusion was systematically documented using a flow diagram, adapted from the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [21]. This systematic documentation enhanced the comprehensibility and replicability of the review. The selection process involved identifying potential studies in databases, reviewing titles and abstracts, verifying the eligibility of full texts, and incorporating them into the review. Figure 1 visually represented this process in the PRISMA flow diagram.

2.3. Data extraction.

After studies were selected systematically, a pre-designed data extraction form was used to consistently extract relevant information from each included article. The data points were carefully chosen to directly address the research questions and to support a thorough analysis of the literature. These data points included the author(s), year of publication, title, place of publication, specific use case for YOLO and IoT, version of YOLO used, IoT devices and architecture involved, main findings and outcomes, and any reported problems or limitations. All of the studies examined followed consistent and complete data collection practices.

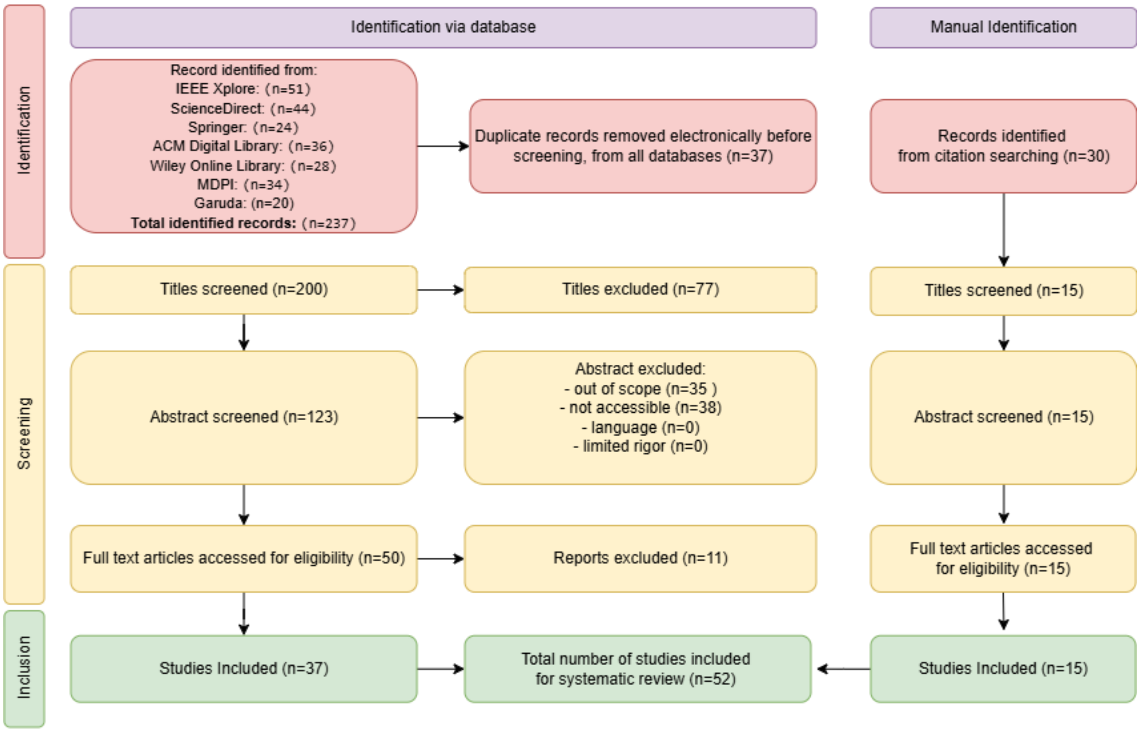


Figure 1. PRISMA Flow diagram YOLO and IoT for .Smart Waste Management

2.4. Data synthesis.

The extracted data were carefully compiled and analyzed using thematic analysis. This qualitative method helped identify recurring themes, patterns, and trends in the use of YOLO and IoT for waste management. The results were then organized and presented in a logical manner, primarily based on the identified application areas and the research questions guiding the study. The studies were systematically compared and contrasted to highlight variations in their approaches, empirical findings, and reported outcomes, which helped develop a clearer understanding of the current state of research by showcasing both common practices and unique contributions in the field.

3. Results and Discussion

This section presented the results of the systematic literature review and provided a detailed analysis of the YOLO algorithm, its integration with IoT, and its diverse applications in smart waste management. The discussion was structured to address the research questions outlined in the introduction. This result was achieved by utilizing the identified studies to highlight significant trends, challenges, and advancements in the field.

3.1. YOLO algorithm for waste detection.

3.1.1. YOLO variants and their key features.

The YOLO framework marked a major shift in the field of real-time object detection. It changed the way computer vision systems viewed and identified objects in images and video streams. Unlike traditional two-stage detectors, which first detected regions of interest before classification, YOLO analyzed the entire image in a single pass to simultaneously detect and localize objects. This single-step approach significantly improved speed and efficiency, making YOLO a vital component in applications such as real-time decision-making in autonomous vehicles, robotic navigation, and surveillance systems [22].

The rapid and diverse evolution of YOLO models suggested that the most recent version might not always be the best choice for every scenario due to specific performance trade-offs an important consideration for real-world applications. Newer iterations, such as YOLOv8 and YOLOv9, introduced additional functionalities and improved performance metrics. In contrast, earlier versions like YOLOv5 offered greater stability and sometimes better performance in certain contexts, particularly in settings with limited computing resources. This assumption remained valid, as YOLOv9 demonstrated high accuracy in specific use cases while facing limitations in others [23]. Table 1 shows YOLO variants and their key features.

Table 1. YOLO variants and their key features.

YOLO Variant	Year	Backbone Network	Key Architectural Changes	Key Performance Improvements
YOLOv3 [24], [25]	2018	Darknet-53	FPN-inspired design, Three-Scale detection; Independent logistic classifiers and binary cross-entropy loss; Anchor boxes.	Improved feature extraction, better detection across scales; Faster than ResNet-101/152; Increased AP for small objects; Enhanced by training heuristics like Mosaic data augmentation and CIoU loss.
YOLOv4 [26]	2020	CSPDarknet53	SPP, PANet, Mish activation, Mosaic data augmentation, CIoU loss, SAT, Weighted Residual Connections; YOLOv3 detection head; CmBN, DropBlock regularization	Higher mAP (43.5% AP, 65.7% AP50 on COCO); Competitive inference speeds (~65 FPS on Tesla V100); More robust to varying object sizes/occlusions; Improved training convergence; Twice as fast as EfficientDet; 10% AP, 12% FPS increase over YOLOv3
YOLOv5[23], [25]	2021	CSPDarknet53	SPPF (replaces SPP), PANet, Focus structure (replaced by 6x6 Conv2d in v6.0/6.1), Multiscale Training, EMA, Mixed Precision Training, BCE/CIoU loss; Transition to PyTorch	Significant step forward in real-time object detection, surpasses previous versions in performance and efficiency; Lightweight models (e.g., YOLOv5n 2.1 MB INT8); Superior speed over R-CNN
YOLOv6[23]	2022	Novel backbone/neck	Anchor-Aided Training (AAT), Self-Distillation; Decoupled head; Extended backbone/neck (YOLOv6-L6); Bi-directional Concatenation (BiC) in Neck; SimCSPSPPF Module.	Balances accuracy/speed, optimized for edge devices (Nano, Tiny variants); Overall better accuracy, 51% faster than previous anchor-based models; YOLOv6-N: 37.5% AP @ 1187 FPS; YOLOv6-S: 45.0% AP @ 484 FPS
YOLOv7[27]	2022	E-ELAN	Planned re-parameterized convolution (RepConvN); Coarse-to-fine auxiliary loss heads; "Bag-of-Freebies" for training; New compound scaling method for concatenation-based models.	Strong balance between high accuracy (56.8% AP) and fast inference speeds (5-160 FPS); State-of-the-art performance; Reduced parameters (40%) and computation (50%) vs. SOTA; Outperforms Transformer/Conv-based detectors.

YOLO Variant	Year	Backbone Network	Key Architectural Changes	Key Performance Improvements
YOLOv8[28]	2023	C2f, CSPDarknet53	Anchor-free detection; Decoupled head; Modified loss function (Task Alignment Score, BCE, CIoU, DFL); Rectified Adam (RAdam), MixUp data augmentation; Modified Mosaic data augmentation; Dynamic Anchor Assignment.	Superior real-time object detection, enhanced detection architecture, balances accuracy and speed, user-friendly; Higher mAP (YOLOv8x: 53.9% mAPval50-95); Improved generalization and small object detection; Handles class imbalance; Supports classification, segmentation, pose estimation.
YOLOv9[29]	2024	GELAN	Programmable Gradient Information (PGI); Auxiliary reversible branch; Multi-level auxiliary information; Optimized anchor-free prediction head	State-of-the-art accuracy, high efficiency, addresses information loss in deep networks; Better parameter utilization; Significant reduction in parameters (49%) and calculations (43%) vs. YOLOv8 deep model (with 0.6% AP improvement); Outperforms existing real-time detectors.
YOLOv10 [30]	2024	Refined CSPNet	NMS-free object detection (Consistent Dual Assignments); Lightweight classification head; Spatial-channel decoupled downsampling; Rank-guided block design; Large-kernel convolution; Partial Self-Attention (PSA) modules; Dual-head design.	Enhanced speed and accuracy; Significant latency reduction (37-70%); 1000 FPS capability; Higher mAP with fewer parameters (up to 57% fewer parameters, 38% fewer calculations than predecessors); Superior precision.
YOLOv11[28], [30]	2024	DarkNet, DarkFPN	C3K2 Blocks; SPPF; C2PSA Block (Cross Stage Partial with Spatial Attention); Dynamic Channel Setting	Faster, more accurate, highly efficient, supports multi-task (segmentation, classification, OBB, pose estimation); Enhanced feature extraction and higher precision with fewer parameters vs. YOLOv8; Optimized for speed and efficiency; YOLO11n: 39.5% mAPval50-95, faster CPU inference vs. YOLOv8n
YOLOv12 [31]	2024	R-ELAN	Attention-enhanced convolutional modules (A^2 - Area Attention Module with FlashAttention); Multi-scale feature fusion; Distribution Focal Loss; 7x7 Separable Convolutions; Removal of Positional Encoding; Adjusted MLP Ratio; Reduced Depth of Stacked Blocks; Maximized Convolution Operations.	Robust performance with occlusion, reflections, small-object detection, multi-object coexistence; State-of-the-art accuracy with competitive speed (YOLOv12-N: 40.6% mAP @ 1.64 ms); Efficiency and parameter reduction (YOLOv12-S: 42% faster, 36% computation, 45% parameters vs. RT-DETR); Expanded versatility (instance segmentation)

3.1.2. YOLO for waste detection: applications and performance.

In the context of waste detection applications, YOLO offered several benefits. Its real-time image processing capability was crucial in scenarios requiring prompt waste detection and response, such as in robotic waste sorting systems [32]. Furthermore, YOLO models consistently demonstrated precise detection of different waste types [33–35], which was essential for efficient sorting and recycling operations. They also showed strong computational efficiency, making them suitable for deployment on devices with limited resources. This characteristic was particularly advantageous for IoT applications in waste management, where edge processing was often necessary [19, 36, 37]. Table 2 illustrated the common use of standard object detection metrics such as precision, recall, F1-score, and mean Average Precision (mAP), to assess the effectiveness and reliability of YOLO-based waste detection systems. Precision reflected how often the model correctly identified trash objects, while recall measured its ability to detect all instances of trash within an image.

Diverse datasets containing images of various waste types from multiple environments were vital for developing and evaluating YOLO models for waste detection. For instance, the UGV-NBWASTE dataset [38] featured images of non-biodegradable waste collected across different settings. Researchers frequently applied data augmentation techniques to strengthen model robustness and enhance adaptability. These methods involved generating new training samples by modifying existing images to improve model performance [12, 39–41].

Table 2. YOLO for waste detection: applications and performance.

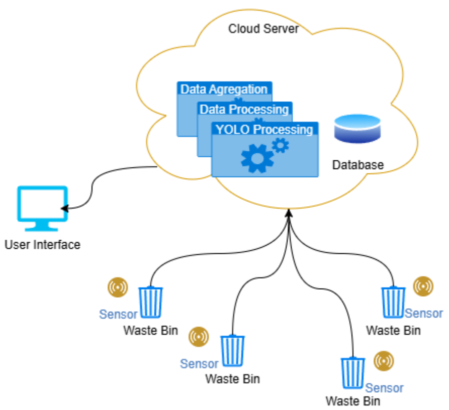
Paper Citation	**YOLO Version Used**	**Waste Detection Applications**	**Key Performance Metrics (mAP, Precision, Recall, F1-score, FPS)**
R et al. [10]	YOLOv5	Automated Waste Classification & Segregation (Plastic bottles, cans, etc.; Biodegradable, Plastic, Metal, Glass, Cardboard, Paper)	mAP50: 0.301 (overall), Precision: 0.458, Recall: 0.281, Accuracy: 80%, FPS: 28
Huang et al.[42]	YOLOv8-CBAM	Household Waste Classification (17 types)	mAP: 89.5% (enhanced YOLOv8-CBAM)
Mustapha et al.[43]	Hybrid YOLOv8 + CNN	Compost/Non-compost Material Identification	F1 score: 0.86, Precision: 0.85, Recall: 0.87, Accuracy: 0.88
Arishi [32]	YOLOv8-CBAM	Household Waste Detection & Classification (17 types)	mAP: 89.5% (enhanced YOLOv8-CBAM)
Yang et al. [44]	YOLOv5	Garbage Classification	Accuracy: 90.2%, Recall: 91.6%, mAP: 95.2%; 93.5% accuracy, 200FPS
Cai et al. [45]	Improved YOLOv4	Multi-category Garbage Classification (15 objects in 3 categories)	Average Accuracy: 64%, FPS: 92f/s
Ren et al. [46]	YOLOv10n, YOLOv10m, YOLOv11n, YOLOv11m	Plastic Waste Classification	YOLO-11m: 98.03% accuracy, 0.990 mAP50; YOLO-11n: 0.992 mAP50, 0.2720s inference time
Bianco et al. [47]	YOLOv12, YOLOv7	Marine Litter Detection (15 categories)	YOLOv12: mAP@50: 0.8354, mAP@50-95: 0.7025; YOLOv7: 71.4% accuracy
Alharbi et al.[48]	YOLOv8	Public Littering Behavior Detection (facial recognition, license plate)	99.5% accuracy (for violator identity detection)
Reddy et al.[14]	YOLO	PET bottles on lake surfaces; Object detection for visually impaired	98% average accuracy, 4-6 FPS (CPU)
Zhao et al. [49]	Enhanced YOLOv8	Riverbed Litter Monitoring	mAP: 78.6% (on reconstructed underwater litter)
Rehman et al.[15]	YOLOv8	Underwater Waste Detection (plastics, bottles, bags, cans)	High speed and accuracy (general claim)

Paper Citation	YOLO Version Used	Waste Detection Applications	Key Performance Metrics (mAP, Precision, Recall, F1-score, FPS)
Rathod et al.[50]	SSD MobileNet V2, YOLOv5x6	Visual Pollution Detection (urban/textile waste classification)	SSD MobileNet V2: 98.7% precision, 98.5% recall, 98% mAP50; YOLOv5x6: 79.2% mAP, 74% recall, 80.6% precision
S & Singh [39].	YOLOv8, YOLOv9	Garbage Detection (drone-based)	YOLOv8: 97-98% detection accuracy; YOLOv9: 7.7% higher mean detection accuracy than baseline
Ashwini et al. [36]	YOLOv5, YOLOv8	Smart Bin Monitoring (fill levels, trash outside/inside)	Good accuracy for most classes, highest for full-trash bin
Pathak et al.[13]	YOLOv5, YOLOv8	Illegal Dumping Detection (trash outside containers)	Good accuracy for most classes, highest for full-trash bin
Munira et al.[11]	YOLOv5	Intelligent Bin for Plastic Bottle Recycling	Precision: 89.8%, Recall: 83.1%, mAP: 89.2%; mAP: 0.973

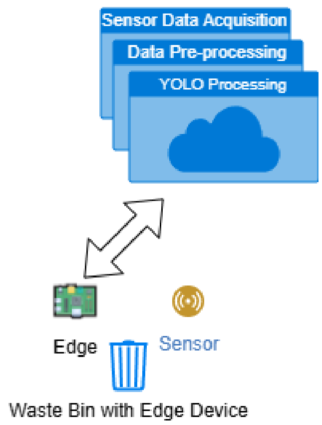
3.2. IoT integration for smart waste management.

3.2.1. IoT architectures for smart waste management.

IoT played a crucial role in waste management solutions by enabling sensor deployment and efficient data collection. These systems used various sensors, such as cameras for identifying and analyzing waste, and fill-level sensors to monitor waste volume. Wi-Fi, LoRaWAN, and cellular networks were among the communication protocols employed to transmit data from these distributed sensors. Protocol selection depended on factors such as range, bandwidth, and power consumption. IoT-based waste management systems primarily relied on centralized and distributed (edge) computing paradigms for data transmission and processing. The system design determined the flow of information, from sensor data collection to device processing and activation.



(a)



(b)

Figure 2. Illustration of centeralized IoT architecture (**a**); distributed, or edge IoT architecture (**b**).

Sensor data was transmitted to a central server or cloud for processing and storage within a centralized IoT framework. This model excelled in complex training, trend analysis, and data analytics due to the central server's high processing power and storage capacity. The server typically facilitated YOLO processing, allowing for comprehensive utilization of its robust capabilities on raw sensor data or consolidated image analysis. However, this approach often resulted in latency, increased bandwidth demands, and potential server bottlenecks, making it less suitable for scenarios requiring real-time responsiveness. For instance, cloud-based IoT systems illustrated this concept through smart waste bins and real-time traffic updates [17].

In contrast, data processing and storage were decentralized across multiple networked devices or nodes in a distributed or edge IoT architecture, typically located near the data source. Edge computing offered clear advantages by processing data closer to the source—often directly on the devices—thereby reducing latency and bandwidth consumption. This was particularly important for real-time applications requiring immediate decision-making. Edge devices such as Raspberry Pis or other embedded systems installed near waste bins were capable of running the YOLO algorithm directly. This enabled instant analysis of waste characteristics, minimized data transmission to central servers, and supported immediate actions such as robotic sorting. While edge architectures provided scalability and fault tolerance, they also required effective communication and synchronization mechanisms to ensure reliable system performance [51].

3.2.2. Applications of YOLO and IoT in waste management.

Integrating YOLO and IoT technologies has led to the development of multiple waste management applications, each tailored to tackle specific challenges and enhance the creation of smarter, more efficient, and sustainable systems. These apps encompass every phase of the waste management lifecycle, from initial detection and classification to specialized handling. Figure 3 illustrates the combined use of YOLO and IoT to address a variety of waste management challenges visually.

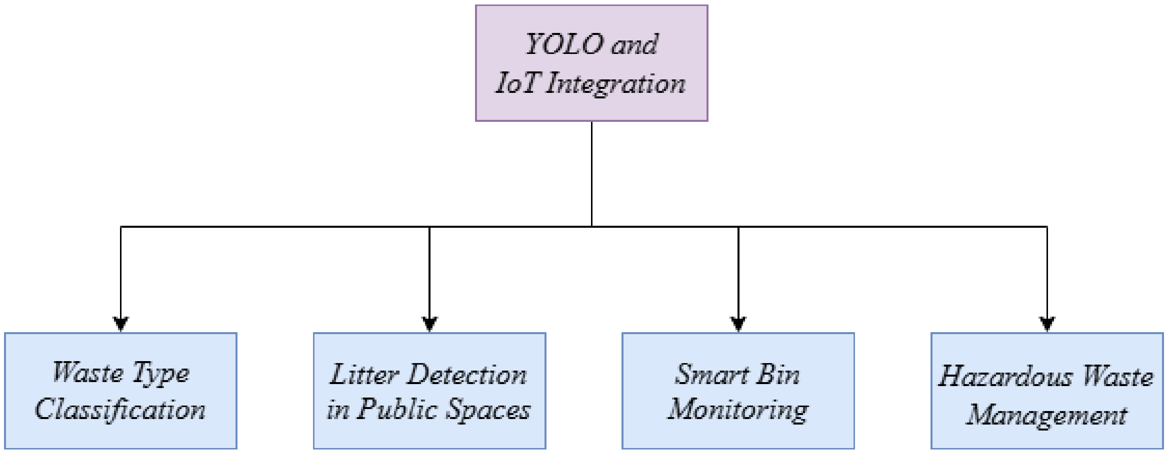


Figure 3. Yolo and IoT integration waste management challenges.

Transformative solutions in these areas are enabled by the synergistic application of IoT for data collection and transfer, alongside YOLO for real-time object identification. Table 3 offers a detailed overview of specific applications, the YOLO versions used, associated IoT devices or architectures, challenges resolved, and notable performance metrics documented in various studies.

Table 3. Applications of YOLO and IoT in Waste Management

Waste Management Applications	Paper Citation	YOLO Version Used	IoT Devices/Architecture	Challenges Addressed	Key Performance Metrics
Waste Type Classification	R et al. [10]	YOLOv5	Jetson Nano, Raspberry Pi	Automated Waste Classification & Segregation (Plastic bottles, cans, etc.; Biodegradable, Plastic, Metal, Glass, Cardboard, Paper)	mAP50: 0.301 (overall), Precision: 0.458, Recall: 0.281, Accuracy: 80%, FPS: 28
	Huang et al.[42]	YOLOv8-CBAM	Edge devices	Household Waste Classification (17 types)	mAP: 89.5% (enhanced YOLOv8-CBAM)
Litter Detection in Public Spaces	Bianco et al. [47]	YOLOv12, YOLOv7	UAVs, Underwater robots	Occlusion, reflections, small-object detection, multi-object coexistence; Challenging environments.	YOLOv12: mAP@50: 0.8354, mAP@50-95: 0.7025; YOLOv7: 71.4% accuracy
	Alharbi et al.[48]	YOLOv8	Surveillance cameras	Real-time public littering behavior detection; Shadowy objects, varying lighting (rain/sun), small objects, low accuracy	99.5% accuracy (for violator identity detection)
	Reddy et al.[14]	YOLO	Portable camera setup, Raspberry Pi	Object detection at a distance for visually impaired	98% average accuracy, 4-6 FPS (CPU)
	Zhao et al. [49]	Enhanced YOLOv8	Aerial-Aquatic Speedy Scanner (AASS)	Motion blur, low resolution, underwater litter	mAP: 78.6% (on reconstructed underwater litter)
	Rehman et al.[15]	YOLOv8	Underwater cameras, ROVs, drones	Low visibility, turbidity, cluttered backgrounds, low light	High speed and accuracy (general claim)
	Rathod et al.[50]	SSD MobileNet V2, YOLOv5x6	UAVs	Visual pollution in urban and textile landscapes	SSD MobileNet V2: 98.7% precision, 98.5% recall, 98% mAP50; YOLOv5x6: 79.2% mAP, 74% recall, 80.6% precision
	S & Singh [39].	YOLOv8, YOLOv9	Drones (UAVs)	Urban environments, remote locations, high proportion of small objects	YOLOv8: 97-98% detection accuracy; YOLOv9: 7.7% higher mean detection accuracy than baseline
Smart Bin Monitoring	Ashwini et al. [36]	YOLOv5, YOLOv8	Raspberry Pi, Wi-Fi module, Ultrasonic sensors, Camera	Fill-level monitoring, detection of trash outside/inside bin,	instant alerts to authorities, temperature monitoring, real-time location tracking
	Pathak et al.[13]	YOLOv5, YOLOv8	Smart bins with sensors, cameras	Illegal Dumping Detection (trash outside containers)	Enables targeted interventions, reduces accumulation, improves reliability
Hazardous Waste Management	B & P [52]	YOLO models (e.g., YOLOv8)	Not mentioned	Plastic Waste Classification	Potential for scalable, impactful solutions in plastic waste classification and recycling
	Munira et al.[11]	YOLOv5	Design of edge device.	Intelligent bin with Detection-Based Reward System (DBRS)	mAP: 0.973 for plastic bottle detection

A. General explanation of YOLO and IoT solutions for waste management.

Combining YOLO and IoT created a strong foundation for efficient waste management. YOLO models enabled the quick identification and categorization of waste objects due to their exceptional real-time object detection capabilities. When integrated with IoT devices, these systems automated numerous waste management tasks, allowing for data collection, transmission, and remote control. This synergy facilitated proactive intervention, informed decision-making, and continuous monitoring in garbage collection and processing. For example, YOLO analyzed visual data to identify waste categories or instances of improper disposal, while IoT sensors collected data on litter presence and bin fill levels. This combined approach boosted productivity, minimized manual work, and promoted environmental sustainability.

B. Summary of specific applications.

– Waste Type Classification: This application is crucial for enhancing recycling efficiency and facilitating automated garbage sorting. Research has demonstrated the efficacy of various YOLO versions, such as YOLOv5 and YOLOv8-CBAM, in categorizing a range of waste materials like glass, paper, and plastic, frequently employing embedded devices such as the Raspberry Pi and Jetson Nano. Improvements have achieved notable accuracy for various waste categories (89.5% mAP for domestic waste using YOLOv8-CBAM); however, challenges remain in intricate real-world situations involving mixed or obscured items and changing environmental conditions.

– Litter Detection in Public Spaces: To maintain urban cleanliness and mitigate pollution, YOLO and IoT are increasingly employed to identify and monitor trash across diverse environments, including parks, roadways, and aquatic systems. Notwithstanding challenges such as occlusion, reflections, diminutive object size, and inadequate visibility, Unmanned Aerial Vehicles (UAVs) and underwater robots equipped with YOLO models (including YOLOv12, YOLOv7, and YOLOv8) have demonstrated efficacy in detecting litter. Real-time technologies capable of precisely identifying persons have been created to detect public littering activity. Despite advancements, detecting litter in congested environments and varying weather conditions remains challenging, necessitating more robust models and data augmentation methods.

– Smart Bin Monitoring: This application aims to enhance collection schedules and save operational expenses by monitoring the real-time status of garbage containers, including fill levels and waste composition. IoT-enabled smart bins, equipped with sensors and cameras, utilize YOLO (YOLOv5, YOLOv8) to monitor fill levels, detect litter outside the bin, and issue alerts to law enforcement. This capability encompasses the identification of illegal dumping, hence indirectly enhancing collecting efforts. The primary problems are attaining low power consumption for extended battery life, ensuring resistance to vandalism, and maintaining reliable performance in diverse outdoor conditions.

– Hazardous Waste Management: While plastic garbage is the primary emphasis of the presented table, the principles of YOLO and IoT are crucial for the management of hazardous waste, as inappropriate disposal presents health and environmental hazards.

YOLO models, such as YOLOv8, are being explored for the classification of plastic trash to facilitate scalable recycling solutions. Advanced systems that attain elevated detection accuracy (0.973 mAP), such as intelligent bins employing a Detection-Based Reward System utilizing YOLOv5, promote the proper disposal of specific hazardous waste categories, including plastic bottles. The main challenges involve combining these systems with rigorous safety rules and the necessity for highly sophisticated detection models to identify minute visual variations in dangerous compounds.

3.3. Cross-cutting limitations and evaluation inconsistencies.

This section synthesized and expanded upon the significant limitations and inconsistencies observed within the existing body of research concerning YOLO and IoT applications in smart waste management. These challenges impeded the extensive and effective implementation of solutions and provided guidance for essential avenues of future research. Firstly, the challenges associated with generalizability and dataset limitations presented a considerable obstacle. While performance metrics frequently demonstrated promise in controlled environments, a significant limitation observed in numerous studies was the lack of generalizability of the models. The high accuracy achieved for specific waste categories or in idealized conditions often did not translate to real-life scenarios, largely due to the absence of general-purpose models trained on large, diverse, and publicly available datasets. This limitation particularly affected applications such as waste type classification, where models trained on clean, well-separated waste items often failed to handle mixed or obscured objects, and litter detection, where varying environmental conditions negatively impacted model performance.

Secondly, evaluation inconsistencies significantly complicated progress. A prominent issue was the lack of uniformity in evaluation metrics and testing protocols across studies. Although standard metrics like mAP, precision, and recall were commonly reported, the thresholds used, such as the Intersection over Union (IoU) for mAP, as well as test setups and baseline references, varied considerably. This variation made direct, side-by-side comparisons of different YOLO versions or integrated systems under identical real-world conditions rare. As a result, benchmarking progress across the field became challenging. The lack of standardized benchmarks hindered comprehensive understanding of the effectiveness of different approaches in specific real-world applications and limited the systematic advancement of the technology.

Thirdly, the existing literature revealed a significant gap in the documentation of long-term, large-scale deployments of YOLO-IoT waste management systems in operational smart cities or municipalities. This absence indicated that the academic studies were largely underexamined and did not address many practical and operational challenges. These challenges included ensuring the durability and long-term accuracy of sensors—particularly in maintaining reliable performance of smart bins—delivering energy-efficient power solutions in harsh outdoor conditions, establishing sustainable maintenance routines, mitigating data transmission delays across large network infrastructures, and implementing strong data security and privacy safeguards. Such operational concerns were especially critical for applications like smart bin monitoring and public litter detection, which required continuous, dependable functionality.

3.4. Future research directions.

In the context of the recognized limitations and challenges, subsequent research in the integration of YOLO and IoT for smart waste management needed to focus on several critical areas to advance the field toward more resilient, scalable, and impactful solutions. First, addressing the challenges associated with generalizability and dataset limitations was essential. A key research emphasis was placed on developing YOLO models capable of generalizing effectively across a wide range of diverse and unpredictable waste environments. These environments included variations in lighting, weather conditions, object occlusion, and the presence of novel or degraded waste items. Future studies explored advanced data augmentation methods, robust domain adaptation strategies, and the strategic use of synthetic data generation to create more resilient models. Additionally, the investigation of meta-learning techniques for rapid adaptation to new waste categories or deployment contexts emerged as a vital research direction.

Second, in response to evaluation inconsistencies, future work promoted the development of standardized benchmarking. This involved creating large-scale, publicly accessible benchmark datasets that captured a broad spectrum of waste types, environmental settings, and deployment scenarios, including drone-based, static camera, and robotic arm systems. Furthermore, the research community was encouraged to adopt standardized evaluation protocols and metrics that extended beyond traditional mAP. These included practical considerations relevant to real-world deployment, such as power consumption, inference latency on specific edge devices, and long-term operational reliability.

Third, the limited documentation of long-term and large-scale deployments highlighted the need for significant progress in edge AI optimization. Future research placed greater emphasis on developing lightweight model architectures through pruning, knowledge distillation, and efficient quantization techniques. Neural architecture search (NAS) tailored to ultra-low-power IoT edge devices also played a pivotal role. Moreover, long-term operational challenges were addressed by designing self-calibrating systems to mitigate sensor drift, implementing robust and energy-efficient power management solutions for remote locations, formulating predictive maintenance strategies, and establishing secure, low-latency communication protocols suitable for widespread and distributed smart waste infrastructures.

4. Conclusions

This study systematically reviewed the integration of You Only Look Once (YOLO) algorithms and Internet of Things (IoT) technologies to address global waste management challenges through intelligent waste management systems. The review highlighted the critical role of YOLO's real-time object detection capabilities, speed, and accuracy, which made it highly suitable for edge deployment across various applications. At the same time, IoT's essential role in connecting sensors, collecting data, and enabling seamless communication through both distributed (edge) and centralized architectures was thoroughly explored. The combined use of YOLO and IoT demonstrated considerable effectiveness across four key areas of waste management: classification of waste types, detection of litter in public areas, monitoring of smart bins, and management of hazardous waste. These integrations illustrated strong potential to shift waste management systems from reactive to proactive, data-driven approaches.

The review also identified several critical limitations and inconsistencies in current implementations. These included limited model applicability across diverse real-world environments due to a lack of varied datasets, inconsistencies in evaluation metrics and protocols, and a scarcity of documented long-term, large-scale deployments that address operational complexities. Overall, the integration of YOLO and IoT provided a solid foundation for more effective waste management, contributing to improved environmental health, cleanliness, and sustainability. To fully realize this potential, future research should prioritize enhancing model generalizability, developing standardized benchmarks, and optimizing energy-efficient solutions for long-term edge deployment.

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Author Contribution

This section defines the contributions of each author to the study, ensuring transparency and responsibility in the research process. Specific responsibilities of the author are as follows: Conceptualization: Trisna Gelar; Setiadi Rachmat Methodology: Sofy Fitriani; Data Collection: Trisna Gelar; Data Analysis: Sofy Fitriani, Setiadi Rachmat; Writing: Trisna Gelar.

Competing Interest

All authors declare no competing financial, personal, or professional interests that could have influenced the work reported in this paper.

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