

Waste Detection and Classification Using Computer Vision to Support Smart Waste Management Systems

Fikri Maulana ^{a,1*}, Anissa Fitri Hapsari ^{b,2}, and Daniel Kwame Mensah ^{c,3}
^a Computer Science Study Program, Universitas Teknologi Mataram, Mataram, Indonesia
^b Information Systems, Universiti Teknologi Malaysia, Johor Bahru, Malaysia
^c Department of Computer Science, University of Ghana, Accra, Ghana
¹ fikri.maulana@gmail.com ^{*}; anissa.hapsari@university.ac.id; daniel.mensah@university.edu;
^{*} Corresponding author

ARTICLE INFO	ABSTRACT
Article history Received: 27 August 2026 Revised: 24 September 2026 Accepted: 25 September 2026 Published: 29 September 2026 Keywords computer vision deep learning smart waste management waste classification waste detection  License by CC-BY-SA Copyright © 2026, The Author(s).	The increasing complexity of solid waste requires intelligent and efficient systems to support waste detection, classification, and management. This study aims to synthesize the development of computer vision-based waste detection and classification technologies and examine their contribution to smart waste management systems. The study employed a structured literature-based design using 19 scientific publications published between 2018 and 2026. The selected publications were analyzed through qualitative content analysis and comparative synthesis based on technological orientation, computational approach, primary task, implementation context, and reported contribution. The findings indicate a technological progression from convolutional neural network-based image classification and transfer learning toward object localization, real-time detection, and YOLO-based approaches. Recent studies also demonstrate increasing integration between computer vision, Internet of Things infrastructure, embedded computing, automated sorting, and cloud-based deployment. The analysis identifies dataset diversity, environmental variability, object overlap, computational efficiency, and deployment architecture as recurring challenges affecting practical implementation. The findings suggest that computer vision should be developed as an integrated component of smart waste management systems rather than as an isolated classification model. Effective implementation requires alignment between visual recognition capability, computational resources, communication infrastructure, and operational requirements. This study provides a structured synthesis of technological developments and highlights directions for developing more adaptive, scalable, and practically applicable computer vision-based waste management systems.

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INTRODUCTION

The increasing volume and complexity of solid waste have created significant challenges for waste management systems, particularly in urban and densely populated areas. Waste generation is associated with population growth, consumption patterns, economic activity, and changes in product packaging and material use. These conditions increase the demand for waste management systems that can identify, separate, monitor, and process different waste materials efficiently. Conventional waste sorting commonly relies on manual inspection, which requires substantial human resources and may produce inconsistent classification results. Manual sorting also becomes less efficient when waste streams contain large quantities of mixed materials with diverse physical characteristics. Consequently, the development of intelligent technologies has become increasingly relevant for supporting waste management processes. Artificial intelligence offers the capacity to process complex information and support automated decision-making across several waste management activities. A systematic review by Abdallah et al. (2020) showed that artificial intelligence has been applied to various areas of solid waste management, including waste classification, collection optimization, monitoring, and operational decision support. The broader development of artificial intelligence-based waste classification has also been documented by Yevle and Mann (2025), who identified an expanding range of computational approaches and research directions. These developments indicate that intelligent waste management increasingly requires systems that can convert environmental information into actionable data.

Computer vision is an important component of this technological development because it enables automated systems to acquire and interpret visual information from waste objects. Through cameras and image-processing techniques, a computer vision system can identify visual patterns associated with different materials, shapes, colors, textures, and object characteristics. The combination of computer vision and deep learning has improved the ability of automated systems to recognize objects without relying exclusively on manually designed feature extraction procedures. Adedeji and Wang (2019) demonstrated the application of deep convolutional neural networks for intelligent waste classification, showing that learned visual representations can support the recognition of different waste categories. Similarly, Aral et al. (2018) examined the classification of the TrashNet dataset using deep learning models and contributed to the early development of benchmark-oriented waste recognition research. These studies established an important foundation for applying deep learning to waste classification. However, image classification systems generally focus on assigning a label to an image or a dominant object within an image. This approach can be insufficient when multiple waste objects appear simultaneously or when an operational system requires information about the position of each object for automated handling or sorting.

Transfer learning has provided another important approach for improving the efficiency and effectiveness of deep learning-based waste classification. Instead of training a neural network entirely from the beginning, transfer learning allows a model to use representations learned from previous large-scale image datasets and adapt them to a specific classification task. Zhang et al. (2021) demonstrated the use of transfer learning and convolutional neural networks for waste image classification. Their work reflects the importance of leveraging pretrained visual models when developing classification systems under practical computational and data constraints. The application of transfer learning is particularly relevant in waste management because the availability of high-quality labeled waste images can vary across locations and waste categories. Waste materials also present substantial visual diversity due to differences in size, damage, contamination, orientation, and environmental conditions. A system that performs well on a controlled dataset may not necessarily achieve comparable performance when exposed to new visual conditions. Therefore, the development of computer vision systems requires consideration of both model architecture and the characteristics of the data used during training and evaluation.

The development of research has gradually shifted from image classification toward object localization and detection. Liang and Gu (2021) developed a deep convolutional neural network capable of simultaneously localizing and recognizing different waste types in images. This development is important because automated waste sorting requires information not only about what an object is but also where the object is located. Object detection therefore provides a more direct connection between computer vision and operational waste management applications. Córdova et al. (2022) compared deep learning approaches for litter detection and showed the relevance of evaluating visual recognition systems under different detection conditions. Jin et al. (2023) further applied a deep learning-based machine vision system to garbage detection and classification in support of sustainable waste recycling. These studies indicate that object detection can provide richer information than conventional image classification and can support applications in which multiple objects must be identified within a single visual scene. Lu and Chen (2022) also emphasized the importance of computer vision for solid waste sorting while identifying practical challenges associated with visual variability, background complexity, and the characteristics of different waste materials.

Recent research has increasingly focused on real-time object detection because smart waste management systems often require rapid processing and immediate responses. The You Only Look Once algorithm, commonly referred to as YOLO, has become a widely investigated approach because it combines object localization and classification within a detection process designed for efficient inference. Maity et al. (2023) developed a YOLO-based automatic waste classification system and demonstrated the relevance of real-time object detection for automated recognition tasks. The continued development of this approach is reflected in the implementation of YOLO for real-time waste object detection on a single-board computer by Firdaus et al. (2025). The use of a single-board computer is particularly relevant because it connects algorithm development with hardware deployment and demonstrates the possibility of implementing waste detection outside conventional high-performance computing environments. More recent work by Afuan et al. (2026) investigated the optimization of YOLOv11 for high-accuracy waste classification. These developments indicate that research has progressed beyond the basic question of whether deep learning can classify waste and now focuses on how detection models can balance accuracy, processing speed, and computational requirements.

The growing diversity of deep learning architectures has also expanded the methodological options available for waste detection and classification. Mounq et al. (2025) reviewed recent computer vision-based waste detection approaches involving R-CNN, YOLO, transformer, and hybrid models. Their review demonstrates that the selection of a computational model should consider the characteristics of the detection task and the requirements of the intended deployment environment. Different architectures may provide advantages in feature extraction, detection precision, inference speed, or computational efficiency. However, a direct comparison between models remains difficult when studies use different datasets, class definitions, evaluation metrics, and experimental conditions. Consequently, the increasing number of available architectures does not eliminate the need for systematic analysis of their practical relevance. A model with strong performance in a controlled benchmark may face limitations when deployed in a waste stream containing overlapping objects, irregular materials, variable lighting, or contaminated surfaces. Ramsurrun et al. (2021) demonstrated the use of computer vision and deep learning for recyclable waste classification, while Rijadi et al. (2025) examined automated waste detection and sorting using computer vision techniques in the context of smart waste management. Together, these studies reinforce the need to connect algorithmic performance with operational requirements.

The implementation of computer vision in waste management also requires integration with broader information and communication technologies. A detection model alone cannot constitute a complete smart waste management system because the system must also acquire data, process visual information, transmit results, and support subsequent operational actions. Mookkaiah et al. (2022) designed and developed an Internet of Things-based solid waste management system using computer vision, demonstrating how visual recognition can be integrated with connected technological infrastructure. Kaya (2023) similarly investigated the classification of waste materials within a smart garbage system designed to support sustainable development. The relationship between object detection and Internet of Things technology has become increasingly important as smart waste management systems seek to connect physical waste environments with digital monitoring and control mechanisms. A systematic literature review by Gelar et al. (2025) confirmed the growing convergence between YOLO and Internet of Things applications in smart waste management. This convergence creates opportunities for systems in which cameras and sensors collect environmental information, computer vision models classify waste objects, and networked infrastructure transmits information for monitoring or operational decision-making.

The architecture of smart waste management systems has also expanded through the use of embedded computing and cloud-based deployment. Firdaus et al. (2025) demonstrated the implementation of a YOLO-based system on a single-board computer, indicating the relevance of localized processing for real-time applications. In contrast, Zahra et al. (2026) implemented computer vision-based smart trash classification using Railway cloud deployment. These approaches represent different computational strategies. Localized or edge-oriented processing can reduce dependence on continuous data transmission and may support rapid inference near the data source, whereas cloud-based deployment can provide greater flexibility for system management and access to scalable computational infrastructure. The selection between these approaches depends on operational requirements, available hardware, communication conditions, and system design. The literature therefore suggests that the performance of a smart waste management system cannot be assessed solely from model accuracy. Deployment architecture, processing latency, computational resources, connectivity, and maintainability also influence the practical value of the system.

Despite the substantial progress in computer vision-based waste detection, important challenges remain concerning generalizability, environmental variability, dataset diversity, and computational efficiency. Waste objects differ significantly in appearance because of material degradation, deformation, contamination, partial occlusion, and variations in object orientation. Environmental conditions can also affect visual data through differences in illumination, shadows, camera distance, background composition, and object density. Córdova et al. (2022) addressed litter detection through comparative deep learning analysis, while Lu and Chen (2022) provided a critical review of computer vision applications for solid waste sorting. Jin et al. (2023) demonstrated the potential of machine vision for garbage detection and classification in recycling applications, but the effectiveness of such systems remains dependent on the relationship between training data and operational conditions. These findings indicate that high performance on benchmark datasets should not be considered sufficient evidence of deployment readiness. Computer vision systems should also be evaluated according to their capacity to maintain reliable performance across diverse environmental and material conditions.

Dataset quality and diversity therefore represent important factors in the development of robust waste detection systems. Aral et al. (2018) used the TrashNet dataset for deep learning-based classification, while Zhang et al. (2021) applied transfer learning to waste image classification. These studies demonstrate the value of structured datasets for model development and evaluation. However, datasets may represent only a limited range of waste objects and visual conditions. Waste categories used in one dataset may not correspond directly to the composition of waste in another location or operational environment. Similarly, the visual distinction between categories can become more difficult when materials are damaged or mixed. This issue is particularly relevant for automated sorting systems because classification errors can affect the separation of recyclable and non-recyclable materials. The challenge is therefore not limited to increasing the number of training images but also involves ensuring that datasets represent the visual and material diversity encountered during actual system operation.

Another important challenge concerns the relationship between detection accuracy and computational efficiency. Real-time systems must process visual information within a limited time while maintaining sufficient classification and localization performance. Maity et al. (2023), Firdaus et al. (2025), and Afuan et al. (2026) illustrate the continued use and development of YOLO-based approaches for waste classification and detection. These studies reflect the practical importance of balancing computational performance with implementation requirements. A highly complex model may provide detailed feature extraction but require greater computational resources, whereas a lightweight model may be more suitable for embedded deployment but face limitations under complex detection conditions. Mounq et al. (2025) further demonstrated the diversity of available architectures, including R-CNN, YOLO, transformers, and hybrid approaches. Therefore, model selection should consider the characteristics of the waste management environment rather than relying exclusively on a single performance indicator.

The relationship between computer vision and sustainability provides an additional rationale for the development of intelligent waste management systems. Effective waste classification can support downstream processes such as material recovery, recycling, and the separation of different waste streams. Kaya (2023) connected smart waste classification with sustainable development, while Jin et al. (2023) positioned deep learning-based machine vision as a tool for sustainable waste recycling. The broader review by Abdallah et al. (2020) also demonstrated that artificial intelligence can contribute to multiple stages of waste management. These perspectives suggest that the contribution of computer vision should be evaluated according to its potential operational role within the waste management process. Automated recognition is not an isolated objective. It can provide information that supports sorting, monitoring, collection planning, and recycling-related activities when integrated appropriately into a larger system.

The literature demonstrates substantial development across artificial intelligence-based waste classification, computer vision, object detection, real-time YOLO-based recognition, and smart waste management infrastructure. However, previous reviews have generally examined these developments from specific perspectives. Abdallah et al. (2020) reviewed the broader applications of artificial intelligence in solid waste management, while Lu and Chen (2022) focused on computer vision applications for solid waste sorting. More recent reviews have addressed particular technological developments, including the convergence of YOLO and Internet of Things technologies (Gelar et al., 2025), computer vision-based waste detection architectures (Mounq et al., 2025), and broader artificial intelligence approaches for waste classification (Yevle and Mann, 2025). These studies provide important foundations for understanding individual technological domains, but they do not explicitly connect the progression from image classification and object detection to real-time deployment while simultaneously examining the relationship between algorithmic development, embedded computing, Internet of Things connectivity, cloud infrastructure, and operational requirements. Thus, the existing literature provides valuable but relatively fragmented perspectives on technological development and system implementation.

The research gap addressed in this study is therefore not the absence of reviews on waste classification or computer vision, but the limited integration of technological progression and system-level implementation within a single analytical perspective. Previous reviews have not explicitly traced how the evolution from image classification to object detection and real-time YOLO-based systems corresponds with requirements for hardware deployment, connectivity, computational efficiency, scalability, and robustness under variable environmental conditions. This study addresses this gap by analyzing these developments as interconnected stages rather than as isolated research topics. The novelty of the study lies in this analytical synthesis, which connects the evolution of computer vision algorithms with the computational infrastructure and operational conditions required for their application in smart waste management. In this perspective, the study does not

seek merely to identify frequently used algorithms or summarize reported performance, but to examine how algorithmic capabilities and deployment requirements interact in the development of practical waste management systems.

Accordingly, this study aims to synthesize the development of waste detection and classification using computer vision and to analyze its role in supporting smart waste management systems. The study examines the progression from convolutional neural network-based image classification to object localization and real-time detection, with particular attention to YOLO-based approaches. It also analyzes the integration of computer vision with Internet of Things infrastructure, embedded computing, and cloud deployment. Furthermore, the study identifies implementation challenges related to dataset diversity, environmental variability, computational efficiency, connectivity, and system scalability. Rather than comparing individual models solely on reported performance, the study interprets the existing literature according to the relationship between visual recognition capabilities, computational infrastructure, deployment conditions, and operational waste management requirements.

This study contributes to the existing literature in three ways. First, it provides an integrated synthesis of foundational and recent studies published between 2018 and 2026 by connecting deep learning-based classification, object detection, YOLO architectures, Internet of Things integration, embedded computing, and cloud deployment within a single analytical perspective. Second, it contributes a system-level analysis by linking the evolution of computer vision tasks with the computational and infrastructural requirements of smart waste management, thereby extending beyond reviews that focus primarily on algorithms, datasets, or individual technological components. Third, it identifies the principal conditions influencing the transition from experimental waste detection models to operational systems, particularly dataset diversity, environmental variability, inference efficiency, connectivity, computational resources, and scalability. By connecting these dimensions, the study provides a structured interpretation of how algorithmic development and deployment architecture jointly influence the practical role of computer vision in smart waste management.

METHODS

Research Design

This study employed a structured literature-based research design to examine the development of computer vision approaches for waste detection and classification and their contribution to smart waste management systems. The study applied qualitative document analysis and comparative synthesis to identify technological developments, methodological patterns, implementation approaches, and recurring challenges reported in the selected literature.

The study did not involve primary data collection or new experimental observations. Instead, the analysis was based on scientific publications that met the predefined selection criteria. The analytical focus included artificial intelligence, deep learning, computer vision, object detection, waste classification, Internet of Things (IoT) integration, embedded computing, and cloud-based deployment. The analysis synthesized reported findings without introducing new variables, datasets, performance measurements, or experimental results.

Literature Search and Data Sources

The literature search was conducted using [database/search engine used in the study]. The search was performed on [search date] for publications published between 2018 and 2026. The search strategy used combinations of keywords related to the research objectives, including [insert the actual search keywords]. Boolean operators AND and OR were used to combine the search terms where appropriate.

The search strategy was designed to identify studies addressing computer vision and artificial intelligence applications in waste detection, waste classification, waste sorting, and smart waste management. The search results were subsequently assessed according to the predefined inclusion and exclusion criteria.

Inclusion and Exclusion Criteria

The selection of publications was based on predefined criteria to ensure that the final literature corpus was relevant to the research objectives. Publications were included when they met the following criteria:

1. the publication addressed artificial intelligence, machine learning, deep learning, computer vision, object detection, waste classification, waste sorting, or smart waste management;
2. the publication contained information relevant to the research objectives;
3. the publication was published between 2018 and 2026; and
4. sufficient information was available to identify the research focus, technological approach, implementation context, or principal contribution.

Publications were excluded when they met one or more of the following conditions:

1. the topic was not directly related to the research focus;
2. the publication was a duplicate record;
3. the publication did not provide sufficient information for the intended analysis;
4. the publication fell outside the defined publication period; or
5. the publication did not provide a substantive contribution to the technological or methodological dimensions examined in this study.

These criteria were applied consistently during the screening process. Therefore, the inclusion of a publication was determined by its relevance to the research objectives rather than by its presence in the original reference list.

Literature Screening and Selection Process

The literature selection was conducted through sequential screening stages. First, potentially relevant publications were identified through the specified database or search engine using the defined search terms. Second, duplicate publications were removed. Third, the titles and abstracts were screened to assess their preliminary relevance to the research objectives. Fourth, publications that passed the initial screening were assessed based on their available full-text content.

At the full-text stage, publications were assessed against the inclusion and exclusion criteria. Publications were eliminated when their content did not sufficiently address the research focus or when the information required for the analysis was unavailable. The reason for exclusion was recorded according to the applicable exclusion criterion.

After the screening and eligibility assessment, 19 publications were established as the final analytical corpus. These publications consisted of journal articles, conference proceedings, systematic reviews, critical reviews, and survey studies published between 2018 and 2026. The selected literature covered artificial intelligence applications in solid waste management, convolutional neural networks, transfer learning, computer vision, object detection, YOLO-based waste detection, smart garbage systems, IoT integration, embedded implementation, and cloud-based deployment.

Data Collection and Literature Extraction

Data were collected through structured document analysis. Each publication in the final corpus was examined using the same extraction categories to maintain consistency across studies. A literature extraction matrix was used as the primary analytical instrument.

The extraction matrix contained the following categories:

Table 1. Characteristics and Extraction Matrix of the 19 Selected Studies

No.	Extraction Category	Information Recorded
1	Author and year	Author(s) and publication year
2	Research focus	Main topic and research objective
3	Computational approach	AI, CNN, transfer learning, object detection, YOLO, IoT, embedded computing, or cloud deployment
4	Analytical task	Image classification, localization, object detection, automated sorting, or system integration
5	Dataset/data context	Dataset, image source, or data environment reported in the study
6	Implementation context	Machine vision, smart garbage system, embedded device, IoT infrastructure, or cloud-based application
7	Main contribution	Principal contribution reported by the publication
8	Relevance	Relationship between the publication and the research objectives

The extraction process was applied to all 19 selected publications. The computational approach category was used to identify the principal technology employed in each study, while the analytical task category distinguished between image classification, object localization, object detection, automated sorting, and system-level integration. The implementation context was used to identify the environment in which the proposed or evaluated technology was applied.

Data Analysis

The extracted data were analyzed using qualitative content analysis and comparative synthesis. The analysis was conducted in three stages.

First, the publications were organized according to their principal technological orientation. The studies were categorized into five analytical groups: (1) artificial intelligence and research synthesis; (2) deep learning and image classification; (3) object localization and detection; (4) YOLO-based real-time detection and automated sorting; and (5) smart system integration through IoT, embedded computing, or cloud deployment.

Second, the publications were compared to identify similarities and differences in research focus, computational approaches, analytical tasks, and implementation contexts. Particular attention was given to the development from conventional image classification toward object localization and detection. The analysis also considered the increasing emphasis on real-time processing, computational efficiency, hardware implementation, connectivity, and system deployment.

Third, the findings were synthesized to identify recurring technological challenges and implementation considerations relevant to smart waste management. The synthesis examined themes reported across the selected literature, including dataset diversity, environmental variability, object overlap, background complexity, computational limitations, deployment requirements, and system scalability.

The analysis was qualitative and did not involve statistical aggregation of study results. No new accuracy values, statistical indicators, effect sizes, or experimental measurements were calculated. All interpretations were based on findings reported in the selected publications and were synthesized according to the predefined analytical categories.

Research Rigor

Research rigor was maintained through the consistent application of the predefined inclusion and exclusion criteria, screening procedure, and literature extraction matrix. The same extraction categories were applied to all 19 publications to ensure comparability across studies with different research designs and technological approaches.

The analysis also distinguished between findings explicitly reported by the selected publications and interpretations developed through comparative synthesis. No empirical data were modified, combined, or newly generated. The final synthesis was therefore based exclusively on the evidence reported in the selected literature.

The documented procedures for literature searching, screening, selection, extraction, and qualitative synthesis provide a transparent basis for tracing the establishment of the final 19-publication corpus and the subsequent analytical process.

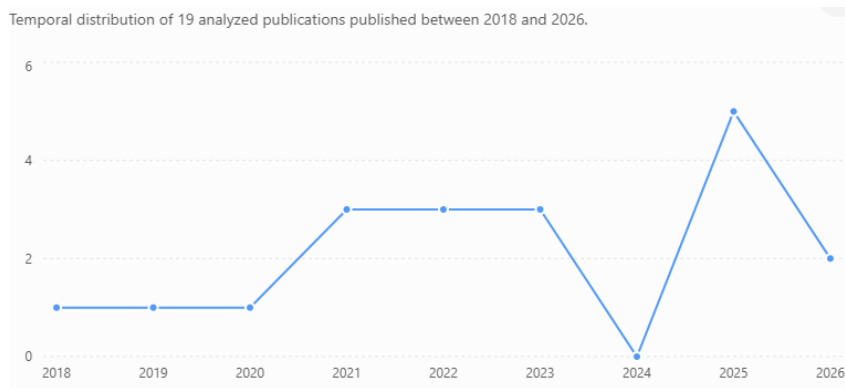
RESULTS AND DISCUSSION

Distribusi Publikasi Berdasarkan Tahun

Analisis dilakukan terhadap 19 publikasi yang termasuk dalam korpus referensi penelitian. Publikasi yang dianalisis mencakup periode 2018 sampai 2026. Distribusi publikasi berdasarkan tahun menunjukkan perubahan intensitas penelitian pada bidang computer vision untuk pengelolaan sampah. Jumlah publikasi tertinggi terdapat pada tahun 2025, yaitu lima publikasi atau 26,32% dari keseluruhan publikasi. Selanjutnya, tahun 2021, 2022, dan 2023 masing-masing menghasilkan tiga publikasi atau 15,79%. Pada tahun 2018, 2019, dan 2020 masing-masing terdapat satu publikasi atau 5,26%, sedangkan tahun 2024 tidak terdapat publikasi dalam korpus yang dianalisis. Pada tahun 2026 terdapat dua publikasi atau 10,53%.

Tabel 1. Distribusi publikasi yang dianalisis berdasarkan tahun

Tahun publikasi	Jumlah publikasi	Persentase (%)
2018	1	5,26
2019	1	5,26
2020	1	5,26
2021	3	15,79
2022	3	15,79
2023	3	15,79
2024	0	0,00
2025	5	26,32
2026	2	10,53
Total	19	100,00



Gambar 1. Distribution of the Analyzed Publications by Year

Distribusi temporal menunjukkan bahwa penelitian computer vision untuk pengelolaan sampah mengalami perkembangan dari kajian awal mengenai klasifikasi citra menuju penerapan sistem deteksi yang lebih kompleks. Penelitian pada periode awal, seperti Aral et al. (2018) dan Adedeji dan Wang (2019), berfokus pada pemanfaatan deep learning dan convolutional neural network untuk mengenali kategori sampah. Abdallah et al. (2020) memperluas cakupan pembahasan dengan menempatkan artificial intelligence dalam konteks pengelolaan sampah secara lebih luas. Periode 2021 sampai 2023 menunjukkan peningkatan perhatian terhadap localization, object detection, transfer learning, machine vision, dan sistem pengelolaan sampah berbasis teknologi cerdas.

Perubahan tersebut menunjukkan bahwa perkembangan penelitian tidak hanya ditandai oleh bertambahnya jumlah publikasi, tetapi juga oleh perubahan fokus teknis. Penelitian awal lebih menekankan kemampuan model dalam mengenali kelas objek berdasarkan citra. Penelitian berikutnya mulai memperhatikan lokasi objek, deteksi beberapa objek, kebutuhan pemrosesan secara real-time, serta integrasi model computer vision dengan perangkat dan infrastruktur pendukung. Dengan demikian, perkembangan temporal dalam korpus penelitian dapat dipahami sebagai perubahan dari pendekatan klasifikasi menuju pendekatan yang lebih berorientasi pada penerapan.

Konsentrasi publikasi pada tahun 2025 memperkuat kecenderungan tersebut. Firdaus et al. (2025) menerapkan deteksi sampah berbasis YOLO secara real-time pada single-board computer, sedangkan Gelar et al. (2025) membahas integrasi YOLO dengan Internet of Things. Mounq et al. (2025) membandingkan beberapa kelompok arsitektur, yaitu R-CNN, YOLO, transformer, dan pendekatan hybrid. Rijadi et al. (2025) membahas deteksi dan pemilahan sampah otomatis berbasis computer vision, sementara Yevle dan Mann (2025) memberikan kajian yang lebih luas mengenai klasifikasi sampah berbasis artificial intelligence. Kehadiran beberapa orientasi penelitian tersebut pada periode yang sama menunjukkan bahwa bidang ini telah berkembang dari pengembangan model menuju evaluasi pendekatan, integrasi sistem, dan implementasi teknologi.

Pola Perkembangan Teknologi Deteksi dan Klasifikasi Sampah

Berdasarkan 19 publikasi yang dianalisis, perkembangan teknologi dapat dikelompokkan menjadi enam orientasi utama, yaitu artificial intelligence dan sintesis penelitian, deep learning dan image

classification, localization dan object detection, YOLO-based real-time detection, smart system integration, serta comparative and critical review.

Tabel 2. Perkembangan teknologi yang diidentifikasi dalam literatur

Orientasi teknologi	Studi representatif	Kontribusi utama
Artificial intelligence dan research synthesis	Abdallah et al. (2020); Yevle dan Mann (2025)	Membahas perkembangan dan penerapan artificial intelligence dalam pengelolaan sampah
Deep learning dan image classification	Aral et al. (2018); Adedeji dan Wang (2019); Zhang et al. (2021); Ramsurrun et al. (2021)	Menerapkan deep learning, CNN, dan transfer learning untuk pengenalan dan klasifikasi sampah
Localization dan object detection	Liang dan Gu (2021); Córdova et al. (2022); Jin et al. (2023)	Mengembangkan pengenalan dari klasifikasi citra menuju localization dan object detection
YOLO-based real-time detection	Maity et al. (2023); Firdaus et al. (2025); Afuan et al. (2026)	Menerapkan arsitektur YOLO untuk deteksi dan klasifikasi sampah otomatis secara real-time
Smart system integration	Mookkaiah et al. (2022); Kaya (2023); Gelar et al. (2025); Rijadi et al. (2025); Zahra et al. (2026)	Mengintegrasikan computer vision dengan smart garbage system, IoT, pemilahan otomatis, dan cloud
Comparative and critical review	Lu dan Chen (2022); Mounq et al. (2025)	Menganalisis tren penelitian, arsitektur model, dan tantangan implementasi

Pola pada Tabel 2 memperlihatkan adanya perluasan fungsi computer vision dalam pengelolaan sampah. Tahap awal terutama berorientasi pada image classification, yaitu menentukan kategori sampah berdasarkan citra. Aral et al. (2018) menggunakan deep learning untuk klasifikasi citra sampah, sedangkan Adedeji dan Wang (2019) menerapkan convolutional neural network dalam klasifikasi sampah. Zhang et al. (2021) kemudian menunjukkan penggunaan transfer learning sebagai pendekatan dalam klasifikasi citra sampah. Ramsurrun et al. (2021) juga memperlihatkan penerapan deep learning untuk pengenalan sampah.

Pendekatan klasifikasi memiliki fungsi penting sebagai dasar pengenalan kategori sampah. Namun, klasifikasi tingkat gambar tidak selalu memberikan informasi mengenai lokasi objek. Keterbatasan tersebut mendorong perkembangan menuju object detection dan localization. Liang dan Gu (2021) menggabungkan proses localization dengan recognition, sedangkan Córdova et al. (2022) membahas deteksi litter melalui pendekatan deep learning. Jin et al. (2023) kemudian menerapkan machine vision untuk mendukung deteksi dan klasifikasi sampah dalam konteks recycling. Perubahan ini menunjukkan bahwa kebutuhan sistem berkembang dari sekadar mengetahui jenis sampah menjadi kemampuan untuk menentukan keberadaan dan posisi objek di dalam citra.

Perbedaan utama antara pendekatan klasifikasi dan object detection terletak pada keluaran sistem. Klasifikasi berorientasi pada penentuan kategori citra atau objek, sedangkan object detection memberikan informasi mengenai kategori sekaligus lokasi objek. Perbedaan tersebut menjadi penting ketika satu citra mengandung beberapa objek sampah atau ketika sistem digunakan sebagai bagian dari proses pemilahan otomatis. Dengan demikian, perkembangan menuju object detection menunjukkan peningkatan kebutuhan informasi visual untuk mendukung proses operasional.

Perkembangan Deteksi Real-Time Berbasis YOLO

Kelompok penelitian berikutnya menunjukkan peningkatan perhatian terhadap deteksi real-time. Maity et al. (2023) menerapkan YOLO untuk klasifikasi sampah otomatis. Firdaus et al. (2025) mengembangkan deteksi sampah real-time menggunakan YOLO pada single-board computer, sedangkan Afuan et al. (2026) mengkaji optimasi YOLOv11 untuk klasifikasi sampah dengan fokus pada akurasi.

Penggunaan YOLO menunjukkan perubahan orientasi dari sekadar kemampuan mengenali objek menuju kebutuhan pemrosesan yang dapat digunakan dalam sistem operasional. Dalam sistem real-time, model tidak hanya harus mampu mengenali objek, tetapi juga harus dapat menghasilkan keluaran dalam waktu yang sesuai dengan kebutuhan aplikasi. Oleh karena itu, pemilihan model perlu mempertimbangkan karakteristik komputasi dan lingkungan implementasi.

Temuan tersebut sejalan dengan kajian Mounq et al. (2025) yang membahas beberapa arsitektur deep learning, termasuk R-CNN, YOLO, transformer, dan model hybrid. Keberagaman arsitektur menunjukkan

bahwa tidak terdapat satu pendekatan yang dapat dipisahkan dari konteks penerapannya. Model yang diterapkan pada perangkat embedded memiliki kebutuhan komputasi yang berbeda dari model yang dijalankan pada lingkungan cloud. Demikian pula, sistem pemilahan real-time memerlukan pertimbangan terhadap waktu pemrosesan selain kemampuan pengenalan.

Dengan demikian, perkembangan YOLO dalam literatur tidak semata-mata menunjukkan pergantian algoritma, tetapi juga mencerminkan perubahan kebutuhan penelitian. Fokus penelitian semakin mengarah pada hubungan antara model deteksi, kebutuhan real-time, sumber daya komputasi, dan lingkungan implementasi. Hal ini menjadi aspek penting karena performa suatu model dalam lingkungan pengujian tidak secara otomatis menunjukkan kesiapan model untuk digunakan dalam sistem operasional.

Integrasi Computer Vision dengan Sistem Cerdas

Perkembangan lain yang terlihat jelas adalah integrasi computer vision dengan Internet of Things, perangkat embedded, sistem pemilahan otomatis, dan cloud. Mookkaiah et al. (2022) mengembangkan sistem pengelolaan sampah berbasis Internet of Things yang menggunakan computer vision. Kaya (2023) mengkaji klasifikasi sampah dalam smart garbage system. Gelar et al. (2025) membahas konvergensi YOLO dan Internet of Things, sedangkan Rijadi et al. (2025) menghubungkan deteksi sampah dengan proses pemilahan otomatis. Zahra et al. (2026) memperluas pendekatan tersebut melalui penerapan cloud untuk klasifikasi sampah cerdas.

Temuan tersebut menunjukkan bahwa computer vision semakin diposisikan sebagai salah satu komponen dalam arsitektur sistem yang lebih luas. Model computer vision berfungsi menghasilkan informasi visual mengenai objek sampah, sedangkan perangkat embedded, sensor, jaringan komunikasi, dan cloud dapat mendukung pemrosesan, komunikasi, penyimpanan, serta akses terhadap informasi tersebut. Dengan pendekatan ini, proses deteksi tidak berdiri sendiri, tetapi menjadi bagian dari alur pengelolaan sampah berbasis sistem cerdas.

Perbandingan implementasi pada single-board computer dan cloud menunjukkan adanya perbedaan kebutuhan arsitektur. Implementasi embedded memungkinkan pemrosesan lebih dekat dengan sumber data, tetapi memiliki keterbatasan sumber daya komputasi. Sebaliknya, cloud dapat menyediakan lingkungan komputasi dan penyimpanan yang lebih luas, tetapi membutuhkan konektivitas jaringan dan arsitektur komunikasi yang sesuai. Oleh karena itu, kedua pendekatan tersebut tidak perlu diposisikan sebagai pendekatan yang saling menggantikan. Pemilihannya bergantung pada kebutuhan operasional, sumber daya perangkat, konektivitas, serta karakteristik sistem yang dikembangkan.

Perbandingan Keunggulan dan Keterbatasan Pendekatan

Sintesis terhadap literatur menunjukkan bahwa setiap kelompok teknologi memiliki fungsi dan keterbatasan yang berbeda. Deep learning dan CNN memberikan dasar bagi pengenalan pola visual, sedangkan transfer learning dapat digunakan untuk memanfaatkan model yang telah dilatih sebelumnya dalam proses klasifikasi. Namun, pendekatan klasifikasi memiliki keterbatasan ketika sistem membutuhkan informasi lokasi objek.

Object detection memberikan informasi yang lebih sesuai untuk skenario dengan banyak objek atau kebutuhan pemilahan berdasarkan posisi. Namun, peningkatan fungsi deteksi juga meningkatkan kebutuhan pemrosesan dan kompleksitas implementasi. Córdova et al. (2022), Liang dan Gu (2021), dan Jin et al. (2023) menunjukkan perkembangan penelitian ke arah deteksi dan localization sebagai respons terhadap kebutuhan tersebut.

YOLO memberikan orientasi yang lebih kuat terhadap penggunaan real-time. Maity et al. (2023), Firdaus et al. (2025), dan Afuan et al. (2026) menunjukkan pemanfaatan YOLO dalam deteksi atau klasifikasi sampah. Meskipun demikian, penggunaan YOLO tidak menghilangkan kebutuhan untuk mempertimbangkan sumber daya komputasi, kondisi visual, dan kebutuhan sistem. Kajian Moung et al. (2025) juga menunjukkan bahwa R-CNN, transformer, dan pendekatan hybrid tetap menjadi bagian dari perkembangan teknologi deteksi.

Integrasi dengan IoT dan cloud memperluas kemampuan sistem dari pemrosesan citra menjadi sistem pengelolaan yang terhubung. Keunggulannya terletak pada kemampuan mendukung komunikasi, monitoring, dan pengelolaan data. Namun, pendekatan tersebut memperkenalkan ketergantungan tambahan terhadap perangkat keras, jaringan komunikasi, konektivitas, dan arsitektur sistem. Oleh sebab itu, semakin terintegrasi suatu sistem, semakin banyak komponen yang harus dipertimbangkan dalam proses implementasinya.

Tantangan Implementasi Teknologi

Sintesis literatur mengidentifikasi beberapa tantangan utama, yaitu keragaman dataset, localization dan multiple-object detection, variasi lingkungan, kebutuhan pemrosesan real-time, integrasi sistem, arsitektur deployment, serta keberagaman model.

Tabel 3. Tantangan implementasi yang diidentifikasi dalam literatur

Tantangan implementasi	Studi pendukung	Implikasi
Keragaman dataset dan variasi kategori	Aral et al. (2018); Zhang et al. (2021); Ramsurrun et al. (2021)	Model membutuhkan data visual yang representatif agar dapat diterapkan pada kondisi sampah yang beragam
Localization dan multiple-object detection	Liang dan Gu (2021); Córdova et al. (2022); Jin et al. (2023)	Sistem perlu mengenali kategori sekaligus posisi objek dalam kondisi visual yang kompleks
Variasi lingkungan	Córdova et al. (2022); Lu dan Chen (2022)	Pencahayaan, latar belakang, dan tampilan objek dapat memengaruhi proses deteksi
Pemrosesan real-time dan efisiensi komputasi	Maity et al. (2023); Firdaus et al. (2025); Afuan et al. (2026)	Implementasi memerlukan keseimbangan antara kemampuan deteksi dan kebutuhan komputasi
Integrasi sistem	Mookkaiah et al. (2022); Kaya (2023); Gelar et al. (2025)	Computer vision perlu dihubungkan dengan sensor, IoT, dan sistem operasional
Arsitektur deployment	Firdaus et al. (2025); Zahra et al. (2026)	Implementasi embedded dan cloud memiliki kebutuhan komputasi dan konektivitas yang berbeda
Keragaman model dan evaluasi komparatif	Moung et al. (2025); Yevle dan Mann (2025)	Pemilihan algoritma perlu disesuaikan dengan kebutuhan aplikasi dan batasan implementasi

Tantangan tersebut menunjukkan bahwa efektivitas teknologi tidak dapat dipisahkan dari kondisi penerapannya. Dataset yang digunakan untuk melatih dan menguji model harus merepresentasikan variasi objek dan kondisi visual yang menjadi target sistem. Selain itu, perubahan pencahayaan, latar belakang, posisi objek, dan keberadaan beberapa objek dalam satu citra dapat meningkatkan kompleksitas proses deteksi. Karena itu, hasil benchmark tidak dapat secara langsung digunakan sebagai satu-satunya dasar untuk menyatakan kesiapan sistem dalam lingkungan operasional.

Permasalahan tersebut juga berkaitan dengan kebutuhan real-time. Sistem yang digunakan untuk pemilahan otomatis membutuhkan waktu respons yang sesuai dengan proses operasional. Model dengan kemampuan pengenalan yang baik tetapi membutuhkan sumber daya komputasi besar dapat menghadapi kendala ketika diterapkan pada perangkat dengan kapasitas terbatas. Sebaliknya, model yang lebih ringan dapat lebih sesuai untuk perangkat embedded, tetapi pemilihannya tetap harus mempertimbangkan kebutuhan pengenalan objek dan karakteristik lingkungan.

Dengan demikian, pemilihan teknologi sebaiknya dilakukan berdasarkan kesesuaian antara karakteristik model dan kebutuhan sistem. Faktor seperti kompleksitas citra, jumlah objek, waktu respons, sumber daya komputasi, kebutuhan konektivitas, dan arsitektur deployment perlu dipertimbangkan secara bersamaan. Pendekatan ini memberikan dasar analisis yang lebih komprehensif dibandingkan pemilihan model hanya berdasarkan performa klasifikasi.

Sintesis Tren dan Research Gap

Secara keseluruhan, korpus penelitian menunjukkan tiga perubahan utama. Pertama, terjadi perubahan dari image classification menuju object detection dan localization. Kedua, penelitian semakin memberikan perhatian terhadap real-time detection, khususnya melalui arsitektur YOLO. Ketiga, computer vision semakin diintegrasikan dengan IoT, embedded computing, automated sorting, dan cloud deployment.

Perubahan tersebut menunjukkan bahwa arah penelitian telah bergerak dari pengembangan model secara terpisah menuju pengembangan sistem yang mempertimbangkan lingkungan implementasi. Pada tahap awal, perhatian utama berada pada kemampuan model dalam mengenali kategori sampah. Pada tahap

berikutnya, perhatian berkembang pada kemampuan mendeteksi lokasi objek dan menangani kondisi visual yang lebih kompleks. Penelitian terbaru kemudian memperluas perhatian pada real-time processing dan integrasi sistem.

Meskipun demikian, hasil sintesis menunjukkan masih terdapat ruang penelitian pada hubungan antara model computer vision dan kondisi implementasi nyata. Literatur telah membahas klasifikasi, object detection, YOLO, IoT, embedded computing, dan cloud secara terpisah maupun terintegrasi. Namun, tantangan seperti keberagaman dataset, variasi lingkungan, keterbatasan sumber daya komputasi, kebutuhan real-time, dan integrasi perangkat menunjukkan bahwa pengembangan sistem belum hanya menjadi persoalan pemilihan algoritma.

Research gap yang dapat diidentifikasi adalah kebutuhan untuk memperkuat hubungan antara karakteristik model, karakteristik data, sumber daya perangkat, dan kebutuhan operasional sistem. Kajian terhadap arsitektur model perlu dihubungkan dengan lingkungan deployment sehingga pemilihan teknologi tidak hanya mempertimbangkan kemampuan deteksi, tetapi juga kesesuaiannya dengan kondisi penggunaan.

Dengan demikian, penelitian selanjutnya dapat diarahkan pada evaluasi yang lebih terintegrasi antara computer vision dan lingkungan implementasi. Fokus tersebut mencakup representasi dataset yang lebih beragam, kemampuan deteksi pada kondisi visual yang berbeda, efisiensi pemrosesan pada perangkat dengan sumber daya terbatas, serta integrasi dengan IoT dan cloud sesuai kebutuhan sistem. Arah tersebut merupakan konsekuensi dari pola yang ditemukan dalam literatur, bukan hasil pengukuran eksperimental baru.

Implikasi terhadap Smart Waste Management

Hasil analisis menunjukkan bahwa computer vision telah berkembang dari teknologi klasifikasi citra menjadi komponen dalam smart waste management. Artificial intelligence menyediakan kemampuan pengenalan, object detection memberikan informasi lokasi dan kategori objek, sedangkan YOLO menawarkan pendekatan untuk kebutuhan deteksi real-time. Integrasi dengan IoT, perangkat embedded, dan cloud selanjutnya memungkinkan hasil deteksi digunakan dalam sistem yang lebih luas.

Implikasi utama dari perkembangan tersebut adalah kebutuhan untuk merancang sistem berdasarkan keterkaitan antara model dan lingkungan implementasi. Model computer vision menghasilkan informasi mengenai objek sampah, sementara perangkat dan infrastruktur jaringan mendukung pemrosesan, komunikasi, monitoring, serta akses terhadap data. Firdaus et al. (2025) dan Zahra et al. (2026) menunjukkan dua arah implementasi melalui single-board computing dan cloud deployment.

Berdasarkan sintesis 19 publikasi, perkembangan teknologi dapat dirangkum sebagai berikut:

CNN/deep learning → transfer learning → object detection/localization → YOLO real-time detection → embedded implementation → IoT integration → cloud-connected smart waste management.

Rangkaian tersebut menunjukkan bahwa perkembangan penelitian tidak hanya berupa peningkatan kompleksitas algoritma, tetapi juga perluasan ruang lingkup penerapan. Teknologi yang dikembangkan semakin diarahkan untuk memenuhi kebutuhan sistem pengelolaan sampah yang terhubung dan dapat digunakan dalam lingkungan operasional.

Secara keseluruhan, analisis deskriptif terhadap korpus publikasi menunjukkan perkembangan yang konsisten menuju teknologi pengelolaan sampah yang lebih terintegrasi, real-time, dan berorientasi pada deployment. Namun, penerapan praktis tetap dipengaruhi oleh keragaman dataset, kondisi lingkungan, efisiensi komputasi, dan integrasi sistem. Oleh karena itu, pengembangan penelitian tidak cukup hanya berfokus pada peningkatan kemampuan model secara individual, tetapi juga perlu mempertimbangkan hubungan antara computer vision, sumber daya perangkat keras, infrastruktur komunikasi, dan kebutuhan operasional smart waste management.

CONCLUSION

This study synthesizes the development of computer vision-based waste detection and classification to support smart waste management systems using the existing scientific literature published between 2018 and 2026. The findings indicate a clear technological progression from conventional image classification using convolutional neural networks toward object localization, real-time detection, YOLO-based architectures, and integrated smart waste management systems. Recent studies also demonstrate the increasing integration of computer vision with Internet of Things infrastructure, single-board computing, automated sorting, and cloud-based deployment.

The analysis shows that computer vision can support automated waste recognition and provide information for sorting, monitoring, and recycling-related processes. However, practical implementation remains influenced by dataset diversity, variations in waste appearance, environmental conditions, object overlap, computational requirements, and deployment architecture. Therefore, model performance should not be evaluated solely through classification or detection capability but also through its suitability for the intended operational environment.

The study implies that the development of smart waste management systems requires an integrated approach that combines reliable computer vision models with appropriate hardware, communication infrastructure, and data-processing mechanisms. Future research should focus on evaluating existing approaches using more diverse real-world waste conditions and comparing different deployment architectures based on the same operational requirements. Such efforts can strengthen the transition of computer vision technologies from experimental research toward scalable and practically applicable smart waste management systems.

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