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Artificial Intelligence in Smart Waste Management: International Applications, Challenges, and Opportunities for Indonesia

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Abstract

Indonesia faces significant waste management challenges due to the high volume of unmanaged waste, inefficient sorting, and continued reliance on conventional disposal practices. This study aims to examine the role and implementation of Artificial Intelligence (AI) in waste sorting and management and its potential application in Indonesia. A Narrative Literature Review (NLR) was conducted by analyzing relevant studies obtained through Google Scholar using keywords related to AI, waste management, computer vision, and waste classification. The findings indicate that AI has been applied to automated waste identification, classification, real-time detection, monitoring, and robotic sorting. Applications of computer vision, deep learning, object detection, and robotic systems demonstrate potential to improve sorting accuracy, processing speed, operational efficiency, and recycling. Comparative evidence from Bangladesh, Vietnam, India, Russia, and the United Kingdom shows diverse approaches to AI-based waste management. For Indonesia, AI adoption should be adapted to local waste characteristics, infrastructure, datasets, and human resource capacity. A gradual integration of AI with digital infrastructure and automated systems can support more efficient and sustainable waste management.

Keywords: artificial intelligence, intelligent waste management, automated waste sorting, computer vision, deep learning, smart waste management.

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Introduction

The waste management problem in Indonesia has reached a critical stage and requires comprehensive, systematic, and technology-driven interventions. Rapid population growth, urbanization, economic development, and changes in consumption patterns have contributed to a continuous increase in waste generation across the country [1]. However, the capacity of existing waste management systems has not developed at a comparable rate. By the end of 2025, national waste management is projected to reach only approximately 25%, equivalent to around

36,684 tons of waste per day, while the remaining 75%, or approximately 105,483 tons per day, remains inadequately managed and continues to pose substantial risks to environmental quality [2]. This imbalance indicates that waste generation and waste management capacity remain significantly disproportionate, creating persistent environmental, social, and public health challenges.

One of the major challenges in Indonesia's waste management system is the continued reliance on conventional disposal practices, particularly open dumping. The open dumping method involves the disposal of waste in open areas without sufficient treatment, containment, or systematic covering [3]. Such practices can generate a range of environmental consequences, including soil, surface water, and groundwater contamination caused by leachate, as well as air pollution resulting from the decomposition of organic waste and the uncontrolled release of gases [4]. In addition to environmental degradation, poorly managed disposal sites can create unpleasant odors, attract disease vectors, and contribute to greenhouse gas emissions. These consequences demonstrate that waste management cannot be addressed solely through waste collection and final disposal; rather, it requires an integrated approach encompassing waste reduction, segregation, collection, transportation, treatment, recycling, recovery, and environmentally responsible final disposal.

Waste sorting represents a particularly important component of an effective waste management system. Proper separation of waste at the source or during subsequent processing can improve the recovery of recyclable materials, facilitate organic waste treatment, reduce the volume of waste transported to disposal facilities, and increase the efficiency of downstream treatment processes. Nevertheless, waste sorting in Indonesia continues to face various operational and technological challenges. Conventional sorting processes frequently depend on manual labor, which may be associated with limitations in sorting speed, consistency, accuracy, and scalability [5]. The heterogeneous composition of municipal solid waste further complicates the identification and classification of waste materials. Consequently, improvements in waste sorting technologies are essential for establishing a more efficient and sustainable waste management infrastructure.

The technological capacity supporting waste management in Indonesia also remains relatively limited compared with the technologies implemented in several developed countries. One example is Waste-to-Energy (WtE) technology, which enables waste to be processed and converted into useful energy while potentially reducing the amount of waste requiring final disposal [6]. Although WtE has been adopted in a number of countries as part of integrated waste management strategies, its implementation in Indonesia remains relatively limited [7]. This situation highlights the need not only to improve waste treatment facilities but also to develop intelligent technologies that can optimize decision-making throughout the waste management process. Accordingly, technological innovation should be directed toward improving waste identification, sorting accuracy, operational efficiency, resource recovery, and environmental monitoring.

The rapid advancement of digital technologies provides new opportunities to address these challenges. Among emerging technologies, Artificial Intelligence (AI) has considerable potential to transform conventional waste management into a more intelligent, adaptive, and data-driven system. AI refers to computational approaches that enable systems to perform tasks commonly associated with human intelligence, including recognition, classification, prediction, optimization, and decision-making [8]. In the context of waste management, these capabilities can be applied to automate waste identification and classification, optimize collection and transportation processes, predict waste generation patterns, monitor waste facilities, and support resource recovery [9]. The application of AI therefore provides an opportunity to move beyond conventional waste management approaches toward systems capable of responding dynamically to changing waste conditions.

Computer vision and machine learning, for example, can be employed to recognize and classify waste materials based on visual characteristics such as shape, color, texture, and material composition. Such technologies can potentially support automated sorting systems and reduce dependence on manual classification. Furthermore, AI can be integrated with sensors and Internet of Things (IoT) technologies to enable continuous monitoring of waste containers, collection points, and treatment facilities [10]. The resulting data can be analyzed to identify waste accumulation patterns, estimate waste volumes, and optimize collection schedules. The integration of AI with digital technologies is considered capable of supporting real-time monitoring of waste conditions, thereby increasing the efficiency and responsiveness of waste management operations [11].

Beyond automated sorting and monitoring, AI can contribute to waste management through predictive analytics and optimization. Historical and real-time data can be processed to identify patterns in waste generation and predict future waste volumes. Such predictions can assist waste management authorities and service providers in allocating collection vehicles, determining optimal routes, planning treatment capacity, and managing operational resources [12]. AI-based optimization can consequently contribute to reductions in unnecessary transportation, fuel consumption, operational costs, and associated environmental impacts. These applications illustrate that the potential contribution of AI extends across multiple stages of the waste management value chain rather than being limited to waste classification.

Despite this potential, the implementation of AI in waste management requires careful consideration of technological, infrastructural, organizational, and contextual factors. AI-based systems depend on the availability and quality of datasets, computational infrastructure, sensors, imaging devices, and reliable digital connectivity [13]. Waste characteristics also differ substantially across geographical regions, communities, consumption patterns, and socioeconomic contexts. Consequently, AI models developed in one country or environmental setting may not necessarily achieve comparable performance when directly applied to another context. Issues related to data availability, model accuracy, system costs, interoperability, scalability, and human resource capabilities must therefore be considered when assessing the feasibility of AI-based waste management solutions.

Moreover, the development of AI-enabled waste management should be viewed within the broader framework of sustainable development and the circular economy. Effective waste management is not merely concerned with reducing the quantity of waste disposed of in landfills or open dumping sites [14]. It also seeks to maximize material recovery, increase recycling, promote resource efficiency, and minimize environmental impacts throughout the waste lifecycle. AI can support these objectives by improving the identification of recyclable materials, optimizing recovery processes, and generating data-driven insights for waste management planning [15]. The convergence of AI, computer vision, IoT, sensor technology, and data analytics therefore has the potential to create more integrated and intelligent waste management ecosystems.

Although research on AI applications in waste management has increased, the existing body of knowledge remains dispersed across different technological applications, waste categories, and geographical contexts. Studies have explored automated waste classification, intelligent collection systems, predictive waste generation, environmental monitoring, and waste-to-energy applications; however, a comprehensive understanding of the role of AI across these different dimensions is still needed [16]. In particular, identifying how AI technologies have been applied in different countries can provide valuable insights into technological trends, implementation approaches, benefits, and challenges. Such an analysis is also important for determining which AI applications may be relevant to the Indonesian context, where waste management challenges are characterized by high waste generation, inadequate management capacity, conventional disposal practices, and limited adoption of advanced treatment technologies.

Therefore, a systematic examination of previous research is necessary to synthesize the current development of AI-based waste management and identify opportunities for further technological development. Understanding the evolution of AI applications across countries can provide a foundation for identifying research gaps and determining future research directions, particularly in relation to automated sorting, intelligent monitoring, predictive analytics, resource recovery, and sustainable waste management [17]. The findings may also contribute to the development of technology-oriented waste management strategies that are more efficient, adaptive, and environmentally sustainable.

Accordingly, this study aims to identify and analyze the role of Artificial Intelligence in waste management and examine its applications across various countries based on previous research. Specifically, the study seeks to synthesize the major applications of AI in waste management, identify the technologies and approaches that have been implemented, examine their potential contributions to waste sorting and management efficiency, and identify challenges and future opportunities for AI-enabled sustainable waste management. The results are expected to provide a comprehensive overview of the current state of AI applications in waste management and serve as a reference for researchers, policymakers, technology developers, and waste management practitioners in designing more intelligent and sustainable waste management systems.

Method

This study employed a Narrative Literature Review (NLR) approach to identify, examine, and synthesize previous research concerning the application of Artificial Intelligence (AI) in waste sorting and waste management. A Narrative Literature Review was selected because it enables the researcher to integrate findings from diverse studies and provide a comprehensive conceptual understanding of a research topic. Unlike a systematic review that generally follows a highly structured protocol for study identification and statistical or structured synthesis, NLR emphasizes the interpretation, comparison, and integration of findings from relevant literature to describe the development of knowledge within a particular field [18]. In this study, the NLR approach was used to examine the development of AI applications in waste management, identify the technological approaches that have been implemented, compare findings across countries, and synthesize the potential contribution of AI to more efficient and sustainable waste management.

The research process consisted of five main stages: (1) topic formulation, (2) literature identification and searching, (3) literature selection, (4) literature analysis, and (5) synthesis and interpretation of findings. These stages were conducted sequentially to ensure that the literature included in the review was relevant to the research objectives.

In the first stage, the research topic and scope were defined by focusing on the application of AI technologies in waste sorting and waste management. The scope included, but was not limited to, AI-based waste classification, computer vision for automated waste sorting, intelligent waste collection, waste monitoring, predictive analysis, and other AI-supported waste management applications. The geographical scope was not restricted to Indonesia because the study also aimed to identify implementations and technological developments in various countries that could provide insights for the Indonesian context.

In the second stage, literature searching was conducted using Google Scholar as the primary literature search platform. Several combinations of keywords were used to identify publications relevant to the research topic, including *"Artificial Intelligence," "AI in waste management," "waste management," "smart waste management," "computer vision," "waste classification," "automated waste sorting,"* and *"AI-based waste sorting."* The search strategy was designed to capture studies addressing both the technological aspects of AI and its practical applications in waste management. Relevant references identified from the initial search were subsequently examined based on their titles, abstracts, keywords, and full-text content where available.

The third stage involved the selection of relevant literature. Articles were considered for inclusion when they discussed the application, development, evaluation, or potential use of AI technologies in waste sorting or waste management. Literature focusing on related technologies, such as machine learning, deep learning, computer vision, image classification, and intelligent monitoring systems, was also considered when these technologies were explicitly applied to waste management. Studies that were not sufficiently related to AI or waste management, publications with insufficiently relevant information, and duplicate records were excluded from the analysis. The selection process was conducted by assessing the relevance of each publication to the research objectives rather than relying solely on publication quantity.

In the fourth stage, the selected literature was analyzed descriptively and comparatively. Information extracted from the reviewed studies included the AI technology or computational approach used, waste management application, waste category, system function, geographical location, principal findings, advantages, and reported limitations. Particular attention was given to studies employing machine learning, deep learning, and computer vision for waste classification and automated sorting, as well as AI applications for waste monitoring, collection optimization, prediction, and resource management. The findings were then compared across studies and countries to identify similarities, differences, technological trends, and recurring implementation challenges.

The final stage involved synthesizing the findings from the selected literature. The synthesis was conducted thematically by grouping studies according to their primary AI application in waste management. The identified themes included automated waste sorting and classification, intelligent waste collection, waste monitoring, predictive waste management, and resource recovery and treatment. This thematic synthesis enabled the study to identify the broader role of AI in improving waste management efficiency and sustainability. Furthermore, the findings from different countries were examined to identify technological practices and implementation approaches that may be relevant to the development of AI-based waste management systems in Indonesia.

The overall analytical process was descriptive rather than statistical. Therefore, the study did not seek to calculate pooled effect sizes or perform meta-analysis. Instead, it emphasized the interpretation and synthesis of findings reported in previous studies to establish an overview of the current development of AI in waste management. The results of the literature analysis were subsequently used to identify opportunities, limitations, and potential directions for the implementation of AI-based waste management technologies in Indonesia [5]. The research procedure can be summarized as Figure 1.

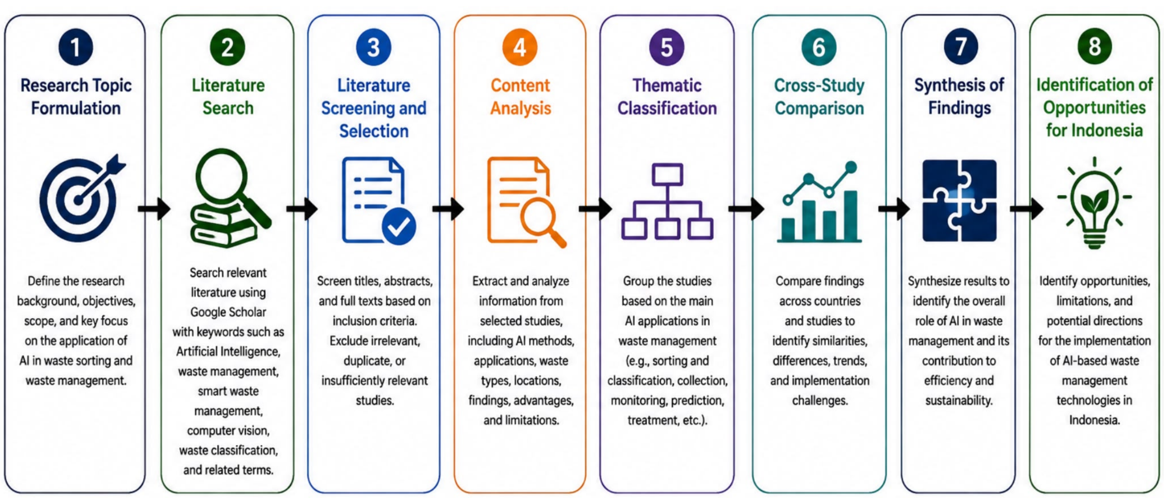

Figure 1. Research Flow

Result and Discussion

The findings obtained from the narrative literature review were synthesized and analyzed thematically to provide a comprehensive understanding of the current conditions of waste management in Indonesia and the potential role of Artificial Intelligence (AI) in addressing existing challenges. The reviewed literature demonstrates that AI has been increasingly applied to waste identification, classification, sorting, monitoring, and recycling in several countries, while its implementation in Indonesia remains relatively limited. To systematically present the findings, the results and discussion are organized into three main areas: (1) waste management conditions and challenges in Indonesia; (2) the roles and applications of Artificial Intelligence in waste sorting and management; and (3) comparative analysis of AI implementation across countries and its potential application in Indonesia.

a. Waste Management Conditions and Challenges in Indonesia

The findings of the literature review indicate that waste management in Indonesia continues to face substantial challenges in terms of waste volume, management capacity, disposal practices, and waste sorting. Indonesia has 520 landfill sites (Tempat Pemrosesan Akhir/TPA), while approximately 75% of the generated waste, equivalent to around 109,023 tons per day, remains unmanaged. This condition demonstrates a considerable gap between the amount of waste generated and the capacity of the existing waste management system. The high proportion of unmanaged waste indicates that increasing the number of disposal facilities alone may not be sufficient to address the problem [19]. Instead, improvements are required throughout the waste management chain, particularly in waste segregation, collection, processing, recycling, and final disposal.

The current condition also suggests that waste management in Indonesia remains heavily dependent on conventional approaches. The existing landfill management system generally consists of three methods: open dumping, controlled landfill, and sanitary landfill [20]. However, the open dumping method remains widely practiced. In this method, waste is deposited in an open area with limited processing, containment, and covering. Such practices can increase the potential for environmental pollution because waste is not adequately isolated from the surrounding environment. The decomposition of waste can generate leachate and gases that may contaminate soil, water, and air [21], [22]. Therefore, the problem is not merely related to the quantity of waste but also to the effectiveness and environmental quality of the management practices used.

Table 1. Current Conditions of Waste Management in Indonesia

Indicator	Current Condition	Major Issue	Management Implication	Technology Need
Number of TPA	520 TPA	High pressure on existing facilities	Requires efficient facility management	Intelligent monitoring
Unmanaged waste proportion	Approximately 75%	Large volume of waste remains unmanaged	Increased environmental burden	Automated management and monitoring

Indicator	Current Condition	Major Issue	Management Implication	Technology Need
Unmanaged waste volume	Approximately 109,023 tons/day	Very high daily waste accumulation	Potential overload of disposal facilities	AI-based prediction and optimization
Waste disposal practice	Open dumping remains dominant	Limited treatment and containment	Higher environmental risk	Smart waste processing
Waste sorting	Conventional/manual methods	Limited speed and consistency	Lower sorting efficiency	Computer vision and AI classification
Environmental control	Limited in conventional systems	Risk of leachate and gas emissions	Soil, water, and air pollution	Sensor and AI-based monitoring
Recycling potential	Constrained by inadequate sorting	Recyclable materials may be mixed with other waste	Lower material recovery	Automated waste classification
Human involvement	Relatively high in manual processes	Exposure to waste and operational limitations	Efficiency and occupational safety concerns	Robotic and AI-assisted systems

Table 1 illustrates that the waste management challenge in Indonesia is multidimensional. The existence of 520 TPA indicates that Indonesia already has a substantial physical waste management infrastructure; however, the continued accumulation of approximately 109,023 tons of unmanaged waste per day indicates that infrastructure availability does not necessarily translate into effective waste management. The proportion of unmanaged waste is particularly important because it indicates that waste management capacity remains insufficient relative to the volume of waste generated [23]. In addition, the continued use of conventional waste sorting creates another bottleneck because mixed waste makes subsequent recycling and treatment more difficult. From a technological perspective, these conditions create opportunities for the implementation of AI-based systems that can support waste identification, classification, monitoring, and operational decision-making. Thus, the principal challenge is not simply increasing disposal capacity, but transforming the existing system into a more integrated, efficient, and intelligent waste management ecosystem [24].

The comparison of the three landfill management approaches further demonstrates why improvements in waste treatment and control are necessary. Open dumping requires relatively limited infrastructure but provides inadequate environmental protection. Controlled landfill introduces a greater degree of operational control, while sanitary landfill represents a more engineered approach with systematic waste placement, covering, and environmental management [25]. These differences have important implications for the sustainability of waste management because the level of environmental protection is closely related to the degree of control implemented throughout the disposal process.

Table 2. Comparison of Waste Management Methods in Indonesia

Aspect	Open Dumping	Controlled Landfill	Sanitary Landfill
Disposal approach	Waste deposited in open areas	Waste disposal with basic operational control	Engineered and controlled waste disposal
Waste covering	Inadequate or irregular	Periodic	Systematic and regular
Waste processing	Very limited	Limited	More structured
Leachate control	Limited	Relatively controlled	More systematic
Gas management	Limited	Partial	More systematic
Environmental protection	Low	Moderate	Higher
Infrastructure requirement	Low	Moderate	High
Operational complexity	Low	Moderate	High
Sustainability potential	Low	Moderate	Higher
Need for monitoring	High	High	High

The comparison in Table 2 indicates that the three methods differ considerably in terms of environmental protection, operational requirements, and technological needs. Open dumping represents the least controlled approach because waste is deposited with limited treatment and containment. This condition increases the possibility of direct interaction between waste and the surrounding environment [26]. In contrast, controlled and sanitary landfill systems provide progressively greater levels of operational and environmental control. Nevertheless, even a more advanced landfill system requires continuous monitoring to ensure that operational standards are maintained. This is where digital technologies, including AI, can provide additional value. AI should therefore not be viewed solely as a replacement for existing landfill methods, but as a technological layer that can enhance monitoring, prediction, classification, and decision-making within waste management facilities [27]. The integration of AI with cameras, sensors, and other digital infrastructure could potentially enable landfill operators to identify waste conditions more rapidly and respond to operational problems more effectively.

One of the most important problems associated with conventional waste management is the limited effectiveness of waste sorting. When different waste materials are mixed, recyclable materials such as plastic, paper, metal, and glass become more difficult to recover [28]. Manual sorting is also affected by human limitations, including fatigue, inconsistent classification, processing speed, and direct exposure to potentially hazardous waste. These limitations can influence both the quantity and quality of recyclable materials recovered from the waste stream. Consequently, improving waste sorting should be considered an essential component of improving the overall waste management system rather than an isolated operational activity.

Table 3. Major Challenges in Conventional Waste Management and Potential Technology Responses

Challenge	Primary Cause	Potential Impact	Potential Technology Response	Expected Improvement
High waste accumulation	Large daily waste generation	Overloaded disposal facilities	AI-based waste prediction	Better capacity planning
Inadequate waste sorting	Manual sorting and mixed waste	Low material recovery	Computer vision and deep learning	Automated classification
Slow sorting process	Dependence on human labor	Reduced operational efficiency	AI-assisted sorting	Faster processing
Inconsistent classification	Human error and fatigue	Reduced sorting accuracy	Machine learning/deep learning	More consistent classification
Leachate generation	Uncontrolled decomposition	Soil and water pollution	Sensor-based monitoring and AI analytics	Earlier detection
Gas emissions	Waste decomposition	Air pollution and environmental risks	Intelligent monitoring	Continuous environmental monitoring
Worker exposure	Direct contact with waste	Occupational health and safety risks	Robotic sorting	Reduced direct human intervention
Limited real-time monitoring	Conventional inspection	Delayed response to problems	AI and computer vision	Continuous monitoring
Low recycling efficiency	Mixed waste streams	Reduced resource recovery	Automated sorting	Increased recyclable material recovery

Table 3 highlights the relationship between existing waste management challenges and potential technological interventions. The table demonstrates that AI can potentially address several limitations simultaneously rather than focusing exclusively on waste classification. For example, computer vision and deep learning can support automatic identification and classification, while AI-based predictive models can assist in estimating waste generation and planning operational capacity. Similarly, the integration of AI with sensors can facilitate continuous monitoring of landfill conditions, while robotic systems can reduce the need for direct human interaction with waste during sorting [29]. This multidimensional role is important because the effectiveness of waste management depends on the interaction between collection, sorting, processing, monitoring, and disposal activities. Therefore, the adoption of AI should ideally be considered as part of an integrated digital waste management strategy rather than as a standalone sorting technology.

The environmental consequences of inadequate waste management further reinforce the urgency of improving the existing system. Open dumping can generate leachate when rainwater or moisture passes through accumulated waste and carries dissolved contaminants into the surrounding environment. In addition, the decomposition of organic waste can produce gases that contribute to air pollution and environmental degradation [30]. These impacts may become increasingly significant when waste accumulation continues without adequate treatment. The problem therefore extends beyond the operational performance of TPA facilities and can affect the broader environmental quality and health conditions of surrounding communities.

From an operational perspective, the large volume of unmanaged waste also suggests that conventional waste management systems may struggle to maintain an appropriate balance between waste generation, collection, sorting, processing, and final disposal. A system that focuses primarily on final disposal without strengthening upstream waste segregation may continue to experience high pressure on landfill capacity [31]. Conversely, improving sorting and recycling at earlier stages can reduce the quantity of waste requiring final disposal and increase the recovery of valuable materials. This creates a strong rationale for the introduction of intelligent technologies capable of supporting waste segregation and resource recovery.

The findings also indicate that technology adoption should be considered in accordance with the characteristics of Indonesian waste management infrastructure. AI-based systems require supporting components such as cameras, sensors, computational resources, reliable data, appropriate algorithms, and trained personnel [32]. Therefore, the implementation of AI cannot be separated from infrastructure readiness and human resource capacity. A technologically advanced AI model may not produce optimal results if the available waste images are insufficiently representative or if the operational environment differs substantially from the conditions under which the model was trained [33]. Consequently, the development of AI for Indonesia should emphasize locally relevant datasets and operational conditions.

Overall, the results demonstrate that the waste management problem in Indonesia is characterized by a combination of high waste volume, inadequate management capacity, conventional disposal practices, inefficient sorting, environmental risks, and substantial dependence on human intervention. These conditions establish a clear technological need for more intelligent waste management approaches [34]. AI offers potential solutions through automated classification, real-time monitoring, predictive analysis, and robotic sorting. However, AI should complement improvements in waste management infrastructure and policy rather than replace them. The transition toward an AI-enabled waste management system therefore requires an integrated strategy involving technology, infrastructure, regulation, data, and human resources.

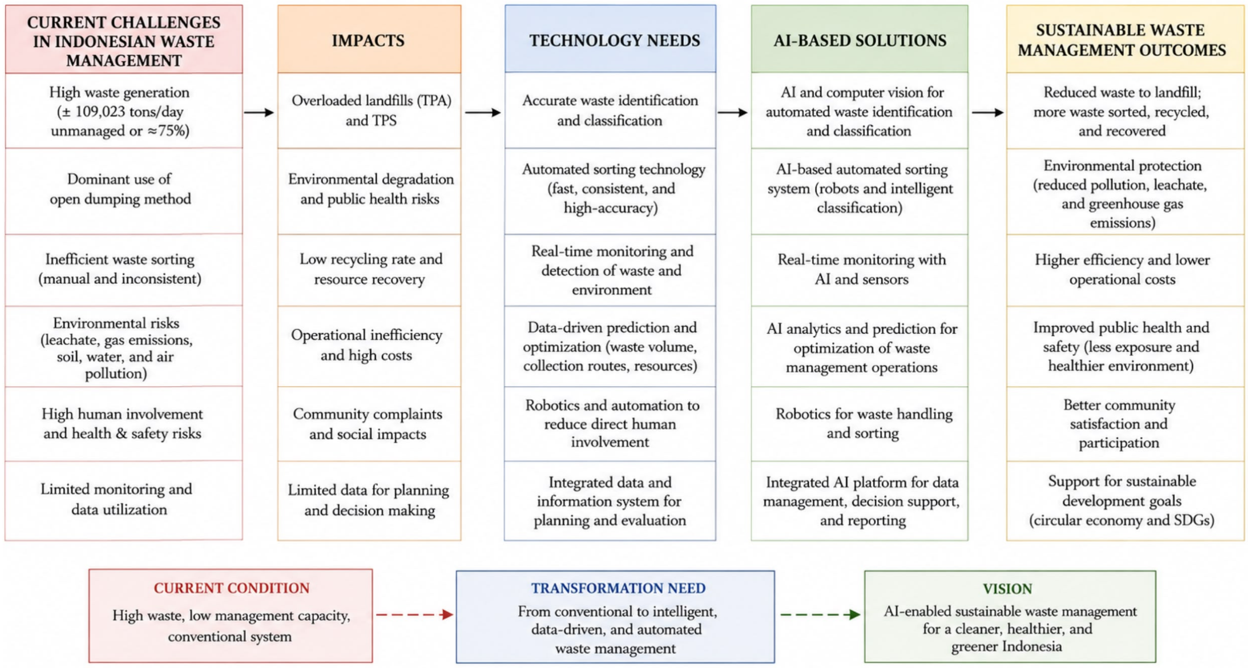

Figure 1. Challenges and Technology Needs in Indonesian Waste Management: From High Waste Generation and Conventional Disposal Practices to AI-Based Waste Sorting, Monitoring, and Sustainable Waste Management

Figure 1 summarizes the relationship between the identified waste management problems and the technological needs emerging from the findings. The diagram emphasizes that the adoption of AI is logically connected to several interconnected challenges rather than to a single problem. High waste generation contributes to increasing pressure on TPA capacity, while inadequate sorting and conventional disposal practices increase environmental risks and reduce opportunities for recycling [35]. These conditions create the need for intelligent technologies capable of identifying waste, monitoring waste conditions, optimizing operations, and supporting automated sorting. The diagram therefore provides a conceptual transition from the existing condition toward a technology-enabled waste management system. Importantly, the proposed transition does not imply that AI alone can solve the waste problem. Instead, AI represents one component of a broader transformation that must also include appropriate infrastructure, environmental regulation, operational standards, and human resource development.

Taken together, the findings from this subsection establish the problem context and technological rationale for the subsequent analysis. The dominant use of conventional waste management practices, particularly open dumping, combined with the substantial proportion of unmanaged waste, demonstrates the need for more efficient and sustainable approaches [36]. The limitations of manual sorting further indicate that automation and intelligent classification could provide significant operational benefits. These findings provide the basis for the next discussion, which examines how AI has been implemented in waste sorting and management, including the use of computer vision, deep learning, real-time detection, and robotic systems in different application contexts.

b. The Roles and Applications of Artificial Intelligence in Waste Sorting and Management

The findings of the reviewed literature demonstrate that Artificial Intelligence (AI) has increasingly been applied to address various challenges in waste sorting and management. Rather than functioning only as a tool for recognizing waste objects, AI can support multiple stages of the waste management process, including waste identification, classification, real-time detection, automated sorting, monitoring, and recycling. The integration of AI with computer vision, deep learning, sensors, and robotic systems enables conventional waste management processes to become more automated, accurate, and responsive [37]. This development is particularly relevant to waste sorting because the heterogeneous composition of municipal waste makes manual identification and separation difficult to perform consistently at large scale. Based on the reviewed studies, four major roles of AI were identified: (1) automated waste identification and classification, (2) improvement of sorting accuracy and processing speed, (3) real-time waste detection and monitoring, and (4) improvement of waste management and recycling efficiency.

Table 4. Roles of Artificial Intelligence in Waste Sorting and Management

AI Role	Main Technology	Primary Function	Expected Contribution
Waste identification	Computer Vision	Detect and recognize waste objects from images or video	Automated recognition of waste materials
Waste classification	Machine Learning and Deep Learning	Categorize waste based on learned visual characteristics	More consistent waste classification
Object detection	YOLO, RetinaNet, Faster R-CNN	Locate and classify waste objects	Real-time detection and monitoring
Image segmentation	Mask R-CNN	Identify individual objects and their regions	More precise object recognition
Automated sorting	AI + Robotic Arm	Convert AI classification results into physical sorting actions	Reduced manual intervention
Real-time monitoring	AI + Camera/Sensor	Continuously detect waste conditions	Faster operational response
Predictive analysis	Machine Learning	Analyze patterns and predict waste-related conditions	Improved planning and resource allocation
Recycling support	AI-based classification	Separate recyclable from non-recyclable materials	Increased material recovery potential

Table 4 indicates that the role of AI in waste management extends beyond a single technological function. Computer vision provides the visual input required to identify waste objects, while machine learning and deep learning algorithms process these inputs to classify materials according to predefined categories. Object detection models such as YOLO, RetinaNet, and Faster R-CNN further enable systems to determine the location of waste objects, which is particularly important when multiple waste items appear simultaneously within a camera frame. Meanwhile, Mask R-CNN provides more detailed object segmentation, enabling individual waste objects to be separated from their surroundings. When these AI capabilities are connected to robotic systems, the resulting system can transform digital recognition into physical sorting actions [38]. Therefore, the reviewed literature suggests that AI can function as an integrated decision-making component within an automated waste management system rather than merely as an image classification tool.

The first major application identified in the literature is automated waste identification and classification. AI-based systems can process images obtained from digital cameras and identify waste materials according to visual characteristics such as shape, color, texture, size, and other image-based features. These characteristics allow the system to distinguish among different categories, including plastic, paper, metal, glass, and organic waste [39]. This capability is particularly important because accurate classification is a prerequisite for effective recycling and resource recovery. When recyclable and non-recyclable materials are mixed, subsequent treatment becomes more difficult and the quality of recovered materials may decrease. AI-based classification can therefore provide an automated mechanism for separating materials before they reach subsequent processing stages.

Table 5. AI Technologies and Their Applications in Waste Sorting

AI Technology/ Model	Input	Main Processing Function	Waste Management Application	Key Benefit
Computer Vision	Digital images/video	Visual feature extraction and object recognition	Waste identification	Automated visual inspection
CNN	Waste images	Image feature learning and classification	Waste category classification	Automated classification
Deep Learning	Image datasets	Hierarchical feature learning	Multi-category waste classification	Improved recognition capability
Mask R-CNN	Images/video	Object detection and instance segmentation	Real-time waste detection and classification	Precise object localization
YOLOv8	Images/video	Real-time object detection	Plastic waste detection	Fast detection
RetinaNet	Images/video	Object detection	Industrial waste monitoring	Detection of waste objects
Faster R-CNN	Images/video	Region-based object detection	Plastic waste detection	Detailed object localization
Robotic Arm + AI	AI classification results	Physical object manipulation	Automated waste sorting	Reduced manual intervention

Table 5 demonstrates the technological progression from visual recognition toward fully integrated automated sorting. Computer vision provides the fundamental capability to interpret visual information, while CNN and other deep learning architectures can learn discriminative features from waste images without relying entirely on manually designed features [40]. The application of object detection models represents a further development because the system can identify both what an object is and where it is located. This distinction is particularly important in practical sorting environments, where several waste items may be present simultaneously. The integration of AI with robotic arms provides an additional level of automation because classification results can be translated into physical actions [41]. Thus, AI technologies can be arranged as interconnected components within a waste sorting pipeline, beginning with image acquisition and ending with automated material separation.

The second major role of AI is improving the accuracy and speed of waste sorting compared with conventional manual approaches. Manual sorting is strongly dependent on human concentration, experience, physical capacity, and working conditions. These factors may result in inconsistent classification and reduced processing speed, particularly when the amount of waste increases. Kelechi et al [42] reported that an AI-based robotic system integrating computer vision and deep learning improved the accuracy and speed of waste classification compared with manual sorting. This finding indicates that the combination of AI and robotics can address two fundamental limitations of conventional sorting: the ability to process waste rapidly and the need to maintain consistent classification decisions.

Evidence from Bangladesh also demonstrates the potential of deep learning for large-scale waste classification. Kannan [43] reported a classification result of 83.11% using a dual-stream deep learning model, while the GELAN-E model for object detection achieved an mAP50 of 63%. Although these performance indicators represent different evaluation dimensions and should not be interpreted as directly equivalent measures, they demonstrate that AI-based systems can achieve measurable recognition and detection capabilities across diverse waste categories.

Table 6. Reported Performance and Applications of AI-Based Waste Management Systems

Study	Country	AI Technology/ Model	Application	Waste Target	Reported Result
Olawade et al [44]	Vietnam	Computer Vision + Deep Learning + Robotic System	Automated waste sorting	Various waste types	Improved sorting accuracy and speed compared with manual sorting
Ahmed et al [45]	Bangladesh	Dual-stream Deep Learning	Waste classification	28 waste categories	Classification result of 83.11%
Jogarao et al [46]	Bangladesh	GELAN-E	Waste object detection	Waste objects	mAP50 of 63%
Nirmala et al [47]	India	Mask R-CNN	Real-time detection and classification	Waste objects	Real-time detection and classification capability
Wang et al [48]	Russia	YOLOv8	Plastic waste detection	Plastic waste	Real-time detection on industrial conveyor
Mingaleva et al [49]	Russia	RetinaNet	Plastic waste detection	Plastic waste	Real-time object detection capability
Ilinykh et al [50]	Russia	Faster R-CNN	Plastic waste detection	Plastic waste	Real-time object detection capability

Study	Country	AI Technology/ Model	Application	Waste Target	Reported Result
Sundar et al [51]	United Kingdom	CNN + Energy-efficient Robotic Arm	Automated waste classification	Six waste categories	Automated classification system

Table 6 provides a comparative overview of the empirical evidence identified in the reviewed literature. The studies differ in terms of algorithms, target waste categories, application environments, and evaluation indicators; therefore, their reported results should be interpreted within their respective experimental contexts rather than used to establish a direct ranking of model performance. Nevertheless, the evidence consistently indicates that AI has practical potential for waste identification and sorting. The Bangladesh study demonstrates the capability of deep learning to handle multiple waste categories, while the Vietnam study highlights the value of combining AI with robotics for physical sorting. The studies in India and Russia demonstrate the importance of real-time detection, particularly for continuous waste streams and industrial conveyors. Meanwhile, the United Kingdom study extends AI application toward energy-efficient robotic sorting. Collectively, these findings indicate that AI applications can be adapted according to the operational requirements of different waste management environments.

The third major role of AI is real-time waste detection and monitoring. Conventional waste management inspections generally depend on periodic observations, which may not provide sufficient information about rapidly changing waste conditions. AI integrated with cameras can continuously analyze video streams and detect waste objects as they appear. Aarthi and Rishma demonstrated the use of Mask R-CNN for real-time waste detection and classification [47]. The ability to identify objects and their geometric characteristics, including their location and orientation, is particularly relevant to automated sorting because a robotic mechanism requires spatial information before it can perform a picking action.

Similarly, Nathaniela et al [52] applied video cameras in combination with YOLOv8, RetinaNet, and Faster R-CNN to detect plastic waste on industrial conveyors in real time. This application demonstrates that AI-based waste detection is not limited to laboratory-based image classification but can also be integrated into continuous industrial processes [53]. Real-time detection allows waste management systems to respond to waste streams continuously and potentially identify recyclable materials before they are mixed with other waste categories.

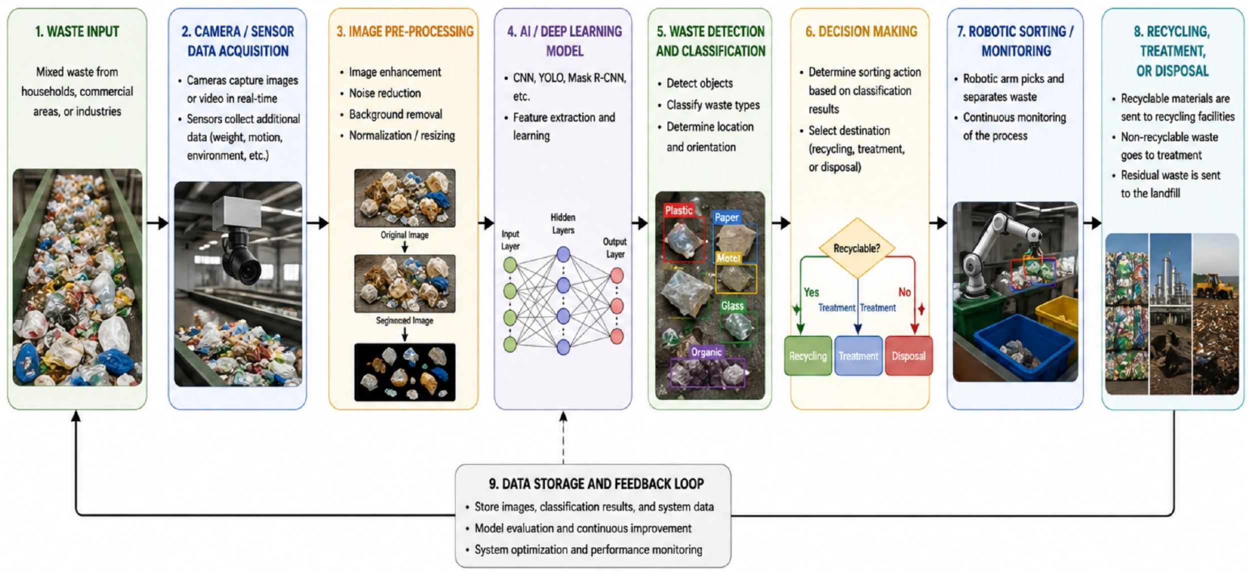

Figure 2. AI-Based Waste Sorting and Management Workflow

The proposed Figure 2 illustrates how AI can function as an integrated component of the waste sorting and management process. The process begins with the acquisition of visual or sensor data from waste streams. These data are then processed and analyzed by AI models to identify and classify individual waste objects. The classification output subsequently becomes a decision-making input for sorting, monitoring, or further waste treatment. When robotic systems are incorporated, the AI output can determine which object should be picked and where it should be placed [54]. This workflow demonstrates that the value of AI is generated through the interaction between data acquisition, intelligent analysis, and physical or operational actions. Consequently, the effectiveness of an AI-based system depends not only on model accuracy but also on the quality of cameras and sensors, computational infrastructure, system integration, and the design of downstream sorting processes.

The fourth role of AI is its contribution to improving the efficiency and sustainability of waste management and recycling. Malik et al [55] reported that deep learning can increase the efficiency and effectiveness of waste processing and sorting. Similarly, Bari et al [56] demonstrated that an AI-based robotic sorting system can improve the efficiency of waste classification while supporting more sustainable waste management. These findings are important because sorting efficiency has implications beyond operational speed. More accurate sorting can improve the separation of recyclable materials, reduce contamination between waste categories, and potentially increase the amount of material that can be recovered for subsequent processing.

The integration of AI and robotics may also reduce direct human exposure to waste. Conventional manual sorting can expose workers to biological contaminants, sharp objects, unpleasant odors, and other potentially hazardous materials. Automated systems can reduce the frequency of direct physical interaction between workers and waste, particularly in high-volume or industrial environments [57]. However, this does not mean that human involvement can be completely eliminated. Human operators remain necessary for system supervision, maintenance, exception handling, data management, and quality control. Therefore, the more appropriate interpretation is that AI can reduce repetitive and hazardous manual tasks while shifting human roles toward system supervision and higher-level operational activities.

Another important implication is the potential for AI to support a more data-driven waste management system. Continuous image and sensor data can provide information about waste composition, accumulation patterns, and operational conditions. When these data are stored and analyzed over time, they can support decision-making related to sorting capacity, collection schedules, recycling processes, and facility management [58]. Consequently, AI has the potential to move waste management from a predominantly reactive model toward a more proactive and predictive model.

Nevertheless, the reviewed findings also indicate that AI implementation should not be interpreted as universally effective without considering contextual factors. Differences in waste composition, environmental conditions, image quality, dataset size, processing infrastructure, and operational environments can influence model performance [59]. A model trained using waste images from one geographical location may experience reduced generalization when applied to another location with different waste characteristics. In addition, real-time AI systems require sufficient computational resources and reliable data acquisition infrastructure [60]. Therefore, the reported performance values in previous studies provide evidence of technological feasibility but should not automatically be interpreted as expected performance for Indonesia.

Overall, the results demonstrate that AI has evolved from a conventional image recognition technology into a broader technological framework for intelligent waste management. Its applications encompass waste identification, classification, real-time detection, automated sorting, monitoring, and recycling support. The reviewed studies provide evidence that the integration of AI with computer vision, deep learning, and robotic systems can improve the efficiency and automation of waste sorting [61]. The findings also indicate that different AI technologies are suited to different operational requirements: classification models are useful for identifying waste categories, object detection models are appropriate for locating waste in real time, and robotic systems can translate AI decisions into physical sorting actions [62]. These findings establish the technological foundation for the next subsection, which compares AI implementation across countries and examines how these approaches can be adapted to the waste management conditions in Indonesia.

c. Comparative Analysis of AI Implementation and Its Potential for Indonesia

The findings of the narrative literature review indicate that the implementation of Artificial Intelligence (AI) in waste management has developed across several countries, although the technological approaches and application objectives vary according to local waste management conditions. The reviewed studies from Bangladesh, Vietnam, India, Russia, and the United Kingdom demonstrate that AI has been applied at different stages of the waste management process, ranging from waste classification and object detection to automated sorting and real-time industrial monitoring [63]. These differences provide an important basis for identifying technological approaches that may be adapted to the Indonesian context. Rather than adopting a particular technology directly, Indonesia can derive lessons from these implementations by considering its waste volume, infrastructure readiness, waste characteristics, human resource capacity, and environmental management requirements.

The comparison of the reviewed studies shows that each country emphasizes different aspects of AI-based waste management. Bangladesh focuses on multi-category waste classification using deep learning, Vietnam integrates AI with robotic sorting, India emphasizes real-time detection and classification, Russia applies object detection to high-speed industrial conveyor systems, and the United Kingdom combines CNN-based classification with an energy-efficient robotic arm [64]. These approaches demonstrate that AI can be configured according to the operational requirements of waste management facilities.

Table 7. Comparison of AI Implementation in Waste Management Across Countries

Country	Study	AI Technology	Main Application	Waste Target	Main Contribution
Bangladesh	Sayem et al. (2025) [8]	Dual-stream Deep Learning and GELAN-E	Classification and object detection	28 waste categories	Multi-category waste classification and detection
Vietnam	Le and Ngo (2025) [7]	Computer Vision, Deep Learning, and Robotic Arm	Automated waste sorting	Various waste types	Automated identification and physical sorting
India	Aarthi and Rishma (2023) [9]	Mask R-CNN	Real-time detection and classification	Waste objects	Object identification and geometric localization
Russia	Shukhratov et al. (2024) [10]	YOLOv8, RetinaNet, and Faster R-CNN	Industrial waste detection	Plastic waste	Real-time detection on high-speed conveyors
United Kingdom	Kure et al. (2025) [11]	CNN and Energy-efficient Robotic Arm	Automated classification	Six waste categories	Intelligent and energy-efficient sorting

Table 7 demonstrates that AI implementation in waste management is not characterized by a single dominant technology. Instead, the technology is selected according to the specific requirements of each waste management environment. The Bangladesh study demonstrates the importance of developing models capable of handling multiple waste categories, which is particularly relevant in environments where heterogeneous waste is generated. Vietnam provides evidence of the benefits of integrating AI with robotics, allowing digital classification to be translated into physical sorting operations. In India, Mask R-CNN supports real-time recognition and provides spatial information that can be useful for automated manipulation. The Russian study demonstrates the application of AI in an industrial environment where detection must operate continuously on high-speed conveyors. Meanwhile, the United Kingdom study extends the concept toward energy-efficient robotic waste classification [65]. Thus, the reviewed studies indicate that the effectiveness of AI depends not only on the selected algorithm but also on its integration with appropriate hardware and operational processes.

From the perspective of application functionality, the reviewed studies can be further compared based on the extent to which AI supports identification, classification, monitoring, automation, and industrial-scale operations. Such comparison is important because an AI system that only performs image classification provides a different level of functionality from an integrated system that detects waste, makes sorting decisions, and physically separates materials.

Table 8. Comparative Analysis of AI Applications in Waste Management

Country	Waste Identification	Classification	Real-Time Detection	Robotic Automation	Industrial Application	Smart Waste Management
Bangladesh	✓	✓	✓	–	–	✓
Vietnam	✓	✓	✓	✓	–	✓
India	✓	✓	✓	–	–	✓
Russia	✓	✓	✓	–	✓	✓
United Kingdom	✓	✓	✓	✓	–	✓

Table 8 indicates that all reviewed countries have implemented AI for waste identification and classification, demonstrating that computer vision and machine learning represent fundamental components of AI-based waste management. However, the degree of automation differs considerably. Vietnam and the United Kingdom have extended AI applications to robotic systems, suggesting a transition from digital recognition toward physical automation [66]. Russia, on the other hand, emphasizes industrial application by implementing object detection on high-speed conveyor systems. India demonstrates the importance of real-time detection and spatial recognition, while Bangladesh emphasizes the ability to classify a relatively broad range of waste categories. These differences are particularly relevant to Indonesia because they suggest that AI implementation does not necessarily have to begin with a fully automated robotic system [67]. A phased approach may be more realistic, beginning with AI-assisted identification and monitoring before progressing toward automated sorting and robotic integration.

The comparative evidence also reveals several lessons concerning the strengths and limitations of AI implementation. Although previous studies demonstrate promising technological capabilities, differences in datasets, experimental environments, waste categories, hardware configurations, and evaluation metrics mean that their performance results cannot be directly compared as a single ranking. For example, the classification result of 83.11% reported by Naser et al [68] and the mAP50 value of 63% obtained using GELAN-

E represent different evaluation measures and should therefore be interpreted according to their respective experimental contexts. This consideration is important when developing an AI strategy for Indonesia because the performance of an existing model cannot automatically be assumed to remain the same when transferred to a different geographical and operational environment.

Table 9. Strengths, Limitations, and Lessons Learned from International AI Implementations

Country	Main Strength	Potential Limitation	Technological Requirement	Lesson for Indonesia
Bangladesh	Multi-category waste classification	Requires representative and diverse datasets	Deep learning and image datasets	Develop Indonesian waste image datasets covering diverse waste categories
Vietnam	Integration of AI and robotic sorting	Requires robotics and system integration	Computer vision, deep learning, robotic arm	Develop automated sorting progressively
India	Real-time detection and object localization	Requires continuous image acquisition and computing resources	Cameras, Mask R-CNN, computing infrastructure	Suitable for real-time monitoring at TPA/TPS
Russia	Industrial-scale detection on high-speed conveyors	Requires specialized industrial infrastructure	Cameras, object detection models, conveyor system	Potential for industrial recycling facilities
United Kingdom	AI combined with energy-efficient robotics	Higher technological and integration requirements	CNN, robotic arm, energy-efficient hardware	Relevant for future smart-city waste management
Indonesia	Large waste volume and diverse waste characteristics	Limited adoption of advanced AI systems	Data, infrastructure, policy, and skilled personnel	Requires context-specific and phased AI adoption

Table 9 provides a more critical interpretation of the international evidence by linking technological achievements with the requirements for implementation. One of the most important lessons for Indonesia is the need to develop locally representative datasets. Indonesian waste streams may differ from those represented in datasets developed in Bangladesh, Vietnam, India, Russia, or the United Kingdom. Differences in packaging materials, waste composition, environmental conditions, lighting, collection practices, and sorting environments may influence model performance [69]. Therefore, directly transferring an existing AI model without local adaptation may result in reduced classification accuracy. The development of Indonesian waste datasets should consequently become an important component of future AI research.

The international comparison also suggests that implementation should be conducted through a phased technological strategy. In the initial phase, AI could be introduced for waste identification, classification, and real-time monitoring at selected TPA or TPS facilities. Computer vision systems equipped with cameras could detect waste categories and generate information regarding waste composition [70]. In the next phase, AI could be integrated with automated sorting mechanisms to separate recyclable materials. More advanced implementation could subsequently incorporate robotic arms and predictive analytics for operational optimization. This phased approach would allow Indonesia to evaluate technological performance and infrastructure readiness before investing in more complex automated systems.

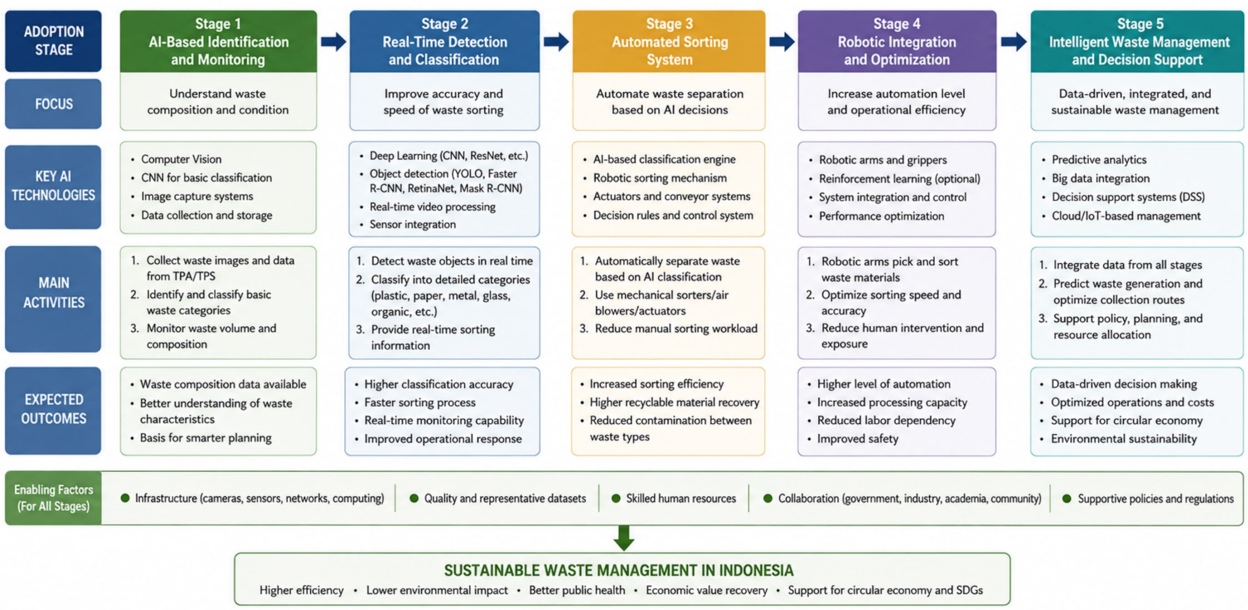

Figure 3. Comparative AI Implementation and Proposed Technology Adoption Pathway for Sustainable Waste Management in Indonesia

The conceptual diagram illustrates how international experience can inform a potential technology adoption pathway for Indonesia. The pathway begins with basic AI capabilities, particularly computer vision-based identification and classification, and gradually progresses toward real-time monitoring, automated sorting, robotics, and integrated intelligent management [71]. Such a progression is important because Indonesia's waste management infrastructure varies substantially across regions. A technology that is feasible in an industrialized recycling facility may not be immediately applicable to all TPA or TPS facilities. Therefore, AI adoption should consider differences in infrastructure, electricity availability, connectivity, equipment, financial resources, waste composition, and human resource capabilities [72]. The diagram also emphasizes that AI should be integrated into the existing waste management ecosystem rather than implemented as an isolated technology. This integration can create a pathway toward data-driven decision-making and more sustainable resource recovery.

The potential application of AI in Indonesia is particularly significant because the country faces a combination of high waste generation, limited sorting efficiency, and continued reliance on conventional disposal methods. The international studies demonstrate that AI can address different components of these challenges. Bangladesh provides an example of multi-category classification, Vietnam demonstrates AI-robotic integration, India provides evidence of real-time object detection , Russia demonstrates industrial-scale monitoring, and the United Kingdom illustrates the integration of AI with energy-efficient robotic systems. These examples collectively indicate that Indonesia has multiple technological pathways from which to develop an appropriate national strategy.

However, technological adoption alone will not guarantee successful implementation. AI-based waste management requires supporting infrastructure, including high-quality datasets, cameras and sensors, computational resources, communication networks, maintenance systems, and trained personnel. Government policies and institutional coordination are also important because waste management involves multiple stakeholders, including central and local governments, waste management operators, recycling industries, communities, and technology developers. Consequently, an AI-based waste management strategy should be accompanied by policies that encourage data standardization, technological innovation, infrastructure development, and capacity building.

Another important consideration is the economic and environmental sustainability of AI implementation. Highly sophisticated robotic systems may provide substantial automation but can also require considerable initial investment and technical expertise. For Indonesia, therefore, the most appropriate solution may not necessarily be the most technologically complex solution. Instead, technology selection should consider the relationship between cost, performance, scalability, maintainability, and environmental benefit [73]. AI systems that can operate using relatively affordable cameras and existing waste processing infrastructure may provide a more practical starting point than fully autonomous robotic facilities. Such an approach could allow AI technologies to be tested and progressively scaled based on demonstrated benefits.

Overall, the comparative findings demonstrate that AI has considerable potential to support the transformation of waste management from conventional, labor-intensive practices toward intelligent, automated, and data-driven systems. Nevertheless, the international evidence should be interpreted as a source of technological lessons rather than as a direct blueprint for Indonesia. The diversity of waste characteristics and infrastructure conditions requires the development of context-specific AI solutions [74]. In particular, Indonesia should prioritize the development of local datasets, AI-assisted waste identification and monitoring, gradual integration of automated sorting, and subsequent development of robotic and predictive systems. With adequate infrastructure, supportive government policies, and strengthened human resource capacity, AI has the potential to improve sorting efficiency, increase material recovery, reduce direct human exposure to waste, and support more sustainable waste management in Indonesia [30].

Conclusion

This study examined the role and implementation of Artificial Intelligence (AI) in waste sorting and management through a

Narrative Literature Review of previous studies from several countries. The findings indicate that Indonesia continues to face substantial waste management challenges, characterized by a high volume of unmanaged waste, limited waste sorting efficiency, and the continued use of conventional disposal practices, particularly open dumping. These conditions contribute to environmental risks and place considerable pressure on existing waste management facilities. Therefore, improving waste management in Indonesia requires not only an increase in physical infrastructure but also the adoption of intelligent technologies capable of improving sorting, monitoring, processing, and decision-making.

The review demonstrates that AI has significant potential to support the transformation of conventional waste management into a more automated, efficient, and data-driven system. AI applications based on computer vision, machine learning, deep learning, object detection, and robotic systems have been used for automated waste identification, classification, real-time detection, monitoring, and physical sorting. Evidence from previous studies shows that AI can improve the speed and consistency of waste sorting while reducing the need for direct human intervention. The integration of AI with robotic systems further enables classification results to be translated into automated sorting actions, potentially increasing recyclable material recovery and improving operational efficiency. Nevertheless, AI performance is highly dependent on the quality and representativeness of datasets, computational infrastructure, environmental conditions, system integration, and human expertise.

The comparative analysis of implementations in Bangladesh, Vietnam, India, Russia, and the United Kingdom demonstrates that AI applications can be adapted to different waste management requirements. The reviewed studies provide examples ranging from multi-category waste classification and real-time detection to industrial conveyor monitoring and AI-integrated robotic sorting. These implementations provide valuable technological lessons for Indonesia; however, direct adoption of existing systems may not be appropriate because waste composition, infrastructure, operational environments, and resource availability differ across countries. Indonesia therefore requires a context-specific approach that prioritizes the development of representative local waste datasets, AI-assisted identification and monitoring, and gradual integration of automated and robotic sorting technologies.

Overall, AI should be considered as an enabling technology within a broader transformation of Indonesia's waste management system rather than as a standalone solution. Its successful implementation requires the simultaneous strengthening of digital infrastructure, data availability, human resource capacity, institutional collaboration, and supportive government policies. A phased adoption strategy, beginning with AI-based identification and real-time monitoring and progressing toward automated sorting, robotic integration, and intelligent decision-support systems, represents a feasible pathway for future development. Such integration has the potential to improve waste management efficiency, increase resource recovery, reduce environmental impacts and human exposure to waste, and contribute to the development of a more sustainable and circular waste management system in Indonesia.

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