

AI-Based Waste Classification and Smart Waste Management Systems: Techniques, Challenges, and Future Directions

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Abstract—Rapid urban growth and the corresponding rise in municipal solid waste have intensified the need for efficient and scalable waste management solutions. Conventional segregation practices, which largely rely on manual intervention, are often time-consuming, inconsistent, and unsuitable for handling large volumes of waste. In recent years, advancements in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) have facilitated the development of intelligent systems capable of automating waste classification and monitoring processes.

This survey provides a detailed review of 13 research studies published between 2021 and 2025, with a focus on AI-driven approaches for waste management. It examines a range of techniques, including Convolutional Neural Networks (CNNs), object detection frameworks, and hybrid learning models, along with the datasets, evaluation metrics, and system designs employed in these works. A comparative assessment is carried out to analyze the performance, advantages, and limitations of the existing methodologies.

The review further identifies critical research gaps, such as the absence of standardized benchmark datasets, limited real-time implementation, lack of multimodal sensor integration, and insufficient emphasis on model interpretability. Based on these findings, the paper outlines potential future directions, including the adoption of edge-based AI systems, integration with IoT-enabled smart infrastructure, and the use of advanced detection models to support scalable and efficient waste management in smart city environments.

KeyWords—Waste Segregation, Deep Learning, Convolutional Neural Networks (CNN), Object Detection, Smart Cities, Internet of Things (IoT), Artificial Intelligence

I. INTRODUCTION

1) **A. Background:** The continuous growth of urban populations, industrialization, and changing consumption patterns has resulted in a substantial rise in municipal solid waste across the globe. Inefficient handling of this waste contributes to serious environmental concerns, including soil degradation, water contamination, and increased greenhouse gas emissions. Effective segregation at the source plays a crucial role in addressing these issues, as it facilitates recycling, reduces reliance on landfills, and supports sustainable waste management practices. However, conventional approaches

largely depend on manual sorting, which is not only time-intensive but also susceptible to inconsistencies and human error, especially in large-scale scenarios.



Fig. 1: AI-based waste classification pipeline from image capture to smart bin segregation

2) **B. Problem Statement:** Manual waste segregation systems face multiple operational challenges that limit their effectiveness. These include inaccurate classification, mixing of recyclable and non-recyclable materials, and higher labor costs. In densely populated urban areas, the diverse nature of waste further complicates the segregation process, ultimately affecting recycling outcomes and environmental safety. Moreover, traditional systems lack the capability to monitor waste conditions in real time or adapt dynamically, making them inefficient for modern waste management requirements. These challenges underline the necessity for intelligent and automated solutions that can operate reliably at scale. As shown in Figure ??,1 the system processes waste images in real time.

3) **C. Role of Artificial Intelligence:** Advancements in Artificial Intelligence (AI), along with Machine Learning (ML) and Deep Learning (DL), have significantly enhanced the capabilities of image-based analysis and object recognition systems. Among these, Convolutional Neural Networks

(CNNs) have proven particularly effective for classification tasks due to their ability to automatically extract and learn hierarchical features from visual data. Such models are widely applied in waste segregation systems to identify categories like plastic, metal, paper, and organic materials.

In addition to conventional CNN architectures, more advanced models such as ResNet and EfficientNet have demonstrated improved accuracy and efficiency, making them suitable for complex classification tasks. Furthermore, object detection frameworks like YOLO enable real-time identification of multiple waste items within a single frame, which is highly beneficial for applications such as automated sorting and smart waste bins. These developments have transformed traditional classification methods into more intelligent and responsive systems capable of real-time operation.

4) **E. Challenges in Current Research:** Despite notable progress, several limitations remain in existing intelligent waste management solutions. A key concern is the absence of standardized datasets, as many studies rely on limited or custom data, making it difficult to benchmark and compare different approaches. Additionally, a significant portion of research is conducted under controlled environments, which does not fully capture real-world conditions such as lighting variations, occlusion, and complex backgrounds.

Another challenge lies in the computational demands of deep learning models, which can hinder deployment on resource-constrained edge devices. Furthermore, many systems lack interpretability, making it difficult to understand model decisions and establish user confidence. The limited use of multimodal approaches, which combine visual data with sensor inputs, also restricts the robustness and adaptability of current systems.

5) **F. Motivation:** The increasing need for sustainable and scalable waste management solutions, combined with the shortcomings of existing methods, motivates this study. There is a clear demand for a structured analysis that not only reviews current techniques but also evaluates their practical applicability and limitations. By identifying research gaps and highlighting emerging trends, this survey aims to provide meaningful insights that can guide future developments in intelligent waste management systems.

II. CONTRIBUTION OF THIS SURVEY

This survey presents a detailed and structured analysis of 25 research works, including 13 IEEE publications and foundational deep learning studies. The major contributions of this paper are summarized as follows:

- 1) A comprehensive review of AI-based waste management systems published between 2021 and 2025 [1]–[13].
- 2) Analysis of various algorithms including CNN, machine learning models, and real-time object detection techniques.
- 3) Evaluation of datasets, input-output frameworks, and performance metrics used in existing research.

- 4) Identification of key research gaps such as lack of standardization, scalability issues, and absence of explainable AI.
- 5) Discussion of technical challenges associated with real-world deployment and edge computing.
- 6) Proposal of future research directions including multimodal sensing, edge AI optimization, and smart city integration.

The findings of this survey provide a strong foundation for the development of next-generation intelligent waste management systems that are scalable, efficient, and environmentally sustainable. This survey presents a comprehensive overview of recent advancements in intelligent waste management systems driven by Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL). With the rapid increase in urban population and waste generation, traditional waste segregation methods have become inefficient and unsustainable. This study analyzes multiple research works published between 2021 and 2025, focusing on automated waste classification and monitoring techniques.

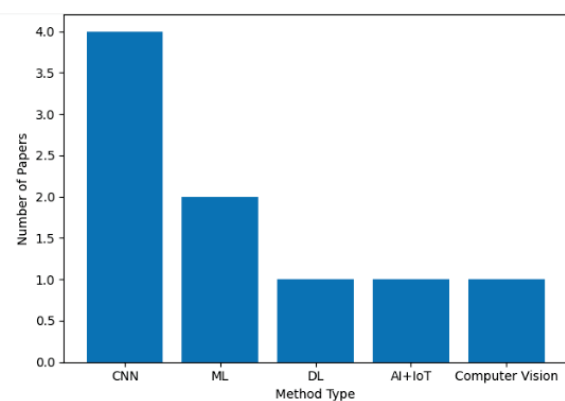


Fig. 2: Distribution of AI Techniques Used in Reviewed Papers

The paper examines various approaches, including Convolutional Neural Networks (CNNs), general machine learning models, and computer vision-based systems. CNN-based methods are widely adopted due to their effectiveness in image classification tasks, particularly in identifying different types of waste such as plastic, paper, metal, and organic materials. Additionally, advanced architectures and object detection models have enabled more accurate and real-time waste identification, improving system efficiency. Some studies also integrate Internet of Things (IoT) technologies with AI models to enable smart monitoring, real-time data collection, and optimized waste management processes.

A comparative analysis of selected research papers highlights the strengths and limitations of existing approaches. While many models achieve high classification accuracy, several challenges remain. These include the lack of standardized datasets, limited validation in real-world environments, and high computational requirements that restrict deployment on edge devices. Furthermore, most systems rely solely

on image data and do not incorporate multimodal inputs such as sensor data, which could enhance performance and reliability.

III. MATH

Before you begin to format your paper, first write and save the content as a separate text file. Keep your text and graphic files separate until after the text has been formatted and styled. Do not use hard tabs, and limit use of hard returns to only one return at the end of a paragraph. Do not add any kind of pagination anywhere in the paper. Do not number text heads-the template will do that for you.

COMPARATIVE ANALYSIS

Despite significant advancements, several research gaps remain in the domain of intelligent waste management systems.

First, there is no standardized dataset available for waste classification. Most studies rely on custom datasets, leading to inconsistencies in performance evaluation.

Second, limited real-time deployment is observed. While some studies propose real-time systems, very few validate them in real-world environments.

Third, the absence of multimodal sensing is evident. Current systems rely primarily on image data, ignoring other important factors such as weight, moisture, and chemical composition.

Fourth, explainable AI techniques are not widely adopted. Most deep learning models operate as black boxes, reducing transparency and trust.

Fifth, scalability remains a major challenge. Existing systems are tested in controlled environments and may not perform effectively in large-scale smart city deployments.

Finally, energy efficiency and computational cost are rarely considered, despite being critical for real-time and edge-based systems.

The comparative evaluation of existing research in intelligent waste management systems reveals several important observations regarding the effectiveness, limitations, and practical applicability of different approaches. A detailed analysis of the reviewed studies indicates that deep learning-based methods, particularly Convolutional Neural Networks (CNNs), dominate the field due to their superior performance in image-based classification tasks. These models are capable of automatically extracting complex and hierarchical features from input data, enabling accurate identification of various waste categories such as plastic, metal, paper, and organic materials.

In contrast, traditional machine learning techniques, while computationally less intensive, generally exhibit lower accuracy and limited adaptability when compared to deep learning models. Although these approaches are easier to implement and require fewer resources, they often fail to capture complex visual patterns, which reduces their effectiveness in real-world waste classification scenarios.

Recent advancements also highlight the integration of Artificial Intelligence with Internet of Things (IoT) technologies, leading to the development of smart waste management systems. These systems leverage sensor data along with image-based inputs to enable real-time monitoring and decision-making. However, despite their potential, such systems are still in the early stages of deployment and face challenges related to scalability and infrastructure requirements.

One of the major limitations observed across the reviewed literature is the absence of standardized datasets. Most studies rely on custom-built datasets, which vary in size, quality, and diversity. This lack of uniformity makes it difficult to perform fair comparisons between different models and limits the generalization capability of trained systems.

Another critical issue is the limited validation of proposed systems in real-world environments. Many studies demonstrate high accuracy under controlled laboratory conditions but do not account for practical challenges such as varying lighting conditions, occlusion, background noise, and mixed waste scenarios. As a result, the real-world performance of these models remains uncertain.

Furthermore, the majority of existing systems rely solely on image data, neglecting the potential benefits of multimodal sensing. The integration of additional parameters such as weight, moisture content, and gas emissions could significantly enhance classification accuracy and system reliability. The lack of such multimodal approaches represents a key research gap in the current literature.

Explainability is another area that requires attention. Most deep learning models operate as black-box systems, making it difficult to interpret their decision-making processes. This lack of transparency can reduce user trust and hinder adoption in critical applications.

Finally, computational complexity and energy efficiency are important challenges that are often overlooked. Many deep learning models require high processing power, which limits their deployment on low-resource edge devices. For practical implementation in smart city environments, there is a need for lightweight and energy-efficient models that can operate in real time.

Overall, while significant progress has been made in the development of AI-based waste management systems, several challenges must be addressed to achieve scalable, efficient, and real-world deployable solutions

A. Technical Challenges

IV. TECHNICAL CHALLENGES

The design and deployment of intelligent waste management systems present a range of technical challenges that must be addressed to ensure reliable and scalable operation. One of the primary challenges is environmental variability. In real-world scenarios, waste classification systems are exposed to diverse and unpredictable

TABLE I: Summary of Reviewed Research Papers

Ref	Year	Method / Algorithm	Dataset	Input	Output	Key Contribution	Limitation
[2]	2024	Enhanced CNN	Custom	Image	Waste Class	Improved accuracy	Limited dataset
[3]	2024	Computer Vision	Custom	Image	Segregation	Automated system	Binary classification
[4]	2024	CNN (TensorFlow)	Custom	Image	Waste Type	Good performance	No real-time capability
[5]	2024	ML + AI	Mixed	Image	Classification	Focus on sustainability	Lack of validation
[6]	2024	Machine Learning Model	Custom	Image	Waste Class	Simple implementation	Low accuracy
[7]	2024	Deep Learning	Custom	Image	Multi-class Output	High accuracy	No deployment analysis
[8]	2025	AI + IoT System	Real-time	Image + Sensors	Monitoring Output	Real-world implementation	Limited scalability
[9]	2025	Machine Learning	Custom	Image	Classification	Simple approach	Lower performance
[10]	2025	Intelligent AI System	Custom	Image	Disposal Suggestion	Decision support	High complexity

TABLE II: Comparative Analysis of Waste Management Techniques

Ref	Algorithm	Accuracy	Real-Time	IoT Integration	Complexity	Scalability
[2]	CNN	High	No	No	Medium	Medium
[3]	Computer Vision	Medium	No	No	Low	Low
[4]	CNN	High	No	No	Medium	Medium
[5]	ML + AI	Medium	No	No	Low	Medium
[6]	Machine Learning	Low	No	No	Low	Low
[7]	Deep Learning	High	No	No	High	Medium
[8]	AI + IoT	Medium	Yes	Yes	High	Medium
[9]	Machine Learning	Low	No	No	Low	Low
[10]	Intelligent AI System	High	Partial	Yes	High	Medium
[11]	Deep Learning	High	No	No	Medium	Medium
[12]	CNN	High	No	No	Medium	Low

conditions, including fluctuations in lighting, complex backgrounds, and partial occlusion of objects. These factors can significantly degrade the performance of vision-based models, particularly when they are trained on limited or controlled datasets.

Another critical issue is class imbalance within available datasets. In many cases, certain categories of waste, such as hazardous or electronic waste, are underrepresented compared to more common classes like plastic or paper. This imbalance can lead to biased model predictions, where the system becomes more accurate for dominant classes while performing poorly on minority categories. Addressing this issue requires careful dataset curation, augmentation techniques, and the use of robust training strategies.

Real-time processing is another major concern, especially for applications involving smart bins and automated sorting systems. Deep learning models, while highly accurate, often demand substantial computational resources, making it challenging to deploy them on low-cost hardware platforms. This limitation becomes more pronounced in edge computing environments, where devices are constrained by limited memory, processing power, and energy availability.

Edge deployment further introduces the challenge of optimizing models without compromising performance. Techniques such as model compression, pruning, and quantization are often required to reduce computational overhead while maintaining acceptable accuracy levels. Achieving this balance between efficiency and performance remains a key research problem.

In addition, the adaptability of these systems across different geographical regions poses a significant challenge. Waste composition varies widely depending on

local consumption patterns, cultural practices, and economic conditions. As a result, models trained on one dataset may not generalize effectively to another region. This necessitates continuous model updating, retraining, and the development of more generalized learning frameworks.

Overall, addressing these technical challenges is essential for the successful implementation of intelligent waste management systems in real-world environments. Future research must focus on improving model robustness, enhancing dataset diversity, and developing efficient algorithms that can operate under practical constraints.

• V. CHALLENGES AND RESEARCH GAPS IN MIXED WASTE PROCESSING

Processing and segregating waste in real-world environments becomes significantly more complex when dealing with clustered or mixed waste. Unlike controlled scenarios where individual waste items are clearly visible, practical waste streams often contain overlapping, partially hidden, and contaminated materials. This introduces several technical challenges that limit the effectiveness of current AI-based systems.

One of the primary challenges is object overlap and occlusion. In mixed waste scenarios, multiple objects may be stacked or partially hidden, making it difficult for vision-based models to accurately detect and classify each item. Traditional classification models, which assume a single object per image, are not well-suited for such conditions. Even advanced object detection models may struggle when objects are tightly clustered or visually similar.

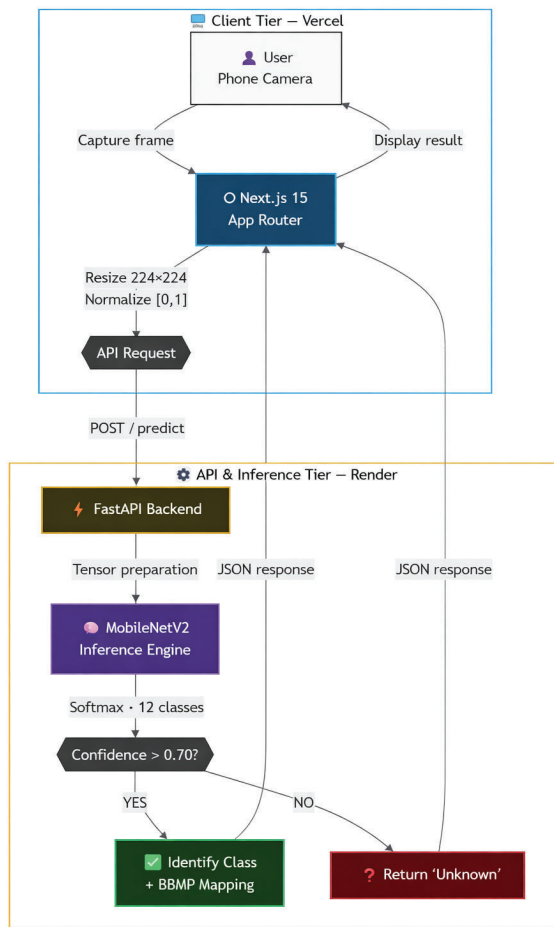


Fig. 3: System Architecture

Another significant challenge is the presence of heterogeneous materials within a single frame. Waste items often differ in shape, texture, and color, and may also be deformed or contaminated. This variability increases the complexity of feature extraction and reduces classification accuracy. Additionally, background noise and clutter further complicate the detection process, especially in unstructured environments.

Real-time processing of clustered waste is also computationally demanding. Detecting multiple objects simultaneously requires more complex models and higher processing power, which can be difficult to achieve on edge devices. This creates a trade-off between accuracy and efficiency, particularly in smart bin or conveyor-based systems.

From a research perspective, several gaps remain unaddressed. Most existing studies focus on single-object classification using clean and well-separated datasets, which do not reflect real-world conditions. There is a lack of large-scale datasets specifically designed for mixed waste scenarios, including images with overlapping and partially occluded objects.

Furthermore, limited research has been conducted on

instance-level segmentation techniques, such as Mask R-CNN, which can distinguish individual objects within a cluster. The integration of multimodal sensing, combining visual data with depth sensors or weight measurements, is also largely unexplored in this context. Another important gap is the absence of robust evaluation metrics for clustered waste scenarios. Current metrics primarily focus on classification accuracy and do not adequately measure performance in detecting multiple objects within a single frame.

Addressing these challenges requires the development of advanced detection and segmentation models, improved dataset diversity, and efficient algorithms capable of real-time processing. Future research should focus on designing systems that can accurately identify and separate mixed waste in complex environments, enabling practical deployment in large-scale smart waste management systems.

VI. FUTURE RESEARCH DIRECTIONS

Future research in intelligent waste management systems should prioritize the development of standardized and publicly available datasets. The absence of uniform datasets currently limits the ability to fairly compare different models and evaluate their generalization capabilities. Creating large-scale, diverse datasets that capture real-world conditions will significantly improve benchmarking and model reliability.

Another important direction is the integration of multimodal sensing techniques. Combining image-based data with additional inputs such as weight, moisture levels, and chemical composition can enhance classification accuracy and provide a more comprehensive understanding of waste characteristics. Such approaches can lead to more robust and reliable systems, especially in complex environments involving mixed or clustered waste.

The optimization of deep learning models for edge deployment is also a critical research area. Techniques such as model compression, pruning, and quantization should be further explored to reduce computational overhead while maintaining performance. This will enable efficient deployment on low-power embedded devices, which are essential for real-time applications in smart bins and automated sorting systems.

Furthermore, there is a need to validate proposed systems in large-scale, real-world environments. Many existing studies are limited to laboratory settings, which do not fully capture the challenges of practical deployment. Future systems must be tested under dynamic conditions to ensure scalability and reliability in smart city infrastructures.

Explainable Artificial Intelligence (XAI) should also be incorporated into waste management systems to improve transparency and interpretability. Providing insights into model decisions can enhance user trust and facilitate adoption in critical applications.

In addition, future systems should extend beyond classification tasks to include waste lifecycle analysis, logistics optimization, and environmental impact assessment. This holistic approach can support more sustainable and efficient waste management strategies. Finally, the adoption of advanced algorithms such as real-time object detection models (e.g., YOLO), transformer-based architectures, and reinforcement learning techniques can further improve system adaptability and performance in complex scenarios. Further research can also explore the use of federated learning approaches to enable collaborative model training without sharing sensitive data across multiple locations. This can improve model generalization while maintaining data privacy. In addition, the incorporation of adaptive learning mechanisms can allow systems to continuously update and improve based on new waste patterns and environmental conditions. The integration of robotics with AI-based classification systems presents another promising direction, enabling fully automated waste sorting in industrial settings. Finally, the development of standardized evaluation frameworks and performance benchmarks will be essential to ensure consistency, reliability, and fair comparison across future intelligent waste management solutions. Moreover, future systems can benefit from the integration of digital twin technology to simulate waste management processes and optimize system performance before deployment. The use of cloud-edge hybrid architectures can further improve scalability and responsiveness, enabling efficient data processing and decision-making across distributed smart waste management networks.

Table III summarizes the key limitations identified in existing studies, highlighting the need for more scalable, real-time, and interpretable waste management solutions.

VII. CONCLUSION

This survey presents a detailed review of recent developments in intelligent waste management systems, with a focus on research published between 2021 and 2025. The analysis reflects a clear transition from conventional machine learning techniques to more advanced deep learning models and integrated real-time solutions. These advancements have significantly improved the accuracy and efficiency of waste classification systems, particularly in image-based applications. Despite these improvements, several challenges continue to limit practical deployment. Issues such as scalability, high computational requirements, and lack of real-world validation remain critical barriers. In addition, the absence of standardized datasets makes it difficult to benchmark and compare different approaches effectively. These limitations highlight the gap between theoretical research and real-world implementation.

The findings of this survey suggest that future work should emphasize the development of robust, scalable, and energy-efficient systems capable of operating in dynamic environments. Integrating Artificial Intelligence with Internet of Things (IoT) technologies and smart infrastructure can further enhance system capabilities and enable real-time decision-making.

Overall, this study provides a consolidated understanding of current methodologies, identifies key research challenges, and outlines potential directions for future work. It is expected that the insights presented will support ongoing efforts toward the development of practical and sustainable intelligent waste management solutions.

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References are important to the reader; therefore, each citation must be complete and correct. If at all possible, references should be commonly available publications.

REFERENCES

- [1] M. R. S. Sandhya Devi, V. R. Vijay Kumar, and P. Sivakumar, "A Review of Image Classification and Object Detection on Machine Learning and Deep Learning Techniques," in Proc. 5th Int. Conf. Electronics, Communication and Aerospace Technology (ICECA), Coimbatore, India, 2021, pp. 1–8.
- [2] K. B., S. R., and P. M., "Enhanced CNN Architecture for Accurate Waste Classification in Smart Cities," in Proc. Int. Conf. IoT Based Control Networks and Intelligent Systems (ICINIS), Bengaluru, India, 2024, pp. 538–543.
- [3] R. L. Kumar, R. Ramya, M. J. Balaji, V. Hari, and M. Malarvizhi, "Garbage Collection and Segregation using Computer Vision," in Proc. Int. Conf. Inventive Computation Technologies (ICICT), Lalitpur, Nepal, 2024, pp. 1023–1028.
- [4] P. Prasanth and R. Raut, "Analyzing and Categorizing Waste Using Convolutional Neural Networks and TensorFlow," in Proc. 2nd World Conf. Communication Computing (WCONF), Raipur, India, 2024, pp. 1–6.
- [5] M. Kumar, S. Kumar, A. K. Luhach, and A. Tiwari, "Advancements in Waste Segregation Through Machine Learning and Integrating AI for Sustainable Waste Management," in Proc. 13th Int. Conf. System Modeling Advancement in Research Trends (SMART), Moradabad, India, 2024, pp. 328–334.
- [6] A. V., B. Nithya, G. M., B. T. M., A. Hiremath, and B. Jayaprakash, "Ingenious Waste Management: Implementing Machine Learning in Waste Segregation," in Proc. Int. Conf. Emerging Smart Computing and Informatics (ESCI), Pune, India, 2024, pp. 1–5.
- [7] A. S. M., S. Ashwath, A. V. Gadagkar, and S. S., "Intelligent Waste Sorting System Using Deep Learning," in Proc. IEEE Int. Conf. Blockchain and Distributed Systems Security (ICBDS), Pune, India, 2024, pp. 1–6.
- [8] M. R. O., S. B. D., V. Vivek, K. Prathik, N. Nishmitha, and S. Bhat, "Design and Testing of an AI-based Campus Waste Management System," in Proc. Int. Conf. Intelligent Systems and Pioneering Innovations in Robotics and Electric Mobility (INSPIRE), Mangalore, India, 2025, pp. 477–481.
- [9] P. D. M., P. A., S. N. V., S. B., G. V., and S. T., "Smart Waste Management System Using Machine Learning," in Proc. 6th Int. Conf. Inventive Research in Computing Applications (ICIRCA), Coimbatore, India, 2025, pp. 1880–1885.

TABLE III: Mapping of Research Gaps in Existing Studies

Gap	Description	Papers Affected
No Standard Dataset	Use of different custom datasets leading to inconsistent evaluation	[2]–[13]
No Real-Time Systems	Majority of models operate offline without real-time implementation	[2]–[7], [11], [12]
No IoT Integration	Lack of sensor-based data integration in most systems	[2]–[7], [9], [11]
No Explainable AI	Models behave as black boxes with no interpretability	All
High Computational Cost	Deep learning models require high processing power	[7], [10], [13]
Limited Scalability	Systems tested only in small or controlled environments	Majority of studies

- [10] S. S., W. A. Breen, M. Narmadha, K. S., and T. Bernatin, "Intelligent Waste Monitoring and Classification System with Automated Disposal Suggestions," in Proc. 5th Int. Conf. Soft Computing for Security Applications (ICSCSA), Salem, India, 2025, pp. 2114–2119.
- [11] L. S. Ramesh, J. D. R., and K. S., "Waste Management System Using Deep Learning," in Proc. Int. Conf. Recent Innovation in Science Engineering and Technology (ICRISET), Chennai, India, 2025, pp. 1–8.
- [12] B. Vishnu, D. Tanuj, and G. Saranya, "Smart Waste Management: A CNN-based Approach for Automated Plastic and Material Classification," in Proc. 5th Int. Conf. Ubiquitous Computing and Intelligent Information Systems (ICUIS), Erode, India, 2025, pp. 778–783.
- [13] A. Gore, A. Bishoi, and R. S. Kute, "AI-Powered Waste Management: Real-Time Garbage Detection and Categorization," in Proc. 12th Int. Conf. Emerging Trends in Engineering Technology - Signal and Information Processing (ICETET-SIP), Nagpur, India, 2025, pp. 1–5.
- [14] H. Yang and J. Thung, "Classification of Trash for Recyclability Status," CS229 Project Report, Stanford University, 2016.
- [15] M. Yang and G. Thung, "TrashNet: A Dataset for Garbage Classification," Stanford AI Project, 2016.
- [16] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," in Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR), 2016, pp. 770–778.
- [17] M. Tan and Q. Le, "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks," in Proc. Int. Conf. Machine Learning (ICML), 2019.
- [18] J. Redmon et al., "You Only Look Once: Unified, Real-Time Object Detection," in Proc. IEEE CVPR, 2016.
- [19] A. Bochkovskiy, C.-Y. Wang, and H.-Y. M. Liao, "YOLOv4: Optimal Speed and Accuracy of Object Detection," arXiv preprint arXiv:2004.10934, 2020.
- [20] G. Jocher et al., "YOLOv5 by Ultralytics," GitHub Repository, 2020.
- [21] A. Howard et al., "MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications," arXiv preprint arXiv:1704.04861, 2017.
- [22] S. Albawi, T. A. Mohammed, and S. Al-Zawi, "Understanding of a Convolutional Neural Network," in Proc. Int. Conf. Engineering and Technology (ICET), 2017.