An End-to-End Risk-Aware and Rule-Guided Intelligent System for Biomedical Waste Segregation

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***Abstract*—Biomedical waste segregation in all healthcare facilities remains as a critical challenge and can lead to various biosafety risks in the hospital environments dealing with infectious and hazardous waste. Any kind of improper waste segregation can directly impact both healthcare workers as well as the patients. This is due to human dependent manual waste segregation which can often lead to misclassification hazards as it is based on manual handling, where human errors are possible or workers might not have been trained adequately. Various factors such as workload and time constraints can further increase the chances of human error. The existing machine learning based waste segregation systems mainly focus purely on accuracy classification and treat all errors with the same weight. Such approaches are not sufficient for safety critical hospital applications. There is a lack of risk differentiation and bio-safety prioritization, due to which there is an absence of safety-aware decision mechanism. This limitation reduces the reliability of automated waste segregation systems in real-world settings. This project proposes a risk- aware and automated waste segregation system in healthcare facilities to overcome this critical problem. It is a hardware- integrated system, which is based on machine learning-based classification. The system is designed to operate in a controlled and practical hospital environment. Key features include camera- assisted learning, real-time segregation and intelligent control logic. These features in the system enable much faster and safer waste handling with minimal human involvement. The performance evaluation of the system focuses on biosafety oriented metrics, highlighting the system's ability to minimize high risk misclassifications and ensure safer waste handling in healthcare settings. Hence, it greatly helps in automating hospital waste workflows. This risk aware approach supports better biosafety practices and promotes safer healthcare waste management in healthcare facilities.**

***Index Terms*—Healthcare, Bio-safety, Biomedical waste segregation, Safety-aware automation, Regulatory compliance, Explainable machine learning**

I. Introduction

Biomedical waste is produced from the treatment given to patients, and from the medicines being prescribed[10],[17]. This is considered as infectious waste because it contains hazardous and sharp materials like needles, syringes, broken glass, that poses a high risk of infection to workers, patients and even the environment near the hospital [4],[6]. It is necessary for proper segregation of biomedical waste, for safe handling and disposal while also reducing health risks. Improper segregation can lead to environmental contamination, due to violations of waste management rules and regulations [5],[30].

The current method in practice used for disposal of biomedical waste is manual segregation done by healthcare workers [8]. Due to this manual method, human errors can easily occur when the workers lack proper training or when they have a high amount of workload which makes them fatigue. These errors can lead to needle stick injuries and spread of infection. Hence, it is an inconsistent practice making it an unsafe disposal method as it might not have proper treatment of hazardous waste. There is a need to find a more effective and automated method to reduce the time taken and workload on the workers, thereby reducing errors made during disposal [6], [7], [9].

Recent studies and research papers have concentrated on automated and machine learning-based biomedical waste segregation methods. They include camera-assisted systems which help in image-based classification [12], [14]. These existing systems mainly focus on classification accuracy, and all errors as the same. This is where the issue arises because not all wastes are equally hazardous. When the more hazardous waste is misclassified, it has a higher dangerous impact on the environment. As a result, there is a lack of bio-safety and risk-aware machine learning-based system that explains the classification and also automates the waste segregation process.

This paper presents a machine-learning system consisting of the risk-aware framework and explaining it's decisions for building trust and transperency. It works in real-time and performs automated segregation. The system ensures to follow all the bio-safety rules and regulations. It is hardware-integrated consisting of Raspberry Pi and Camera module, used to capture images of the waste for classification. It also includes confidence-based decisions, which improve the efficiency and prevent misclassifications.

II. Literature Review

The rapid growth of healthcare facilities especially post the CoVID-19 pandemic, has lead to a corresponding rise in hazardous waste generation. This has increased the attention on biomedical waste management systems. Recent studies primarily focus on automating waste classification using machine learning and artificial intelligence, computer vision and IoT technologies to minimise human error and segregation risk.

A. Image-Based Biomedical Waste Classification

Researchers have worked on deep learning techniques for identifying and classifying biomedical waste through visual features. Sharma and Gupta introduced a deep learning based segmentation and classification framework that showed the effectiveness of image based biomedical waste recognition [15], [32]. Akkajit and Sukkea leveraged CNN models with transfer learning to classify common medical waste such as syringes and gloves with high classification accuracy [31], [33]. Based on these studies it is confirmed that visual images and cues are sufficient for automated biomedical waste identification. These techniques however, primarily focus on accuracy and do not concentrate on the various safety implications of different misclassification types.

B. IoT Enabled Smart Waste Management Systems

To enable real time waste monitoring and automation, several projects have integrated IoT components with computer vision. Ashwini et al. proposed an IoT enabled smart biomedical waste bin using the You Only Look Once algorithm and Raspberry Pi for real team waste detection and monitoring [20]. Their system does not focus on decision reliability nor safety enforcement but works on operational efficiency, bin level monitoring and notification mechanisms [2], [18], [24]. Similarly, Hannath and Bose presented an integrated IoT and deep learning framework for biomedical waste segregation and monitoring emphasising on real time alerts and automated waste handling [27]. These systems assume that every automated decision is correct and safe and do not have mechanisms to handle uncertainty or unsafe predictions [19], [25], [28].

C. Hardware Integrated Automated Segregation System

Several studies have developed hardware centric segregation solutions such as the Arduino based automated biomedical waste segregation devices using infrared sensors for waste classification developed by Padmapriya et al [1]. Likewise, Bhandari et al. implemented a Raspberry Pi based system using image processing and servo controlled conveyor mechanisms to physically segregate the biomedical waste [22], [34]. Both these systems demonstrate the feasibility of end to end automation but do not incorporate the semantic understanding of waste risk nor any regulatory validation.

D. General Intelligent Waste Classification Systems

Broader intelligent waste classification research such as a deep learning based intelligent garbage classification system using an embedded Linux platform and a lightweight CNN model by Fu et al [3]. provide useful architectural insights. Their work emphasizes the importance of efficiency and real time operation [11], [13], [26].

E. Identified Research Gaps

A comparative analysis of existing literature displays several critical gaps: 1. Uniform Error Treatment: Majority of the systems treat all classification errors equally and ignore the severity of risks posed by misclassifying sharps or infectious wastes. 2. Lack of Decision Abstention: Current models force a classification even when the confidence is low, hence increasing the possibility of unsafe actions. 3. No Violation Monitoring: Improper disposal by the mechanisms are not detected or logged by current systems. 4. Accuracy Centric Evaluation: Performance is measured using generic metrics and are not built specifically for biosafety. 5. Limited Explainability: Most models function as black boxes and do not explain their decisions prompting reduced trust and auditability.

F. Motivation for the Proposed System

The literature review confirms the technical feasibility of automated biomedical waste segregation and highlights accuracy and automation while ignoring the aspects of safety, compliance and decision reliability. This motivates the need for developing a risk aware, confidence guided and rule enforced biomedical waste segregation system that prioritizes bio-safety over pure classification performance. The proposed work directly addresses these gaps by introducing safety centric decision mechanisms with explainable outputs and compliance driven logic into the automated segregation system.

III. Proposed System and Methodology

This section gives an overview about the design and implementation of the methodology for the automated biomedical waste segregation system. It presents the system architecture, hardware and software components, and the techniques used to achieve real-time and bio-safety oriented waste segregation and disposal . The methodology mainly includes integrating machine learning–based classification with embedded hardware to enable real-time, risk-aware, and compliant waste handling in healthcare environments.

A. System Architecture Overview

The proposed system is used to automate the biomedical waste segregation generated in healthcare facilities. It includes embedded hardware for capturing the image, and real-time machine-learning based classification [23]. The system makes use of a camera module to capture the images, and processes them with the help of a trained machine learning model. Depending on the training, the model classifies the waste and uses a servo mechanism to direct it to the correct disposal category. It also treats errors differently by taking into consideration the risks associated with different types of hazardous wastes, ensures that it follows bio-safety rules and also explains its decisions to build trust. This overall design aims for minimal manual work, reducing the time consumed and increasing efficiency which operates in real-time.

B. Hardware Components

- The hardware architecture consists of embedded and mechanical components namely Raspberry Pi, Camera module and Servo motors.
- Raspberry Pi acts as a central processing unit, which is responsible for interfacing with external devices and controlling operations. A camera module is connected to the microprocessor to capture images of the waste items for further classification [21]. A servo motor acts as an actuator, as it directs the waste into the appropriate disposal category.
- There is also an assembly of the 4 types of bins based on different types of medical waste namely - red, yellow, blue and white.
- These hardware components work together to enable automated operation which works in real-time and also reduces human intervention waste segregation.

C. Software Components

The software framework consists of a machine-learning based approach for classification of different types of waste. The model is trained on different datasets containing labeled images of wastes to be disposed in their respective blue, white, red and yellow color bins. The images are captured and techniques such as resizing and normalization are applied to improve the reliability and accuracy of the classification. The trained model generates an appropriate output corresponding to the pre-defined categories.

The trained model is deployed on the embedded platform for real-time interference. Based on the decision given by the model, the software sends control signals to the hardware for actual disposal using a servo mechanism. The software framework acts as a bridge between the results and the actuation. This combined approach helps to reduce the time taken to manually classify waste and also improves the efficiency.

D. Implementation Tools and Technology Stack

Hardware Components

- Raspberry Pi – Central processing unit and control unit
- Camera Module – Image capture for waste classification
- Servo Motors – Actuation mechanism for waste segregation
- Mechanical Bin Assembly – Physical segregation of 4 different waste categories
- Power Supply Module – Powering the embedded system

Software Frameworks

- Python – Primary programming language
- Tensorflow/Keras – Machine learning model [2] development and training
- OpenCV – Image capture and processing
- NumPy – Numerical computations
- GPIO libraries – Hardware control and actuation

Machine Learning Components

- Supervised Learning Model – Multi-class waste classification [12]
- Image Dataset – Labeled biomedical waste images (Blue, White, Red, Yellow)
- Pre-processing Techniques – Resizing and normalization

Decision and Control Components

- Classification Output Module – Determines waste category
- Control Logic Module – Converts decisions into actuation signals
- Real-Time Inference Engine – Enables on-device prediction

E. Risk-Aware Decision Logic

The proposed system focuses on risk-aware decision logic to make sue biosafety rules are followed during waste segregation. The research gap identified suggests that existing systems treat all waste categories equally. However, this system aims to differentiate waste depending on the how hazardous each of the category is. Infectious and sharp materials pose higher risks, can cause infections, hence, they are assigned greater priority when the model gives output to minimize the effects of the errors which could occur.

The decision generated by the machine learning model is evaluated using the waste management rules before the actual actuation. In case the model shows low confidence, which is a sign of uncertainty, the system avoids the automated segregation. It will isolate that waste for manual disposal later. This reduces risk of misclassifications and also builds higher trust on the trained system.

To improve transparency, the system provides explainable outputs clearly explaining why it classified a particular waste item into that category. The decision logic is strictly designed to follow the biomedical waste management rules, without violating any guidelines that could cause harm to the environment.

F. *Workflow of the Proposed System*

The workflow starts with placing the waste item into the system input area. A camera module connected to the Raspberry Pi, captures the image on which pre-processing techniques such as resizing and normalization are applied. This image is sent to the machine learning model which will provide a prediction of what bin category it should be disposed to based on its training.

The predicted output is evaluated using risk-aware decision logic and the waste management rules. The system identifies the hazard level associated with predicted category and verifies whether the confidence level is above the predefined safety threshold. If the decision is considered as safe, then the decision is converted to control signals to activate the servo. The servo mechanism is used to direct the waste the respective bin.

In case the confidence level is below the set threshold or if the regulatory safety rules are not satisfied, then the system is designed to isolate that waste item for manual disposal later by stopping the automated segregation.

Additionally, the system focuses on providing explainable outputs to describe the reason behind each decision it gives for any waste item. This enables real-time and safe biomedical waste segregation.

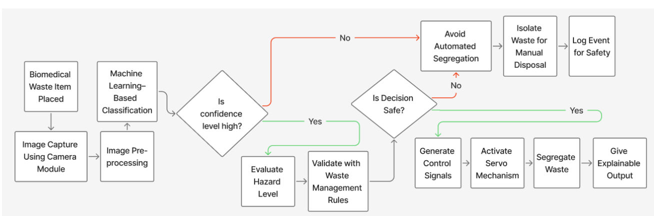

Fig. 1. Workflow for Biomedical Waste Classification

IV. Results and Discussion

This section includes the experimental results obtained from the prototype of the proposed biomedical waste segregation system detailed in the previous sections and discusses them from the contexts of biosafety, regulatory compliance and practical deployment in healthcare facilities. Unlike the conventional studies that mainly focus on classification accuracy, the evaluation of this system focuses upon risk reduction, decision reliability and safety aware behaviour.

A. *Classification Performance Across Waste Categories*

The machine learning model developed was evaluated on a four class biomedical waste dataset - the Yellow, Red, Blue, and White categories as defined under Biomedical Waste Management Rules. Upon conducting a detailed analysis of the system performance it revealed that classification difficulty varied across categories. Visually distinct wastes such as glass vials (Blue category) and plastic tubing (Red category) were classified with higher consistency, while items with visual features which overlapped such as contaminated gloves and cotton wastes introduced the occasional ambiguity. This observation reinforces the limitation of relying solely on overall accuracy as a performance indicator in biomedical applications [31].

B. *Impact of Risk Aware Classification Strategy*

The key contribution of this proposed system is its risk aware classification design where misclassification including high risk wastes are treated with greater severity. During evaluation, the model's decision thresholds were adjusted accordingly to prioritise minimising high risk misclassification events instead of just maximising aggregate accuracy on a whole. As a result, a substantial reduction in high risk misclassification rates was demonstrated, especially in the White category wastes which contained sharp objects. This led to a marginal increase in conservative decisions for low risk categories but, the trade off was beneficial from the view of biosafety. These results highlight that a small compromise in general overall accuracy can yield significant improvements in safety vital outcomes which are the key part of healthcare waste handling [15].

C. *Confidence Based Safe Decision Behaviour*

Unlike conventional automated segregation systems that force a classification decision for every input regardless of the confidence score, the proposed system integrates a confidence based decision system where each prediction is accompanied by a confidence score, and segregation is executed only when this score exceeds a predefined safety threshold. Experimental observations demonstrated that uncertain samples which may have risen from poor lighting or mixed waste scenarios were successfully diverted to a manual inspection path. This behaviour effectively prevented the unsafe segregation during ambiguity. The system's ability to refuse a classification decision when the confidence was low contributed to a noticeable reduction in unsafe mechanical classification events, demonstrating the value of uncertainty aware automation in safety critical systems [32].

D. *Effectiveness of Rule Guided Segregation Logic*

Biomedical waste management rules were explicitly embedded into the system segregation logic, enabling the system to validate machine learning outputs against regulatory constraints before physical execution. During testing, several test scenarios were introduced where visually plausible classifications conflicted with rule based constraints, such as unsafe combinations of waste types. In these cases the system either corrected the decision or blocked the segregation entirely. This layered decision process by combining perception with rule enforcement proved effective in preventing regulatory violations that could otherwise have occurred due to any isolated model errors. These results indicate that integrating domain rules directly into the automated pipelines of the segregation system significantly enhances system robustness in real world settings such as in hospitals.

E. Segregation Violation Detection and Monitoring

This system showed its capability to identify and log all segregation violations such as mixed waste disposal or incorrect category placements. These violation events were recorded with their timestamps and the category details, thus enabling manual analysis [29]. The violation detection mechanism successfully identified any kind of improper disposal attempts that may have gone unnoticed in manual checks. This feature makes the system an active monitoring and compliance support system which can assisti in hospital audits and for staff training initiatives.

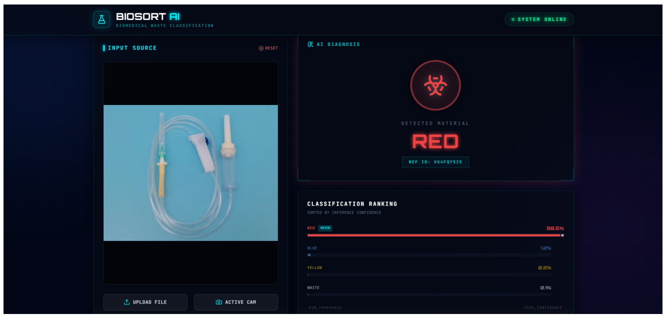

Fig. 2. Classification of plastic IV tubing as **RED** waste (98.5% confidence)

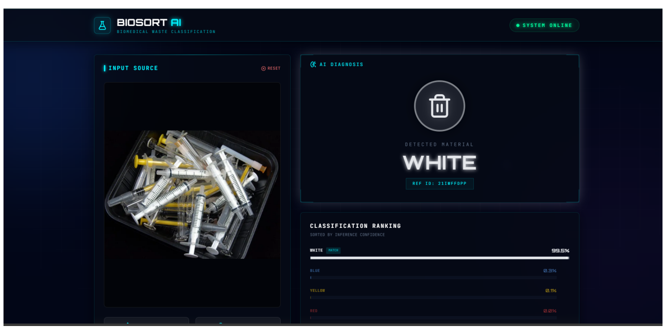

Fig. 3. Classification of waste syringes as **WHITE** waste (99.5% confidence)

F. Explainability and System Transparency

Each segregation decision generated a concise explanation describing the visual and logical factors that influenced its outcome. These explanations were useful to address trust concerns and allowed operators to understand the reasoning behind system behaviour regarding any blocked wastes. This improved accountability, transparency and traceability in the use cases.

G. Discussion and Practical Implications

Overall the experimental results validated the effectiveness of the proposed risk aware rule guided and explainable biomedical waste segregation system. The findings suggest that biowaste management systems should not merely aim for high accuracy but must be able to handle uncertainty, enforce regulations, and prioritize human safety. This architecture of the systems is such that it can be expanded in the future with features such as hospital integration and additional waste categories. The results from the prototype show that the system can help significantly improve reliability and trust in healthcare environments such as hospitals or biological laboratories .

V. Conclusion

This system demonstrates a risk-aware, explainable and automated biomedical waste segregation system which is designed to enhance bio-safety in healthcare facilities. Unlike the existing systems, this system emphasizes on the different hazard level for each waste, building trust, improving transparency by providing explainable outputs, and also disposing the waste only when the model is confident. By integrating machine learning with embedded hardware, the system operates in real-time and also provides automated segregation without human involvement. Experimental evaluation using bio-safety oriented metrics demonstrates the effectiveness of the proposed approach in reducing high-risk misclassifications and supporting safer biomedical waste management practices [17], [18].

VI. Future Work

Future enhancements include adding more diverse images to datasets with different lighting, angles making it more efficient for the model to classify in any environment making it prone to lesser mistakes. Incorporating real-time monitoring and connectivity with hospital information systems can enable centralized tracking and analytics. Further research may also explore the use of adaptive learning mechanisms to continuously improve system performance in dynamic healthcare environments [34].

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References

[1] P. Padmapriya, D. Banupriya, J. Saminathan, J. William, and M. Loganathan, "A Novel Automated Solution for Biomedical Waste Management," Journal of Environmental Nanotechnology, vol. 14, no. 2, pp. 330-340, July 2025. doi: 10.13074/jent.2025.06.2511386.

[2] N. C. A. Sallang, M. T. Islam, M. S. Islam, and H. Arshad, "A CNN-Based Smart Waste Management System Using TensorFlow Lite and LoRa-GPS Shield in Internet of Things Environment," IEEE Access, vol. 9, pp. 153560-153574, 2021. doi: 10.1109/ACCESS.2021.3128314.

[3] B. Fu, S. Li, J. Wei, Q. Li, and J. Tu, "A Novel Intelligent Garbage Classification System Based on Deep Learning and an Embedded Linux System," IEEE Access, vol. 9, pp. 131134-131146, 2021. doi: 10.1109/ACCESS.2021.3114496.

[4] N. Arshad, S. Nayyar, and F. Amin, "Health Care Waste: Avoiding Hazards to Living and Non Living Environment by Efficient Management," Fortune Journal of Health Sciences, vol. 5, no. 1, pp. 10-21, 2022.

[5] H. S. Bansod and P. Deshmukh, "Biomedical Waste Management and Its Importance: A Systematic Review," Cureus, vol. 15, no. 2, p. e34589, Feb. 2023. doi: 10.7759/cureus.34589.

[6] P. Mathur, S. Patan, and A. S. Shobhawat, "Need of Biomedical Waste Management System in Hospitals - An Emerging issue - A Review," Current World Environment, vol. 7, no. 1, pp. 117-124, 2012. doi: 10.12944/CWE.7.1.18.

[7] P. Mathur, S. Patan, and A. S. Shobhawat, "Need of Biomedical Waste Management System in Hospitals - An Emerging issue - A Review," Current World Environment, vol. 7, no. 1, pp. 117-124, 2012. doi: 10.12944/CWE.7.1.18.

[8] R. D. Totad and P. Ganganahalli, "Knowledge and practice survey of biomedical waste management among health care workers in tertiary care hospital of Vijayapura district," International Journal of Community Medicine and Public Health, vol. 7, no. 11, pp. 4536-4540, 2020. doi: 10.18203/2394-6040.ijcmph20204760.

[9] P. Pasupathi, S. Sindhu, B. S. Ponnusha, and A. Ambika, "Biomedical waste management for health care industry," International Journal of Biological and Medical Research, vol. 2, no. 1, pp. 472-486, 2011.

[10] G. Khandelwal, "Biomedical Waste: Types, Current Status, Management and Treatment," International Journal for Research in Applied Science and Engineering Technology (IJRASET), vol. 9, no. 5, 2021.

[11] S. U. Krishna, A. N. B. Lakshman, and R. Mukund, "Deep learning based garbage classification: A promising approach for sustainable waste management," AIP Conference Proceedings, vol. 3216, no. 1, p. 050005, 2024. doi: 10.1063/5.0226464.

[12] S. Forhad, I. Jahan, and A. Rashid, "DeepSegRecycle: Deep Learning and Image Processing for Automated Waste Segregation and Recycling," 2024 3rd International Conference on Advancement in Electrical and Electronic Engineering (ICAEEE), Gazipur, Bangladesh, 2024, pp. 1-6. doi: 10.1109/ICAEEE62219.2024.10561709.

[13] S. Kadali, "Developing Smart Bin Systems for Reducing Improper Waste Disposals," International Journal of Engineering Research and Technology (IJERT), vol. 9, no. 10, Oct. 2020.

[14] A. Tank and D. Khambhati, "A New Approach for Effective Biomedical Waste Segregation and Disposal," International Journal of Innovative Technology and Exploring Engineering (IJITEE), vol. 10, no. 4, pp. 236-238, Feb. 2021. doi: 10.35940/ijitee.D8591.0210421.

[15] F. R. Sayem, "Enhancing waste sorting and recycling efficiency: robust deep learning-based approach for classification and detection," Neural Computing and Applications, vol. 37, no. 6, pp. 4567-4583, 2024. doi: 10.1007/s00521-024-10855-2.

[16] J. Manzoor and M. Sharma, "Impact of Biomedical Waste on Environment and Human Health," Environmental Claims Journal, vol. 31, no. 4, pp. 311-334, 2019. doi: 10.1080/10406026.2019.1619265.

[17] E. Janik-Karpinska, et al., "Healthcare Waste—A Serious Problem for Global Health," Healthcare, vol. 11, no. 2, p. 242, 2023. doi: 10.3390/healthcare11020242.

[18] M. M. Ahmed, E. Hassanein, and A. E. Hassanien, "IoT-based intelligent waste management system," Neural Computing and Applications, vol. 35, no. 9, pp. 6943-6962, 2023. doi: 10.1007/s00521-023-08970-7.

[19] A. Ramaa, A. C. Patil, and N. Joshy, "IoT Enabled Biomedical Waste Management System," 2020 International Conference on Mainstreaming Block Chain Implementation (ICMBI), 2020.

[20] Ashwini G, Sahana K, T. R. Bhoomika, S. Behera, T. Thulasi, and U. Desai, "IoT Enabled Biomedical Smart Waste Bin Monitoring System using YOLO Algorithm," 2024 IEEE International Conference on Communication, Computing and Signal Processing (IICCCS), 2024. doi: 10.1109/iicccs61609.2024.10763584.

[21] Y. T. Liang, "Smart Underground Cylindrical Parking System," Bachelor's Thesis, Faculty of Information and Communication Technology, Universiti Tunku Abdul Rahman, Kampar, Malaysia, 2022.

[22] C. S. Grace, M. Sreeja, and M. Deepika, "Non-human Intervention Robot in Biomedical Waste Management," International Journal of Health Technology and Innovation, vol. 2, no. 1, pp. 2-4, 2023. doi: 10.60142/ijhti.v2i01.75.

[23] S. Vishnu, S. R. J. Ramson, M. S. S. Rukmini, and A. M. Abu-Mahfouz, "Sensor-Based Solid Waste Handling Systems: A Survey," Sensors, vol. 22, no. 6, p. 2340, 2022. doi: 10.3390/s22062340.

[24] T. Maddileti and H. Kurakula, "IoT Based Smart Dustbin," International Journal of Scientific and Technology Research, vol. 9, no. 4, pp. 315-318, 2020.

[25] P. Kanade, P. Alva, J. P. Prasad, and S. Kanade, "Smart Garbage Monitoring System using Internet of Things(IoT)," 2021 5th International Conference on Computing Methodologies and Communication (ICCMC), pp. 330-335, 2021. doi: 10.1109/ICCMC51019.2021.9418359.

[26] M. Deepika, S. Sangeetha, M. Vanitha, and M. Baskaran, "SMART WASTE MANAGEMENT USING AI," Information Technology in Industry, vol. 9, no. 3, pp. 213-216, 2021. doi: 10.17762/itii.v9i3.454.

[27] N. Hannath and A. Bose, "Smart Handling of Biomedical Waste using Intelligent Deep Learning and IOT," International Journal For Multidisciplinary Research (IJFMR), vol. 6, no. 3, May-June 2024. doi: 10.36948/ijfmr.2024.v06i03.19806.

[28] S. Vishnu, et al., "IoT-Enabled Solid Waste Management in Smart Cities," Smart Cities, vol. 4, no. 3, pp. 1004-1017, 2021. doi: 10.3390/smartcities4030053.

[29] A. Agrawal et al., "Intelligent Waste Bin Monitoring with IoT Integration," International Journal of Advancement and Innovation in Technology and Research, vol. 3, no. 1, pp. 262-275, 2026.

[30] S. V. Jaiswal, K. P. Bhansali, K. S. Ugle, N. Khan, and K. R. R. Reddy, "Survey of Biomedical Waste Management," International Journal of Advanced Research in Science, Communication and Technology (IJARSCT), vol. 4, no. 2, March 2024. doi: 10.48175/ijarsct-15788.

[31] M. Malik, et al., "Waste Classification for Sustainable Development Using Image Recognition with Deep Learning Neural Network Models," Sustainability, vol. 14, no. 12, p. 7222, 2022. doi: 10.3390/su14127222.

[32] S. M. G. Ali et al., "Real-Time Household Waste Detection and Classification for Sustainable Recycling: A Deep Learning Approach," Sustainability, vol. 17, no. 5, p. 1902, 2025. doi: 10.3390/su17051902.

[33] M. Chhabra, B. Sharan, K. Gupta, and R. Astya, "Waste Classification Using Improved CNN Architecture," SSRN Electronic Journal, July 2022. doi: 10.2139/ssrn.4157549.

[34] Ashwini G, Sahana K, T. R. Bhoomika, S. Behera, T. Thulasi, and U. Desai, "WasteSortBot: An Innovative Solution for Multi-Categorical Waste Separator Bin Using Vision-Based Control With Robot Operating System and Cloud Computing," IEEE Access, vol. 13, pp. 183056-183074, 2025. doi: 10.1109/ACCESS.2025.3411449.