

Optimizing Waste Classification using AI

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Abstract—

As smart cities expand, effective waste management becomes increasingly essential for sustainability. This paper presents an AI-driven automated waste segregation system that classifies waste into dry, wet, and paper categories. A moisture sensor detects wet waste, while an ESP32-CAM captures images for real-time classification of dry and paper waste using computer vision and machine learning. The Arduino UNO acts as a central component, ensuring smooth communication between components and enabling real-time monitoring. By reducing manual sorting and improving classification accuracy, the system enhances efficiency and supports recycling efforts. Experimental findings highlight the system's ability to improve the efficiency of material segregation, reduce environmental harm, and support eco-friendly waste management strategies in densely populated areas.

Keywords—

Waste Management, Smart Cities, AI-driven Segregation, Automated Waste Sorting, Computer Vision, Moisture Sensor, Recycling Efficiency, Sustainability, Resource Recovery, Environmental Impact

revolutionizing waste management by automating classification, optimizing resource utilization, and decreasing the ecological impact of mismanaged waste.

AI-powered waste segregation systems utilize advanced sensing technologies, machine learning algorithms, and computer vision to detect and categorize waste in real-time. These systems incorporate smart sensors, such as moisture sensors and optical cameras, which work in tandem to analyze waste properties and classify them into categories such as wet, dry, or recyclable materials. By utilizing deep learning techniques, such as convolutional neural networks (CNNs) and object detection methods like YOLO (You Only Look Once), the system enhances classification accuracy, reducing contamination in recycling streams. Furthermore, IoT-enabled connectivity allows real-time data collection and monitoring, improving decision-making for waste management authorities. By automating the sorting process, the system reduces the likelihood of manual errors and significantly speeds up waste categorization, enabling more effective recycling and decreasing the volume of waste sent to landfills.

Despite advancements in AI-driven waste segregation, challenges such as system scalability, cost of implementation, and adaptability to diverse waste types remain areas of concern. Existing solutions often require high computational resources and large datasets for training, which may limit their accessibility in developing regions. Moreover, differences in waste types and disposal habits across various urban regions require intelligent models that can update in real time based on real-world waste patterns. This research aims to analyze current AI-based waste sorting methodologies, identify their limitations, and propose an enhanced framework for an automated waste segregation system. By integrating real-time sensing and image processing techniques, the proposed system seeks to improve efficiency, reduce dependency on manual labor, and foster sustainable waste management solutions suitable for smart city applications.

I. INTRODUCTION

The surge in urban population has drastically increased waste production, making effective waste management increasingly complex and demanding. Traditional methods primarily rely on manual sorting, which is not only labor-intensive but also prone to inaccuracies, leading to improper waste disposal and environmental pollution. Additionally, inefficient sorting techniques reduce the effectiveness of recycling programs, contributing to overflowing landfills and increasing greenhouse gas emissions. To tackle these challenges, it is essential to adopt intelligent, technology-based solutions that can automate the waste segregation process efficiently and reduce reliance on manual labor. The integration of artificial intelligence (AI) and the Internet of Things (IoT) has emerged as a transformative approach to

II. LITERATURE REVIEW

The growing complexity of urban waste management has led researchers to explore Artificial Intelligence (AI) as a solution for improving waste segregation efficiency. Among various AI techniques, Convolutional Neural Networks (CNNs) have emerged as powerful tools due to their exceptional performance in classification of images, making them well-suited for identifying different types of waste. For instance, Shah and Kamat (2022) developed a CNN-based system that classifies waste into organic and recyclable categories, achieving an accuracy of 94.9%. Their work underscores the potential of deep learning algorithms to automate waste classification, thereby reducing human intervention and enhancing recycling processes.

Malik et al. (2022) investigated deep learning approaches, specifically using CNNs, to automate waste classification with the goal of advancing sustainable development. Their study emphasizes the importance of image recognition techniques in accurately identifying and categorizing waste materials, contributing to more effective recycling strategies.

Recent advancements in object detection models have further improved waste classification systems. A study published in *Procedia Computer Science* (2024) investigated the application of YOLOv8 models for waste classification, training three variants—nano, small, and medium—on an augmented dataset of 3,500 labeled images. The nano variant achieved an accuracy of approximately 89%, demonstrating the efficacy of YOLOv8 in real-time waste classification tasks.

Integrating AI with hardware has also been researched to enhance waste segregation. Gupta et al. (2022) proposed a hardware solution that embedded deep learning approaches with infrared sensors to categorize garbage. Their system utilizes image categorization techniques to identify waste types, facilitating automated sorting and contributing to environmental sustainability.

Furthermore, Nafiz et al. (2023) introduced "ConvoWaste," an automatic waste segregation machine that employs deep convolutional neural networks and image processing techniques. The system achieves precise waste classification while also utilizing ultrasonic sensors and GSM modules to monitor and communicate bin levels to authorities, illustrating a seamless fusion of AI and IoT for smarter, real-time waste management solutions.

Agarwal and Reddy (2023) introduced a computer-vision-powered automatic waste sorting bin that leverages machine learning for efficient waste classification. Their system employs a camera to capture images of discarded items, which are then processed using a model that is trained to categorize waste accurately. The hardware design consists of multiple compartments, including an inbox for initial waste collection, a grab bin for temporary storage, and sorted bins for final disposal. Their approach demonstrates the potential of integrating image recognition with automated sorting mechanisms to streamline waste segregation processes. The study shows the effectiveness of AI-driven classification in real-time scenarios, emphasizing its role in minimizing manual sorting efforts and improving waste management efficiency.

Recent advancements have focused on integrating AI with Internet of Things (IoT) devices to enhance waste segregation systems. Anjanappa et al. (2022) developed a smart dustbin utilizing an ESP32-CAM module to capture images of waste items, which are then processed by a Convolutional Neural Network (CNN) model for classification. The system also employs IoT technology to monitor the fill levels of the bin, facilitating efficient waste collection and management. Similarly, Shenoy et al. (2022) proposed a waste segregation system that combines a Pi camera with a CNN algorithm that identifies and sorts waste into appropriate categories. Equipped with an ultrasonic sensor, the system continually monitors the bin's fill level, while a GSM module ensures that waste management authorities are promptly notified when the bin is full. This integration facilitates timely waste collection. These studies highlight the effectiveness of integrating AI models with IoT devices, such as cameras and sensors, to automate waste classification and enhance overall waste management efficiency.

Despite the advancements in AI-powered waste segregation, real-world deployment faces multiple challenges, including hardware limitations, scalability, and adaptability to diverse waste conditions. Studies by Kumar et al. (2023) emphasize that AI models trained in controlled environments may struggle when exposed to varying lighting, backgrounds, and waste compositions in real-world scenarios. The effectiveness of IoT-based waste management systems often depends on consistent network access and stable power, which can be difficult to ensure in remote or resource-limited areas. To overcome these limitations, researchers are turning to federated learning and domain adaptation approaches. These methods enable AI models to improve over time by learning from decentralized data sources while keeping energy and processing demands low—making the technology more accessible and sustainable in diverse deployment environments. Such innovations are important for ensuring the long-term sustainability and efficiency of AI-driven waste segregation systems.

Given these findings, the integration of AI into waste management has shown considerable promise in enhancing the efficiency and accuracy of waste segregation. Ongoing research is key to overcoming challenges and enabling broader adoption of smart waste management technologies for sustainable cities.

III. METHODOLOGY

The AI-powered waste segregation system follows a structured approach to ensure accurate classification and disposal of waste. The system integrates both hardware and software components, including sensors, motors, and a CNN-based AI model. The methodology involves multiple stages: hardware setup, AI-based classification, motor control, and testing. Each stage plays a key role in enhancing the system's efficiency and real-world applicability. The goal is to automate waste segregation by using deep learning techniques and sensor-based validation, reducing human intervention and improving waste management practices.

Assembly of Hardware and Connectivity Setup:

The hardware setup comprises an ESP32-CAM module for capturing images of waste, a moisture sensor for identifying wet waste, and an Arduino Uno for system control. A NEMA 17 stepper motor rotates the waste bin compartment, while a servo motor controls the disposal flap. Ultrasonic sensors are incorporated to monitor bin levels and prevent overflow. The system is powered with different voltage levels to ensure stability, including 5V for the servo motor and 9V-12V for the stepper motor. The Arduino Uno acts as the primary control hub, processing data from sensors and AI predictions to execute appropriate disposal actions.

The setup process begins with assembling the waste containers and securely mounting the cameras, sensors, and motors in their designated positions. Each hardware component is carefully installed to ensure optimal functionality and accurate data collection. Once the assembly is complete, all components are connected to the single-board computer, establishing proper communication between the sensors, motors, and AI processing unit. A stable power supply is ensured to support seamless operation, allowing the system to function efficiently for real-time waste segregation.

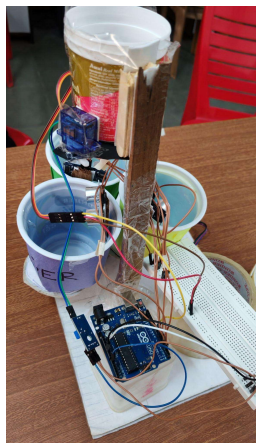


Fig 1. Hardware components setup

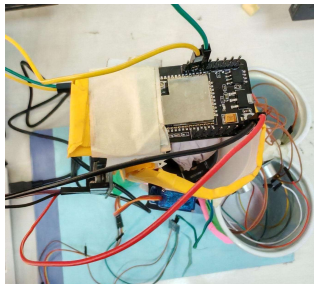



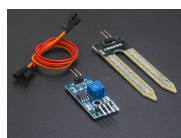




Fig 2. Camera mounted on setup

Table 1 Hardware Components Used in the System

Component	Image	Function
Arduino Uno		Acts as an interface between sensors and motors
ESP32-CAM		Captures images of waste for AI-based classification
HC-SR04 Ultrasonic Sensor		Monitors waste bin levels to trigger alerts when full
Moisture Sensor		Determines moisture level to classify wet and dry waste
SG90 Servo Motor		Controls waste flap to direct waste into appropriate bins
NEMA 17 Stepper Motor		Rotates the waste disposal unit for correct bin placement

Using Convolutional Neural Networks (CNN) to Classify Waste:

For waste classification, the system employs a Convolutional Neural Network (CNN) trained on a dataset of waste images. When waste is deposited, the ESP32-CAM captures an image and sends it to the model, which classifies the waste into dry, wet, or paper categories. If the waste is detected as wet, the moisture sensor provides an additional validation layer. If classified as dry or paper, the CNN model directly determines the category. The classification results are then communicated to the Arduino Uno, which processes the data and triggers the necessary motor actions to ensure proper waste disposal.

The convolution operation plays a fundamental role in feature extraction within the CNN. It is mathematically represented as:

$$O(i, j) = \sum_{m=0}^{k-1} \cdot \sum_{n=0}^{k-1} (I(i+m, j+n) \cdot W(m, n) + b)$$

where $O(i, j)$ represents the output at a specific position, $I(i+m, j+n)$ corresponds to the input image patch, $W(m, n)$ denotes the convolution filter (or kernel) of size $k \times k$, and b is the bias term. This operation enables the model to identify spatial patterns in waste images, improving classification accuracy. The trained model is then deployed for real-time waste recognition, facilitating automated and efficient waste segregation.

Machine Learning Model Training and Optimization:

To develop and train the waste classification model, machine learning frameworks such as TensorFlow are utilized. The dataset is split into training, and test sets to ensure the model generalizes well to new data. The AI model, CNN built using TensorFlow/Keras, is trained on a comprehensive dataset of labeled images categorized as dry, wet, or paper waste. During the training process, the CNN extracts relevant features from images through its convolutional layers, refining its ability to identify various waste categories accurately. In real-time operation, the system processes input images, predicts the waste category with a confidence score, and provides the classification result for appropriate disposal.

Motor Control and Waste Disposal Mechanism:

The motor control mechanism ensures precise waste segregation based on classification results. If waste is identified as wet, the servo motor moves the disposal flap by 180° to direct it into the wet waste bin. For dry and paper waste, the stepper motor rotates the bin compartment to align with the appropriate disposal section before the flap opens. This rotation is controlled using the A4988 driver to ensure accurate positioning. Additionally, ultrasonic sensors continuously monitor the bin levels. When a bin reaches a predefined threshold, an alert mechanism is triggered to notify users or initiate waste disposal protocols. These measures ensure the system operates efficiently while preventing overflow issues.

Energy Efficiency and Power Management:

To ensure sustainable and continuous operation, the system incorporates energy-efficient components and optimized power management techniques. Low-power microcontrollers like the ESP32 and Arduino Uno are used to minimize energy consumption. The stepper motor and servo motor are programmed to operate only when necessary, reducing idle power usage. Additionally, a sleep mode is implemented for sensors and processing units during periods of inactivity to conserve energy. For off-grid applications, the system can be integrated with a solar panel and rechargeable battery setup, making it an eco-friendly solution for waste segregation in areas with

limited power availability. These energy-saving measures enhance the system's longevity and sustainability while reducing operational costs.

System Testing and Performance Evaluation:

Testing and validation are conducted at multiple levels to ensure the system's accuracy and reliability. Unit testing is performed on individual components, such as verifying the moisture sensor's ability to detect different levels of liquid content and ensuring precise angle adjustments of the servo motor. Integration testing evaluates communication between the CNN model, sensors, and motor control system. Stepper motor rotation accuracy is tested using predefined movements, while ultrasonic sensors are assessed for their accuracy in monitoring waste levels and for triggering alerts when the bin reaches its capacity.

The model's performance is evaluated using standard classification metrics such as accuracy, precision, recall, and F1-score. These metrics help assess the model's effectiveness in correctly identifying waste categories.

Accuracy, calculated as,

$$(TP + TN) / (TP + TN + FP + FN)$$

which measures the ratio of correctly classified instances to the total number of predictions made.

Precision, defined as,

$$TP / (TP + FP)$$

which evaluates the fraction of correctly predicted positive instances out of all positive predictions, indicating the model's reliability in classifying a specific waste type.

Recall, computed as,

$$TP / (TP + FN)$$

which determines the ability of the model to detect actual positive cases, ensuring minimal misclassification of waste items. The model undergoes fine-tuning based on these performance results, adjusting hyperparameters and optimizing training strategies to enhance classification accuracy. Through continuous evaluation and refinement, the system improves its ability to efficiently and accurately segregate waste in real-time applications.

As a final step, the complete system undergoes real-world testing to assess its overall functionality. The CNN model's performance is assessed using a number of waste materials to ensure its ability to accurately classify different types of waste, including dry, wet, and paper. The moisture sensor's response is analyzed by testing it with waste containing different moisture levels. The system's efficiency is measured on the time taken from waste insertion to disposal. Any misclassifications or motor misalignments are recorded, and necessary adjustments are made to enhance performance. These refinements ensure that the AI-powered waste segregation system operates with high accuracy, optimizing waste disposal and reducing human intervention.

IV. RESULTS

The AI-Powered Waste Segregation System was evaluated based on classification accuracy, activity response and sorting efficiency.

Table 2 Waste Classification Results Using Moisture Data and AI Predictions




Waste Item	Moisture Level	Predicted Waste Type	Classification Accuracy
Dry 	80	Dry	85%
Wet 	120	Wet	80%
Paper 	85	Paper	87%



Fig 3. Classification Result from AI Model

The system achieved an overall waste sorting success rate of 85.5%, confirming its operational reliability in controlled conditions.

V. FUTURE WORK

Future scope will aim to improve AI model accuracy by training on larger datasets, expanding waste classification to include more categories, and refining the mechanical design for faster and more reliable operation. This project lays the groundwork for integrating AI into real-world waste management, promoting a more efficient and sustainable approach to waste segregation.

VI. CONCLUSION

In conclusion, conventional waste management systems often face issues such as inaccurate segregation and inefficient collection. The combination of AI and IoT in smart waste bins offers a transformative solution,

improving classification accuracy and streamlining waste disposal. By leveraging these advanced technologies, the system enhances sustainability and minimizes the environmental impact of waste management in metropolitan areas.

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REFERENCES

- [1] Ruparel, Y., Chaudhary, L., & Rathod, A. (2024). AI-Based Smart Bin for Efficient and Sustainable Waste Classification. *World Journal of Environmental Engineering*, 9(1), 1-6. <https://doi.org/10.12691/wjee-9-1-1>
- [2] Shah, J., & Kamat, S. (2022). A Method for Waste Segregation using Convolutional. <https://arxiv.org/abs/2202.12258>
- [3] Reshmi, W., Sundaram, R., & Kumar, M. R. (2014). Sensor Unit for Waste Management: A Better Method for Frequent Data Updating System. In *Proceedings of the International Conference on Science, Engineering and Management Research* (pp. 1-5). IEEE. [ResearchGate+2CiiT Research+2Semantic Scholar+2](https://www.researchgate.net/publication/364028676_Smart_Wastage_Segregation_using_Arduino_UNO)
- [4] Mehta, P., & Verma, R. (2022). Smart Wastage Segregation using Arduino UNO. https://www.researchgate.net/publication/364028676_Smart_Wastage_Segregation_using_Arduino_UNO
- [5] Nafiz, R., Islam, S., & Chowdhury, T. (2023). *ConvoWaste: An Automatic Waste Segregation Machine Using Deep Learning | IEEE Conference Publication | IEEE Xplore*
- [6] M. Arebey, M. Hannan, H. Basri, and H. Abdullah, The IEEE Student Conference on Research and Development (SCORED), 16-18 November 2009, UPM Serdang, Malaysia, 2009 [Solid waste monitoring and management using RFID, GIS and GSM | IEEE Conference Publication | IEEE Xplore](https://www.researchgate.net/publication/364028676_Smart_Wastage_Segregation_using_Arduino_UNO)
- [7] Wang, Ke., Zhao, Yafei., Gangadhari, Rajan Kumar., & Li, Zhixing. (2021). [\[2205.01067\] Analyzing the Adoption Challenges of the Internet of Things \(IoT\) and Artificial Intelligence \(AI\) for Smart Cities in China](https://doi.org/10.1007/s10311-023-01604-3)
- [8] Bhat, K., & Sharma, S. (2023). Real-Time Waste Management for Urban Areas using Deep Learning. *Journal of Environmental Science and Pollution Research*. <https://doi.org/10.1007/s10311-023-01604-3>

- [9] Kadus, T., Nirmal, P., & Kulkarni, K. (2020). Smart Waste Management System using IoT. *International Journal of Engineering Research & Technology (IJERT)*, 9(04).
<https://doi.org/10.17577/IJERTV9IS040490>
- [10] Agarwal, T., & Reddy, P. (2023). Computer-vision powered Automatic Waste Sorting Bin: A Machine Learning-based Solution on Waste Management. ResearchGate.
https://www.researchgate.net/publication/373029972_Computer-vision-powered_Automa
- [11] Fayomi, G. U., Mini, S., Chisom, C., Fayomi, O., Udoye, N. E., Agboola, O., & Oomole, D. (2021). Smart Waste Management for Smart City: Impact on Industrialization. *IOP Conference Series: Earth and Environmental Science*, 655
- [12] Shahab, Sana., & Anjum, Mohd. (2022). Solid Waste Management Scenario in India and Illegal Dump Detection Using Deep Learning: An AI Approach towards Sustainable Waste Management. Sustainability
- [13] Fang, B., Yu, J., Chen, Z., Osman, A. I., Farghali, M., Ihara, I., Hamza, E. H., Rooney, D. W., & Yap, P.-S. (2023). Artificial intelligence for waste management in smart cities: a review. *Environmental Chemistry Letters*, 21, 1959–1989.
<https://doi.org/10.1007/s10311-023-01604-3>
- [14] Abdallah, M., Abu Talib, M., Feroz, S., Nasir, Q., Abdalla, H., & Mahfood, B. (2020). *Artificial intelligence applications in solid waste management: A systematic research review*. *Waste Management*, 109, 231–246.
<https://doi.org/10.1016/j.wasman.2020.04.057>
- [15] Namoun, A., Tufail, A., Khan, M. Y., Alrehaili, A., Syed, T. A., & BenRhouma, O. (2022). *Solid Waste Generation and Disposal Using Machine Learning Approaches: A Survey of Solutions and Challenges*. *Sustainability*, 14(20), 13578.
<https://doi.org/10.3390/su142013578>
- [16] Dutta, S., Das, A., & Ghosh, S. (2021). *AI-Enabled Smart Waste Management System: A Sustainable Approach for Urban Areas*. *Resources*, 10(4), 28.
<https://www.mdpi.com/2079-9276/10/4/28>
- [17] Zhang, L., Wang, Y., & Chen, X. (2023). *An AI-Powered Sustainable Waste Management System for Smart Cities: Challenges and Future Directions*. *Sustainability*, 15(23), 16454.
<https://www.mdpi.com/2071-1050/15/23/16454>
- [18] Awe, O., Mengistu, R., & Sreedhar, V. (2017). *Smart Trash Net: Waste Localization and Classification*.
<https://cs229.stanford.edu/proj2017/final-reports/5226723.pdf>
- [19] Sarraf, V., Purohit, R. R., Jain, A., Jain, R., Yashwanth, M., Mathews, A., & VaraLakshmi, S. (2024). *A Study on: AI Powered Waste Management*. *International Journal of Research Publication and Reviews*, 5(3), 3618–3625.
<https://doi.org/10.55248/gengpi.5.0324.0793>
- [20] P. S. Gade, D. S. Shinde, and V. P. Bhoje, "IoT-based automated waste segregator for efficient recycling," *ResearchGate*, Jun. 2019. [Online]. Available: <https://www.researchgate.net/publication/333563393>
- [21] R. M. Patil and P. S. Tambe, "Interfacing of automatic waste segregation system using Arduino UNO,"