© March 2026 | IJIRT | Volume 12 Issue 10 | ISSN: 2349-6002

Biomedical Waste Identification Using Yolov8

Dr. Amol Gaikwad[1], Pornima Bhurle[2]. Raksha Padalwar[3], Harsh Batule[4], Piyush Chafle[5], Gaurav Rinayat[6]

[1,2,3,4,5,6] *Department of Information Techonology Yeshwantrao Chavan College of Engineering Nagpur, India*

***Abstract*—Biomedical waste (BMW) management is one of the biggest challenges in healthcare. The volume of waste generated is growing, which increases the risks of infection and environmental pollution. Traditional waste segregation methods rely a lot on manual work. This ap- proach is slow, prone to mistakes, and can be dangerous for workers. To solve this problem, this research introduces a real-time biomedical waste identification and classification system using YOLOv8, along with an integrated hardware-assisted bin-indication mechanism. The proposed model has been trained on a custom multi-class biomedical waste dataset comprising 12 categories within a clinical environment. The system achieves high accuracy in object detection and maps each detected item to its corresponding CPCB-compliant bin category. The hardware unit comprised Arduino-based LED indicators for immediate disposal guidance. Experimental results have clearly shown enhanced performance after the re-optimization process with higher precisions, recalls, and mAP values of the model. This system is designed to minimize human error in waste segregation and strive for safer and more efficient handling of biomedical waste.**

***Index Terms*—Biomedical Waste, YOLOv8, Object Detection, Deep Learning, Image Processing, Waste Classification, Ar- duino Integration, Smart Segregation System.**

I. INTRODUCTION

In today's healthcare industry, the in-effective management of biomedical waste (BMW) poses serious risks to the environ- ment and public health. Hospitals, diagnostic laboratories, and research centers produce large amounts of biomedical waste every day. This includes items such as syringes, sharps, gloves, masks, glassware, and pathological materials. If this waste is not handled and disposed of correctly, it can lead to the spread of infections, toxic exposure, and severe environmental pollution.

To address these challenges, the Government of India in- troduced the Biomedical Waste Management Rules in 2016. These rules require the separation of biomedical waste into color-coded containers (yellow, red, blue, and white) based on characteristics of biomedical waste. However, despite these regulations, manual segregation is still the most common practice in healthcare facilities, leading to human errors, inefficiency, and risks to waste handlers, highlighting the need for an automated solution .

Fig. 1. Risks Posed By Biomedical Waste Mis- management

This research presents an automated system for the detection and classification of biomedical waste using the YOLOv8 model. The system is trained on a custom dataset with 6,587 labeled images across 12 categories of biomedical waste, including plastics, syringes, gloves, masks, glassware and tissues. The trained model is connected to an Arduino-based hardware setup with LED indicators that signal the correct color-coded disposal bins in real time.

II. PROBLEM STATEMENT

This project addresses the challenge of accurate and efficient biomedical waste identification in healthcare environments, where human errors and limited scalability hinder proper seg- regation. It proposes a real-time waste detection system using the YOLOv8 object detection model and image processing to identify and classify biomedical waste, providing hardware feedback through LED indicators. The solution enhances com- pliance with biomedical waste management rules, minimizes risks to staff and the environment, and offers a scalable, cost- effective alternative to expensive specialized systems.

III. LITERATURE REVIEW

[1] V. Rami Reddy, ”A Review On YOLOv8 and its advancements,” ACM, 2024. This paper addresses the de- velopment and improvements in the YOLOv8 framework, demonstrating how enhancements in loss functions and data augmentation lead to improved benchmark performances over prior YOLO versions[1].

P. Manopapapin, K. Joompabuth, P. Boonyaanan, T. Ganokratanaa, M. Ketcham, ”A Waste Detection and Sepa- ration System Based on Image Recognition and Embedded Artificial Intelligence,” ACM, 2024. This study developed an AI-driven waste detection system using image recognition for automated separation, aiding recycling processes and minimiz- ing landfill contributions[1].

N. H. Mohamed, S. Khan, S. Jagtap, ”Waste 4.0: trans- forming medical waste management through digitalization and automated segregation,” Springer, 2024. An IoT and barcode- powered framework is proposed for biomedical waste manage- ment, offering enhanced automated segregation and recycling, and reducing disease transmission risks[1].

A. Ishaq, S. J. Mohammad, A. D. Bello, S. A. Wada, ”Sustainable Waste Management Using IoT and AI Technolo- gies: Smart Waste Bin Monitoring Using IoT for Sustainable Biomedical Waste Management,” Springer, 2023. The authors cite IoT as crucial in real-time waste monitoring, leading to optimized biomedical waste collection and segregation, thus reducing hazardous risks[1].

B. Gupta, S. P, M. Shanmathi, J. P. Bhimavarapu, P. J. Augustine, K. S. Rajasekaran, ”A Smart Handling of Bio- Medical Waste and its Segregation with Intelligent Machine Learning Model,” IEEE, 2023. Machine learning-based models are shown to outperform previous waste management ap- proaches by increasing efficiency in real-time segregation and predictive analytics[1].

W. A. Bagwan, ”An investigation of the bio-medical waste produced in India during the COVID-19 pandemic and Ma- harashtra state pre-COVID-19 and post-COVID-19 analysis: a GIS-based approach,” Springer, 2023. This research uses GIS to analyze the surge in biomedical waste during the COVID- 19 pandemic, underlining the evolving challenges and the need for efficient compliance mechanisms[1].

K. Jangsamsi, ”Conventional Machine Learning Approach for Waste Classification,” ACM, 2023. Classical ML methods (Fourier descriptors, HOG, LBP, SVM) are shown to enable robust waste classification, particularly where datasets are limited or highly diverse[1].

M. M. Abed, A. M. Jamal, K. N. Manoj, A. K. Hameed, ”Automated waste-sorting and recycling classification using artificial neural network and features fusion: a digital-enabled circular economy vision for smart cities,” ACM, 2022. The
use of neural networks and feature fusion techniques provides
sharper classification accuracy for waste sorting in smart city environments[1].

D. Bhavana, ”Garbage Segregation System with SMART Technology,” IEEE, 2022. An AI-driven system is described which uses cameras and real-time image processing for robotic waste segregation, supporting IoT-based remote monitoring[1].

T. J. Sheng, M. S. Islam, N. Misran, M. H. Baharuddin,

H. Arshad, ”An Internet of Things Based Smart Waste Man- agement System Using LoRa and Tensorflow Deep Learning Model,” IEEE, 2020. This paper integrates LoRa, TensorFlow, GPS, and RFID to realize smarter waste management bins, streamlining sorting and tracking in operational practice[1].

S. Brindha, V. Praveen, S. Rajkumar, V. Ramya, V. Sangeetha, ”Automatic Medical Waste Segregation System by Using Sensors,” 2024. The conveyor-based system leverages sensors and image processing for comprehensive medical waste analytics and segregation in real time[1].

M. Subburaj, ”Smart Biomedical Waste Management De- vice In Hospitals,” 2021. Describes an IoT-enabled smart bin equipped with various sensors for live monitoring and categorization of biomedical waste, reducing manual effort[1].

IV. METHODOLOGY AND IMPLEMENTATION

This section describes the systematic workflow adopted for the development of the biomedical waste detection and automated bin–segregation system. The methodology inte- grates data acquisition, preprocessing, deep learning model development, real-time detection, bin–mapping, and hardware actuation using an ESP32 microcontroller.

A. Data Collection

The dataset used for model development consists of 6,587 biomedical waste images collected from Kaggle, web sources, DMMC, and simulated clinical setups. The data covers 12 categories including syringes, gloves, masks, gauze, glassware, metal tools, plastic tubes, paper equipment, organic waste, and body tissue samples. All images were manually annotated using LabelImg to generate bounding box coordinates and class labels in YOLO format. The dataset was then divided into training (80%), validation (10%), and testing (10%) subsets.

B. Data Operations

Before training, exploratory data analysis (EDA) was con- ducted to examine class distribution, image quality, feature variations, and potential imbalance. Some categories such as Plastic Equipment and Syringe Needles were over-represented, while classes like Body Tissue had limited samples. To ad- dress this imbalance, data augmentation techniques including rotation, flipping, zooming, contrast adjustment, color jittering, Gaussian blur, and noise injection were applied. All images were resized to 640×640 resolution and normalized to improve model consistency. The final dataset ensured diversity in lighting conditions, orientations, and backgrounds to improve generalization.

C. Data Preprocessing

To prepare the dataset for training, each image was normal- ized and preprocessed according to YOLO input requirements. Augmentation techniques were applied to create variations and reduce overfitting. The preprocessing pipeline consisted of:

- Resizing all images to 640×640 pixels
- Brightness and contrast adjustment
- Rotation, flipping, cropping, and scaling
- Normalization to the 0–1 pixel range

This standardized the input data and ensured robustness against real-world variations.

D. Model Training

The YOLOv8 architecture was selected due to its lightweight design and high real-time performance. The model was trained for 50 epochs using a batch size of 16, AdamW optimizer, and a cosine–decay learning rate schedule. The training pipeline included:

- Input acquisition from the training dataset
- Automatic feature extraction using convolutional layers
- Bounding box regression using CIoU loss
- Class probability estimation using BCE loss
- Evaluation on validation data at each epoch

YOLOv8 learns hierarchical visual features through resid- ual connections and attention mechanisms, enabling accurate detection even in visually complex medical environments.

E. Object Detection and Classification

During inference, the model divides the input frame into a grid and predicts bounding boxes, class labels, and confidence scores for each detected object. The system supports multi- object detection, enabling simultaneous identification of mul- tiple waste categories within a single frame. Detected waste items are mapped to CPCB-compliant bin categories (Red, Yellow, Blue, White) using a rule-based bin allocation module.

F. Hardware System Workflow

To enable automated physical segregation, the bin recom- mendation is communicated to an ESP32 microcontroller. The workflow is as follows:

1) The software performs real-time YOLOv8 detection from a connected camera.
2) The predicted bin category is transmitted to the ESP32 via USB serial or Wi-Fi.
3) The ESP32 activates the servo motor corresponding to the color-coded bin lid.
4) The correct bin lid opens automatically to allow dis- posal.
5) After a delay, the servo closes the lid and resets the cycle.

This integration enables a touch-free, hygienic, and auto- mated waste segregation mechanism.

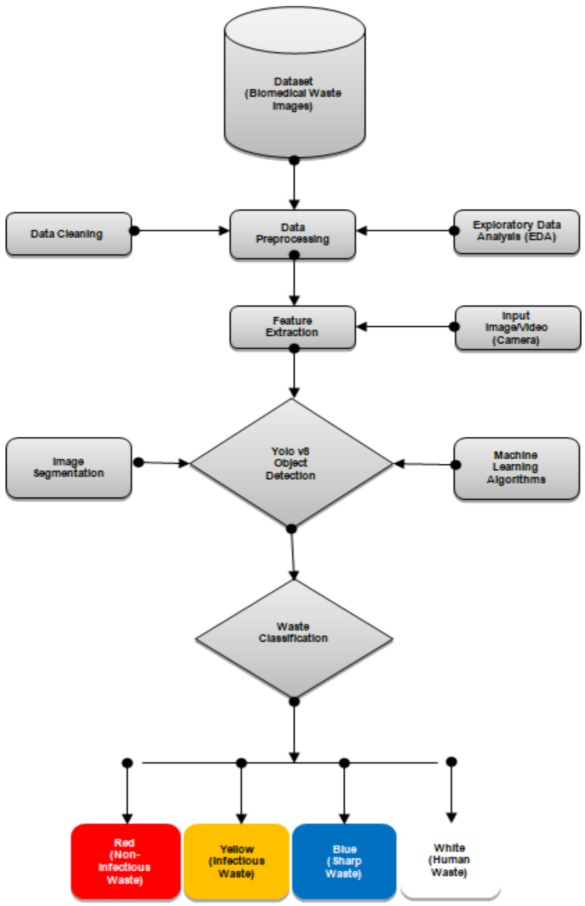

Fig. 2. System Architecture (Yolov8)

G. Hardware Components

1) ESP32 Microcontroller: The ESP32 is a dual-core 32- bit MCU with 240 MHz processing capability, built-in Wi-Fi (802.11 b/g/n), Bluetooth 4.2, 520 KB SRAM, and extensive GPIO interfaces supporting UART, I2C, SPI, and PWM. It functions as the hardware controller for servo actuation, receiving classification signals from the host system.

2) Servo Motors: Standard PWM-controlled servo motors are used to open and close the bin lids. Each motor receives a PWM signal from a dedicated GPIO pin on the ESP32. The servo rotates to a defined angle to open the lid and resets to its default position after disposal.

3) Circuit Design: Three-wire connections (VCC, GND, Signal) interface each servo with the ESP32. Ground is shared for stability, and noise-filtering capacitors may be added to ensure consistent servo operation. Each bin servo is indepen- dently controlled via separate GPIO pins.

Fig. 3. ESP32 Microcontroller

Fig. 4. Servo Motor

H. Output Generation and System Integration

Once an item is detected, the system generates:

- Annotated output frames with bounding boxes and labels
- Real-time confidence scores
- Automatic text-based bin recommendations

The user interface developed using Gradio displays these outputs as a real time object detector with classification over-

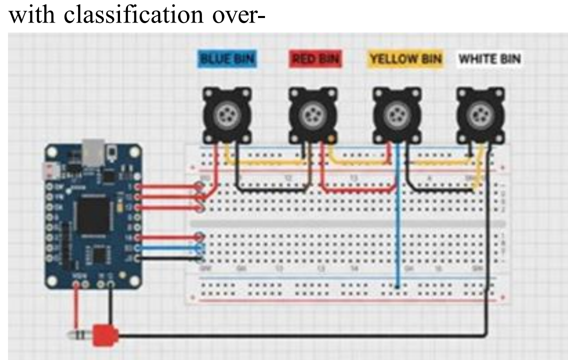

Fig. 5. Circuit Design

Fig. 6. Output User Interface

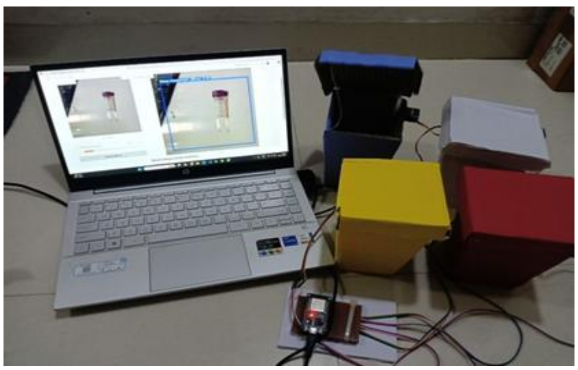

Fig. 7. Setup for Biomedical Waste Detection

lays. The final integrated system combines YOLOv8 software

execution with ESP32-based hardware actuation. The system handles all computational tasks, while the ESP32 performs real-time physical control. This architecture ensures low cost, high accuracy, and efficient real-time hospital applicability.

I. Experimental Results

The proposed YOLOv8-based biomedical waste detection system demonstrated strong performance in real-time classifi- cation and localization of biomedical waste items. Extensive testing on still images and live video streams showed that the model can accurately distinguish infectious, non-infectious, sharp, and hazardous waste categories. The system additionally provides bin recommendations and visual annotations such as bounding boxes and class labels. Performance metrics including accuracy, precision, recall, and F1-score confirm that the system is reliable for hospital waste management workflows. These results indicate strong potential for deploy- ment in healthcare environments requiring safe, hygienic, and regulation-compliant waste disposal.

1) Accuracy and Confusion Matrix: A confusion matrix was generated to evaluate category-wise classification per- formance after training. The diagonal entries correspond to correct classifications, while off-diagonal entries represent misclassifications.

Most categories achieved near-perfect accuracy. The model achieved 100% classification accuracy for categories such as Glass Equipment, Metal Equipment, Plastic Equipment,

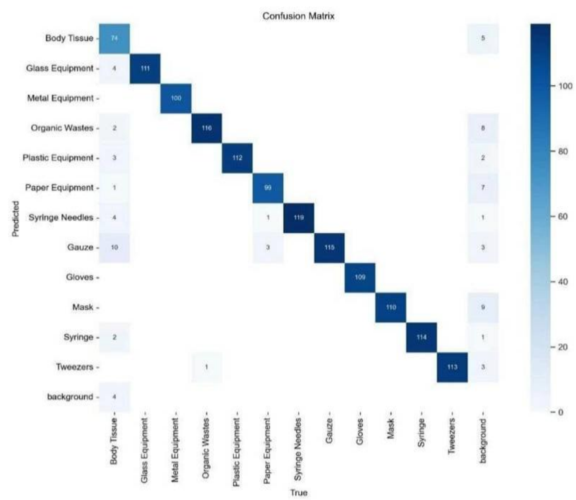

Fig. 8. Confusion Matrix

Syringe Needles, Gloves, Masks, Syringes, and Tweezers. Organic Waste and Paper Equipment achieved accuracies of 99% and 96%, respectively, with occasional misclassifications due to visual similarities in texture and color.

The Body Tissue/Organs class achieved a lower accuracy of 71%, primarily due to similarities with Gauze and Organic Waste and the limited number of available training samples. This suggests a need for improved sampling or enhanced feature extraction for visually ambiguous classes.

Overall, the system achieved an average accuracy of 91.6%, aligning with validation performance and confirming robust real-time classification capability.

2) Precision: Precision was evaluated using a precision- confidence curve. Precision peaked at 1.00 when the confi- dence threshold reached 0.987, indicating zero false positives at high confidence levels. This is particularly important for biomedical waste segregation, since misclassifying hazardous items could cause contamination risks. The results show that at confidence levels above 98.7%, predictions are consistently correct and reliable for operational use.

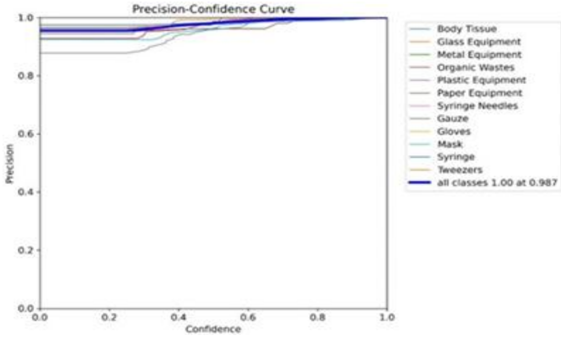

Fig. 9. Precision-Confidence Curve

3) *F1-Score:* The model achieved an overall F1-score of
0.98 at a confidence threshold of 0.676. This high F1-score
demonstrates excellent balance between precision and recall, even at moderate confidence levels. Despite class imbalance, the model maintained strong performance across both major- ity and minority classes. The F1-score reflects the model's ability to generalize well in real-world conditions such as varying backgrounds, lighting inconsistencies, and overlapping objects.

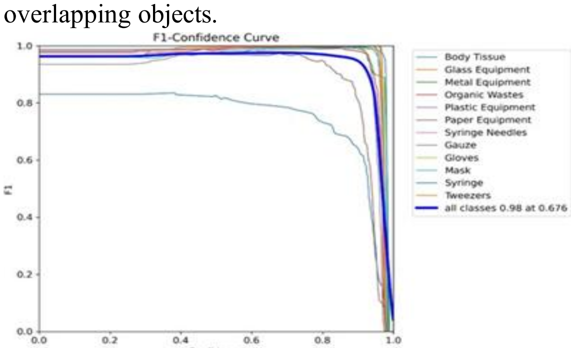

Fig. 10. F1-Confidence Curve

4) *Recall:* The recall-confidence curve indicated that the system sustained a high recall of 0.98 even at low confidence thresholds. This highlights the model's capability to capture nearly all relevant waste items, which is essential in hospi- tal settings where missed detections could lead to improper disposal. Slight recall drops were observed only at higher confidence thresholds for categories like Gauze and Body Tissue, likely due to visual ambiguity and dataset limitations.

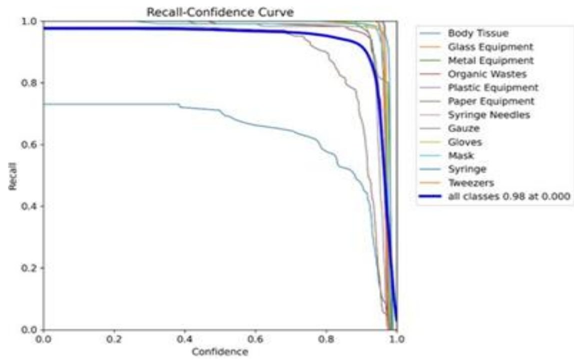

Fig. 11. Recall-Confidence Curve

5) *Bias Analysis:* Bias assessment showed that the model exhibits low bias and fits the training data effectively without oversimplification. The high F1-score and confusion matrix patterns indicate that the model captures essential data patterns across most categories. Misclassifications mainly occurred for Gauze and Body Tissue due to visual similarities, rather than systematic bias. Overall, the model generalizes well across diverse biomedical waste classes.

6) *Variance Analysis:* Variance analysis showed moderate variance. Training and validation performance remained con- sistent, with only minor fluctuations in challenging classes.

The stable precision, recall, and F1-score across varying thresholds confirm that the model does not overfit. Misclas- sification trends are attributed to class imbalance and feature similarities rather than excessive variance. Additional samples and enhanced augmentation could further reduce variance.

7) *Cross-Validation:* A 5-fold cross-validation strategy was used to assess model robustness. Each fold involved training on four partitions and testing on the remaining partition. Table I summarizes the results.

TABLE I K-FOLD CROSS VALIDATION PERFORMANCE

Fold	Accuracy (%)	Precision	Recall	F1-Score
1	91.2	0.93	0.91	0.92
2	92.0	0.95	0.92	0.93
3	90.5	0.94	0.91	0.92
4	91.8	0.94	0.93	0.94
5	92.5	0.95	0.93	0.94
Average	91.6	0.94	0.92	0.93

The results show low variance across folds and consistent performance, confirming model stability. Visual similarity between classes such as Gauze, Body Tissue, Plastic, and Paper caused small metric fluctuations, but overall reliability remained high. The cross-validation results validate strong generalization capability suitable for real-world deployment.

V. CONCLUSION

This project successfully developed a real-time biomedical waste identification and classification system that integrates YOLOv8 object detection with image processing techniques. The system efficiently classifies waste into six main cat- egories—biodegradable waste, sharps, used surgical equip- ment, plastics, infected organs, and expired drugs—facilitating compliance with biomedical waste management guidelines. By interfacing the detection model with an Arduino-based hardware module that triggers LED indicators, the project enables automatic visual feedback for proper waste segre- gation. The experimental results show improved detection accuracy, precision, and recall, ensuring reliable performance in healthcare settings. The solution not only minimizes human error in waste disposal, but also addresses scalability and cost-effectiveness by using commonly available hardware without relying on expensive specialized devices. In general, this sys- tem contributes to safer hospital waste management, reducing environmental risks and promoting public health.

REFERENCES

[1] H. Poddar, R. Paul, S. Mukherjee, and B. Bhattacharyya," Automated Waste Sorting with Delta Arm and YOLO v8 Detection," 2024.

[2] S. K. Gupta, R. Singh, and A. Verma," Smart Handling of Bio-Medical Waste from Intelligent Deep Learning and IoT," 2024.

[3] M. T. Sharma, A. Kumar, and S. Patel," YOLO v8-Based Waste Detection System for Recycling Plants," 2024.

[4] S. K. Choudhary, M. R. Saxena, and A. Rajput," Au- tomated Waste Management System Using Object Detection," 2024.

[5] K. D. Sharma, P. Tiwari, and A. Mishra," Modernized Management of Biomedical Waste Assisted with Artificial Intelligence," 2024.

[6] A. N. Rathi and P. Mehta," Automated Segregation of Bio-Medical Waste," 2023.

[7] M. T. Yadav and S. Jha," Smart Waste Bin Monitoring Using IoT for Sustainable Biomedical Waste Management," 2024.

[8] A. Wadhwa and S. A. Patel," A Waste Management Technique to Detect and Separate Non-Recyclable Waste Us- ing YOLO Algorithm," 2024.

[9] R. Kumar and L. B. Sharma," Solid Waste Detection Using Enhanced YOLO v8 Lightweight Model," 2024.

[10] R. Gupta and P. K. Ghosh," A Case Study on IoT- Enabled Waste Management in Smart Cities," 2024.

[11] G. Singh and A. P. Kumar," Multi-Class Waste Segre- gation Using Computer Vision and Robotic Arm," 2024.

[12] A. Mishra and A. M. Roy," Garbage Classification Detection System Based on the YOLOv8 Algorithm," 2024.

[13] S. K. Jain and N. Sharma," An Intelligent Waste Management Application Using IoT and Deep Learning," 2024.

[14] A. S. Kumar and S. D. Thakur," Robust Deep Learning- Based Approach for Classification and Detection of Waste Materials," 2024.

[15] S. K. Joshi and A. Tiwari," Smart E-Waste Manage- ment System Utilizing Internet of Things and Deep Learning," 2024.