Detection and Classification of Microwaste in Temple Environment

Vaishnavi Dhane*, Purva Chaudhari**, and Karpagavalli Subramanian***

Department of Electronics and Computer Science, Pillai College of Engineering, Navi Mumbai - 410206, India
*dvaishnavi22ecs@student.mes.ac, **purvac22ecs@student.mes.ac, ***karpagavalli@mes.ac.in

Abstract. Waste management remains a significant urban challenge, particularly in high-footfall areas such as temples, where large volumes of offerings and ritual materials accumulate daily. Currently, temple waste is primarily managed manually, with workers separating and disposing of debris by hand. However, no automated system exists that can efficiently identify, classify, and segregate mixed temple waste—particularly micro-waste—without human interaction. This gap emphasizes the necessity for an automated smart waste-segregation system based on computer vision and deep learning. The proposed system is trained on four critical classes—floral waste(leaves and flowers), plastic wrappers, plastic caps, and ritual waste(coconut shells and incense sticks)—which are frequently observed in religious environments and are among the major contributors to drainage problems. The finalization of the ML model is accomplished by comparing a few established image-processing approaches, such as KNN, SVM, and classical CNN-based classifiers,YOLOv8 to assess their performance on diverse temple-waste photos. However, these systems battled with issues like overlapping objects, micro-waste detection, and excessive background clutter. According to the results, YOLOv8 outperformed other algorithms in terms of detection accuracy and localization precision. Experiments with our proprietary dataset demonstrate that the model can accurately identify and localize small-scale waste items in congested and complicated temple settings. The proposed technique not only presents a new application domain for YOLOv8, but it also provides a useful tool for enhancing cleanliness and promoting sustainable waste management practices in religious and cultural settings.

Keywords: YOLOv8, Object Detection, Deep Learning, Temple Micro Waste Management, Environmental Sustainability.

1 Introduction

One of the most important environmental issues facing contemporary society is waste management. Particularly in places of worship like temples, where daily offerings like flowers, leaves, plastic wrappers, incense sticks, and other ritual items build up and cause hygienic and drainage issues, rapid urbanization and in- creased public activities produce substantial volumes of waste. Micro-waste, which includes microscopic pieces of plastic, bottle caps, and flower remnants, is a major cause of waterlogging and drainage blockage yet is sometimes overlooked during hand cleaning. This emphasizes the necessity of an

P. Goyal et al. (eds.), *Proceedings of the Conference on Technologies for Future Cities (CTFC 2025)*, Atlantis Highlights in Sustainable Development 7,
https://doi.org/10.2991/978-94-6239-650-0_5

intelligent, auto- mated vision-based technology that can identify micro-waste in congested temple settings. Machine learning and deep learning frameworks have been used in a number of research to investigate waste classification and small-object recognition. WasteInNet, a deep learning model for real-time multi-category waste identification, was presented by Rahmatulloh et al. [1]. A thorough investigation by Nikouei et al. [2] brought attention to the difficulties in identifying small things in intricate settings, a problem that is closely linked to temple micro-waste. Surekha et al. [3] demonstrated the applicability of ML for micro-scale environmental contaminant detection by utilizing ANN-based models for environmental pollution monitoring using IoT data. While Williams et al. [5] looked at reliability testing of ML models for microplastic spectral datasets, highlighting the need for robust detection frameworks, Biswas [4] reviewed the state-of-the-art approaches for microplastic detection, including machine learning and imaging-based techniques.

A YOLO-based IoT system for automated medical waste sorting was implemented in applied domains by Moktar et al. [6], proving that YOLO architectures work well for small-scale waste streams. In a similar vein, Shankar et al. [7] created a mobile garbage classification system that uses TensorFlow Lite to identify glass, metal, and plastic in real time. More general studies, like Sankhala et al. [8], highlighted the growing significance of AI in environmental sustainability by discussing the potential of AI and ML for monitoring plastic and microplastic contamination.

Small-object detection has been a major focus of recent developments in YOLO designs. Ni et al. [9] used multi-scale feature improvement to improve YOLOv8s for UAV-based small-object detection. Li and Zheng [10] used attention mechanisms to optimize YOLOv8s for cigarette butt identification, demonstrating its efficacy for small, irregular waste objects. Ren et al. [11] proposed MRS-YOLO for high-precision waste categorization, whereas Liu et al. [12] introduced EcoDetect-YOLO for lightweight real-time household trash detection. SS-YOLOv8 is a lightweight model created by Fan et al. [13] for outdoor surface litter identifcation. S-BIRD, a multi-class sewage waste imagery dataset developed by Patil et al. [14], enables reliable machine learning research for challenging waste situations. Zhang et al. [15] demonstrated how pre-trained CNN frameworks enhance classification performance by using transfer learning for multi-label garbage identification. Danı¸sman [16] confirmed that YOLO is appropriate for very small waste materials by using it to detect cigarette butts.

Nevertheless, despite these developments, the majority of current research focuses on UAV photography, surface litter, marine microplastics, sewer habitats, or general waste streams. Temple-specific micro-waste, which comprises irregular, dispersed, and seemingly similar debris photographed under varying lighting, perspectives, and backgrounds, is the subject of very few investigations. The majority of current solutions rely on structured datasets and do not assess effectiveness in intricate religious settings where waste is mixed and challenging to identify. There is an obvious research void as a result.

The current study suggests a YOLOv8-based method for identifying temple micro-waste in order to close this gap. The technique concentrates on four main waste categories that are frequently present in temple environments and cause drainage problems:

floral trash, plastic wrappers, plastic caps, and ceremonial waste. Real photos taken in temple settings were manually annotated using Roboflow to produce a custom dataset. In order to contribute to cleaner and more sustainable temple environments, the model attempts to give precise micro-trash localization and facilitate future integrations like IoT-based alarms and robotic waste collectors.

2 Workflow of Proposed System

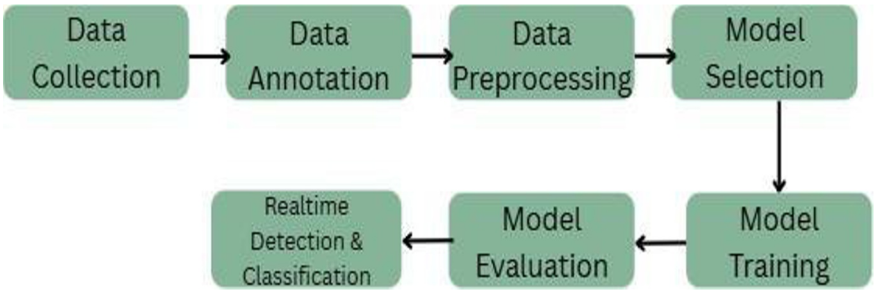


Fig. 1. Block Diagram of the Proposed Workflow

The proposed system follows a structured flow for detecting temple waste using the YOLOv8 model as shown in Fig. 1. The complete workflow can be divided into the following main stages:

1. **Data Collection:** The raw photos were manually collected from the actual temple surrounds using a mobile camera held at various distances, angles, and viewpoints. To guarantee that the dataset accurately depicts practical, real-world circumstances, images were shot in a variety of lighting conditions, including strong sunlight, partial shade, evening light, and low-illumination inside areas. The temple flooring and environs also varied substantially, with stone tiles, marble, rough concrete, and natural ground surfaces, which contributed to backdrop variation. This diversity in lighting, distance, and background ensures that the model learns to recognize microwaste accurately even in difficult and congested conditions. A few raw photos from the obtained dataset are included in Fig. 2.

Fig. 2. Sample of Micro waste in temple

2. **Data Annotation:** To ensure highly precise object localization, data annotation was performed manually on the Roboflow platform. Each photograph was thoroughly examined, and all apparent waste items were labeled with accurate bounding boxes. The annotation procedure followed four predetermined categories: Floral Waste, Plastic Wrappers, Plastic Caps, and Ritual Waste, allowing for uniform class- level classification across the dataset. During annotation, additional emphasis was placed on small, overlapping, partially visible, and scattered waste objects that are frequent in temple settings. This thorough labeling approach not only gives the model unambiguous spatial bounds, but it also allows it to learn the fine-grained visual cues required to distinguish microwaste in tough backgrounds and lighting situations. As a result, the annotated dataset serves as a solid foundation for developing a robust detection model capable of dealing with real-world temple waste complexity. An example from the annotated dataset is included in Fig. 3.

Fig. 3. Sample of Annotated Data

3. **Data Preprocessing:** To guarantee constant input dimensions during training, all annotated photos were uniformly downsized to 640 × 640 pixels as per the YOLOv8 framework requirements. In addition to resizing, multiple data augmentation approaches were used to increase dataset heterogeneity and improve model robustness. These enhancements included contrast scaling, brightness adjustment, random rotation, horizontal flipping, and minor geometric changes. Such modifications assist to imitate real-world settings in which garbage pieces may appear in varied orientations, under shifting lighting, or partially hidden inside temple surroundings. By incorporating these modifications into the dataset, the model is encouraged to generalize better, prevent overfitting, and function consistently across varied temple contexts with uneven lighting, angles, and backdrops.
4. **Model Selection:** Various machine learning and deep learning models, including SVM, KNN, Naïve Bayes, CNN classifier, and YOLOv8, were evaluated to discover the most effective model for detecting micro-waste in temples. YOLOv8 consistently outperformed the other models in terms of class-wise precision, recall, F1-score, and accuracy, especially when detecting small and overlapping rubbish objects. As a consequence, YOLOv8 was selected as the final model. For small-object detection in complex temple environments, the chosen YOLOv8-s variant, which uses a CSPDarknet backbone, PAN neck, and anchor- free detection head, provides an excellent balance of speed and accuracy.
5. **Model Training:** The model weights were set up from scratch (no transfer learning).The model was trained on a bespoke dataset using hyperparameters including batch size, image size (e.g., 640×640), and number of epochs. Optimizer: SGD/Adam, with learning rate scheduling.
6. **Model Evaluation:** A different validation dataset is used to test the trained model.

Confusion matrices, precision-recall curves, and detection visualizations are used to assess the data. Even in backgrounds that are busy, the model detects micro-waste with excellent accuracy.

7. **Real-Time Detection and classification:** For inference on unseen temple photos, the final model (best.pt) was utilized. Bounding boxes and class labels for every micro-waste object are displayed in the output visualizations that are produced.

3 Model Architecture

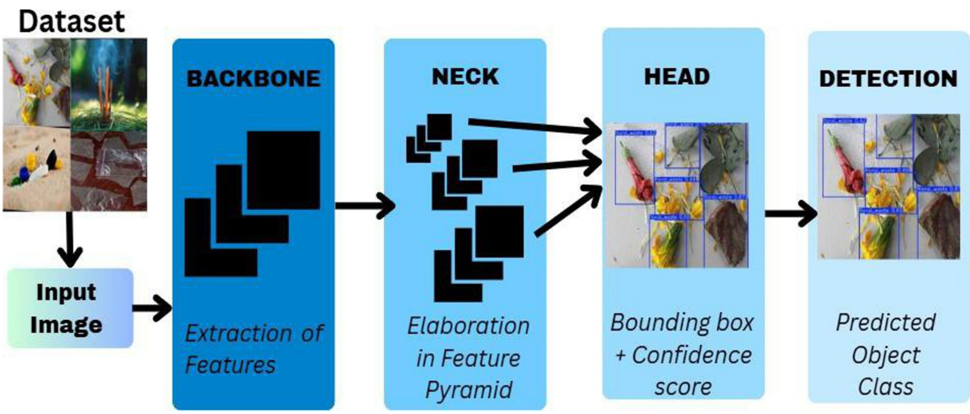


Fig. 4. Model Architecture of Micro Waste Detection in Temple Areas

YOLOv8 is a state-of-the-art, real-time object detection algorithm that predicts object locations and classes in a single pass. Its modular design—backbone for feature extraction, neck for multi-scale aggregation, and anchor-free head—enables fast and accurate detection. Key advantages include real-time processing, anchor-free detection, built-in data augmentation, and flexible scaling for speed-accuracy trade-offs. For our Temple Micro Waste Detection project, YOLOv8 effectively identifies and classifies temple waste (floral, plastic, paper, and mixed), ensuring timely monitoring and robust performance across varied conditions, making it ideal for automated waste management.

The proposed architecture for Micro Waste Detection in Temple Areas as presented in Fig. 4 utilizes the YOLOv8 (You Only Look Once version 8) framework, a state-of-the-art deep learning model designed for real-time object detection with enhanced accuracy and speed. YOLOv8 offers a fully convolutional and anchor-free detection structure, making it particularly suitable for detecting micro waste in complex and cluttered temple environments.

3.1 Input Layer:

Images of raw temple rubbish, such as flower waste, plastic wrappers, plastic caps, and ritual waste taken from the actual temple environs, are fed into the system. To mimic real-world situations, these photos are taken from a variety of perspectives, distances, and lighting conditions, including strong sunlight, shade, nighttime ambient light, and dimly lit interior spaces. Each image is downsized to 640 × 640 pixels, standardized for intensity consistency, and improved using augmentations like rotation, horizontal flipping, brightness modification, and contrast variation before being fed into the model. These preprocessing procedures guarantee consistent training, decrease overfitting, and make it possible for the model to identify micro-waste objects found in a variety of congested temple settings.

3.2 Backbone (Feature Extraction):

YOLOv8 extracts significant features from the input photos using a CSP-Darknet-based backbone. It has C2f modules and CBS blocks (Convolution + BatchNorm + SiLU) that enhance feature flow while maintaining the network's lightweight design. The SPPF (Spatial Pyramid Pooling – Fast) layer assists in gathering data at various scales, enabling the model to efficiently identify micro-waste objects of different sizes.

3.3 Neck (Feature Aggregation):

The neck combines features from multiple scales using a combination of FPN (Feature Pyramid Network) and PAN (Path Aggregation Network) structures. This facilitates strong information flow between shallow (fine-grained) and deep (semantic-rich) layers, improving detection accuracy for tiny waste objects such as plastic caps and floral residues.

3.4 Head (Detection Layer):

To combine data from several feature levels, the neck combines PAN (Path Aggregation Network) and FPN (Feature Pyramid Network). This enhances the model's capacity to identify minuscule trash objects like plastic caps and microscopic flower bits by fusing semantic information from deeper levels with fine details from shallow layers.

3.5 Output Layer:

For every waste item found, the output layer produces the final detection results in the form of bounding boxes, class labels, and confidence ratings. By choosing only the bounding box with the highest confidence for each object, YOLOv8 uses the Non-Maximum Suppression (NMS) strategy to eliminate redundant or overlapping predictions. This guarantees that the end product is correct, non-redundant, and aesthetically pleasing, enabling exact localization of various micro-waste pieces within intricate temple surroundings.

4 Results and Analysis

This section presents the results of the YOLOv8-based Micro Waste Detection in Temple Environment. The analysis includes a description of the dataset, training details, quantitative and qualitative results.

4.1 Dataset Description

The micro waste in temple environment consists of images across four classes: *Floral Waste, Plastic Wrap- pers, Plastic Caps, Ritual Waste*. The dataset was split into training, validation, and testing sets with a ratio of 70:20:10, respectively. Data augmentation techniques such as rotation, flipping, zooming, and other trans- formations were applied to improve model generalization under varying temple surroundings and lighting conditions.

Table 1. Distribution of Dataset

Splits	Number of Images
Train	1050
Validation	100
Test	50
Total	1200

As shown in Table 1, the dataset consists of 1,200 images collected from temple surroundings. The majority (70%) were used for training to learn class features effectively, while 20% and 10% were allocated for validation and testing, respectively. This distribution ensures balanced learning, helps prevent overfitting, and allows accurate evaluation of the YOLOv8 model's detection performance on unseen images.

4.2 Training Details

To select the best model for temple micro-waste detection, multiple machine learning and deep learning approaches were tested, including SVM, KNN, Na¨ıve Bayes, a basic CNN classifier, and the YOLOv8 model. All models were trained on the same four waste classes to ensure fair comparison. Traditional classifiers could only perform image-level classification, whereas deep learning models handled features more effectively. The Table 2 presents the class-wise precision, recall, F1-score, and accuracy achieved by each model.

Table 2. Class-wise Performance Comparison of Different Models

Model	Class	Precision	Recall	F1-Score	Accuracy
CNN	Floral Waste	0.00	0.00	0.00	0.18
	Plastic Caps	0.33	0.10	0.15	
	Plastic Wrappers	0.17	0.89	0.29	
	Ritual Waste	0.00	0.00	0.00	
SVM	Floral Waste	0.50	0.44	0.47	0.56
	Plastic Caps	0.50	0.40	0.44	
	Plastic Wrappers	0.50	0.67	0.57	
	Ritual Waste	0.71	0.77	0.74	
KNN	Floral Waste	0.60	0.83	0.70	0.64
	Plastic Caps	0.62	0.80	0.70	
	Plastic Wrappers	0.67	0.67	0.67	
	Ritual Waste	1.00	0.23	0.38	
Na¨ıve Bayes	Floral Waste	0.43	0.17	0.24	0.26
	Plastic Caps	0.33	0.20	0.25	
	Plastic Wrappers	0.17	0.44	0.24	
	Ritual Waste	0.31	0.31	0.31	

The CNN model did not do well in detecting temple microwaste. While it performed poorly for Plastic Caps (Precision 0.33, Recall 0.10, F1-score 0.15) and Plastic Wrappers (Precision 0.17, Recall 0.89, F1-score 0.29), it utterly failed for Floral Waste and Ritual Waste, with all metrics approaching zero. Its overall accuracy was 0.18, and the misclassified results demonstrated that CNN cannot detect small or low-contrast trash objects. As a result, CNN is ineffective for detecting microwaste in temples. Few examples showing wrong predictions generated by CNN model are presented in Fig. 5.

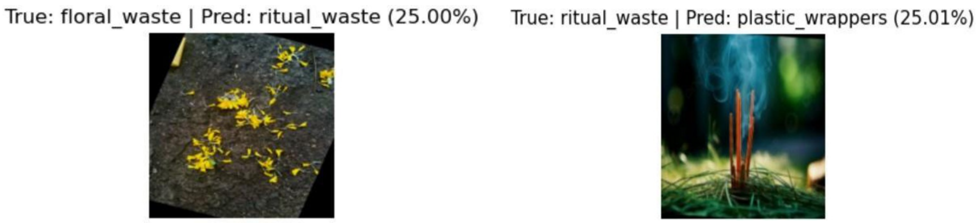


Fig. 5. Example of wrong predictions generated by the CNN model.

The SVM model did not perform well for detecting temple microwaste. Except for Plastic Wrappers (Precision 0.21, Recall 0.91), all other classes had extremely low precision, recall, and F1 ratings. The overall accuracy was only 0.20. Because SVM is primarily intended for numerical feature-based data rather than raw pictures or object detection, it suffers with small and intricate waste patterns. As a result, SVM is unsuitable for this task.

Next, The KNN model also showed weak performance for temple micro-waste detection. Except for Plastic Wrappers (Precision 0.17, Recall 0.87), all other classes had very low precision, recall, and F1-scores. The overall accuracy was only 0.19, indicating that KNN struggled to differentiate between small and visually similar waste objects. Since KNN depends heavily on distance-based feature matching, it fails to handle complex image patterns, making it unsuitable for this task.

The Naïve Bayes model performed the weakest among all evaluated models. It showed extremely low precision, recall, and F1-scores across every class, with an overall accuracy of only 0.16. Since Naïve Bayes assumes feature independence, it cannot handle complex visual patterns or variations present in micro-waste images. As a result, it consistently misclassified objects and failed to detect small waste items, making it unsuitable for temple micro-waste detection.

Based on the comparative analysis of all models, including SVM, KNN, Naïve Bayes and CNN it is observed that traditional classifiers struggle with small-object detection and show low accuracy. Among all, YOLOv8 achieves the highest precision, recall, and overall performance as shown in Table 3. Hence, YOLOv8 is selected as the final model for temple micro-waste detection.

4.3 Quantitative Results

Table 3. Class-wise Performance Metrics

Class	Precision	Recall	F1-Score

Floral Waste	0.78	0.52	0.61
Plastic Caps	0.96	0.95	0.96
Plastic Wrappers	0.95	1.00	0.97
Ritual Waste	0.85	0.79	0.81
Average	0.87	0.92	0.89

Table 3 presents the class-wise performance metrics of the proposed YOLOv8 model on the temple micro-waste dataset. The model demonstrates strong detection accuracy, particularly for *Plastic Wrappers* and *Plastic Caps*, which achieved F1-scores of 0.97 and 0.96, respectively. These high values indicate that the model effectively identifies and classifies these waste types even in complex and cluttered backgrounds.

However, the relatively lower precision (0.78) and F1-score (0.61) for *Floral Waste* suggest challenges in detecting objects with irregular shapes and overlapping textures. This indicates scope for improvement through the use of attention mechanisms or enhanced feature extraction techniques. Overall, the model achieves an average precision of 0.87, recall of 0.92, and F1-score of 0.89, reflecting its robustness and reliability in detecting micro-waste items in temple environments.

4.4 Qualitative Results

Sample detection results of YOLOv8 on micro waste detection and classification in temple environment Fig. 6 shows that the model successfully identified the incense sticks placed near the worship area, demonstrating its ability to recognize fine ritual elements. Fig. 7 (a) shows that the model identified four to five plastic caps scattered across the temple premises, showcasing its capability in recognizing small-sized recyclable plastic waste. Fig. 7 (b) shows that the YOLOv8 model efficiently classified natural organic waste materials such as wilted flowers and dry leaves. Fig. 7 (c) shows that the model accurately identified lightweight plastic wrappers, highlighting its performance in detecting thin and irregularly shaped plastic waste.

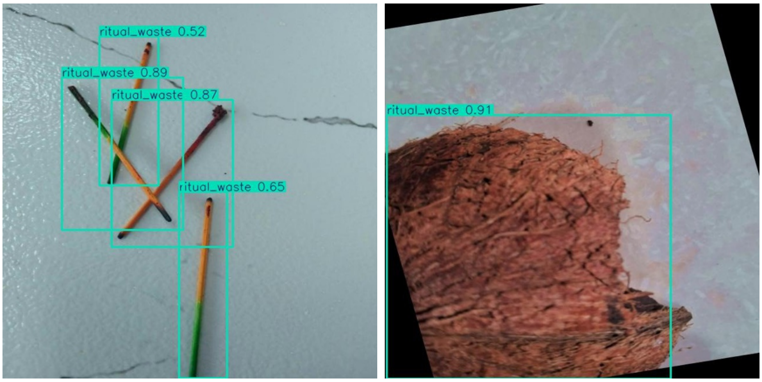
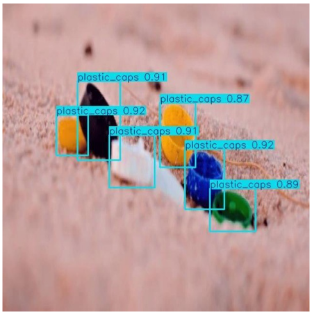
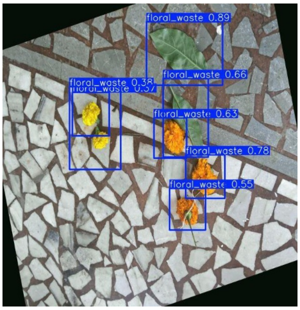


Fig. 6. Ritual waste



(a) Plastic Caps



(b) Floral Waste

(c) Plastic Wrapper

Fig. 7. Different types of temple waste

4.5 Training and Validation Curves

The training and validation loss curves, indicating stable convergence of YOLOv8 for micro waste detection and classification in temple environment. Fig. 8 shows the training and validation curves of YOLOv8 across 50 epochs. The training losses (box, classification, and distribution focal loss) gradually decrease, indicating effective learning. Similarly, vali- dation losses show stable convergence without overfitting. Precision, recall, and mAP metrics consistently improve, confirming robust model generalization. Fig. 9 presents validation performance curves for mAP@50 and mAP@50–95 across epochs. Both metrics show a steady rise and later stabilize, with mAP@50 reach- ing around 0.87 and mAP@50–95 around 0.55, reflecting good detection accuracy and convergence of the YOLOv8 model.

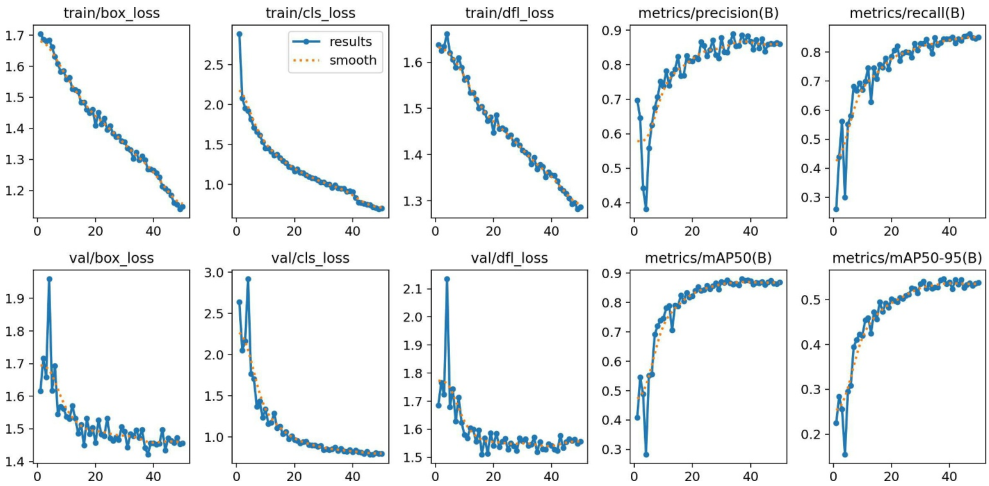


Fig. 8. Train-Val plots

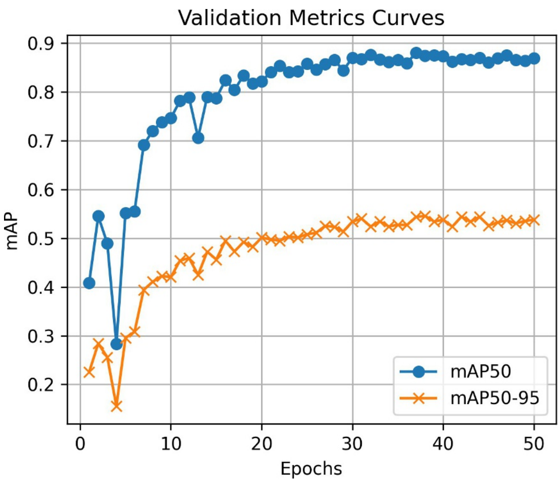
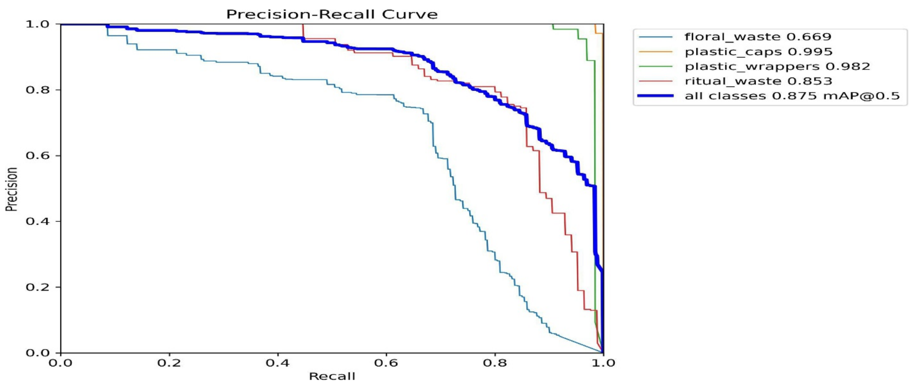


Fig. 9. Validation metrics curves

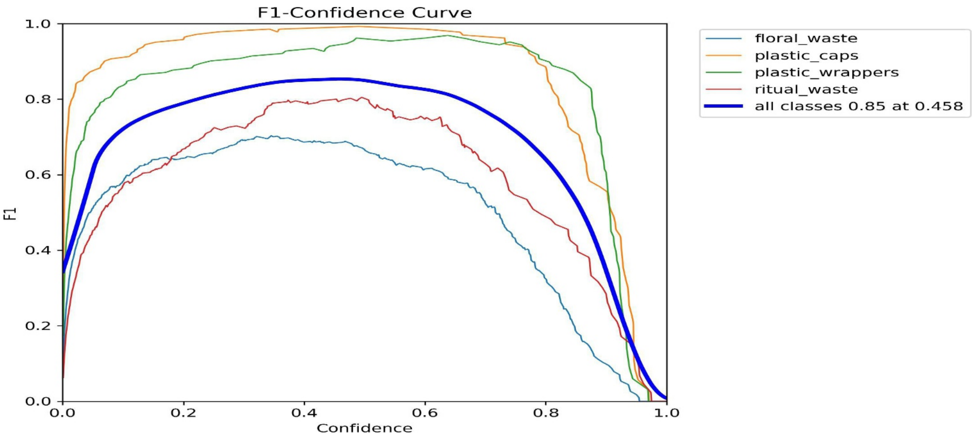
4.6 Final results

The final evaluation results of the YOLOv8 model are shown in Figure below. These include key performance plots such as Precision-Recall (PR) curve, F1-Confidence curve, Precision Confidence curve, Recall Confidence curve for each class and the confusion matrix. These results demonstrate the effectiveness of YOLOv8 in accurately detecting and classifying micro waste in temple areas. In addition, the YOLOv8 model also demonstrated its capability to detect multiple micro waste simultaneously. Fig. 10(a) shows the training and validation curves of YOLOv8 across 50 epochs. Fig. 10 (b) shows the balance between precision and recall. The peak indicates the best confidence threshold. Plastic caps and plastic wrappers have the highest F1 scores, showing strong overall performance. Fig. 10 (c) shows the increase in precision as confidence rises. Higher confidence gives fewer false positives. Plastic caps and plastic wrappers achieve the best precision, indicating accurate detections. Fig. 10 (d) shows how recall changes with different confidence levels for all four classes.

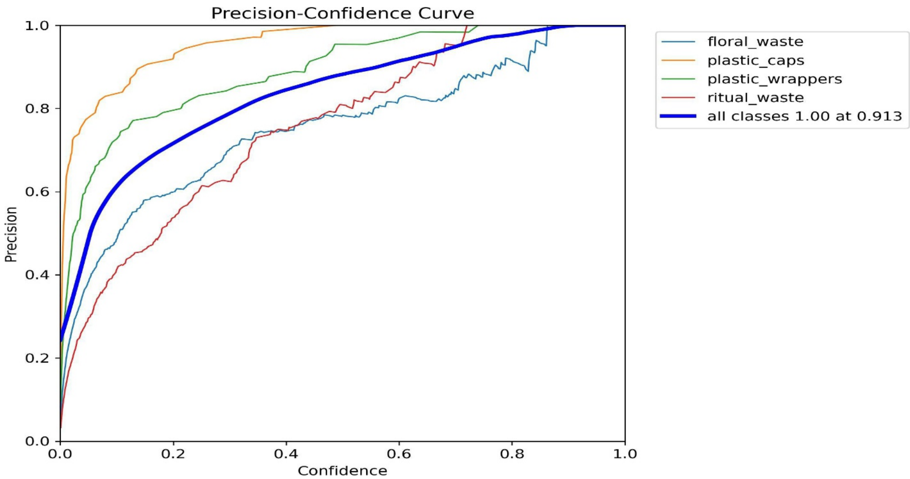
Higher recall at lower confidence means more detections but less certainty. Plastic caps and plastic wrappers maintain high recall, showing good detection coverage. Fig. 11 effectively illustrates the model's strong classification performance across all five classes. High correct predictions are observed for floral waste (78), ritual waste (49), and plastic wrappers (28), indicating accurate detection. Misclassifications are minimal, with some overlap mainly between floral waste and background (37) and ritual waste and background (44). Plastic caps shows clear predictions with very few errors. Overall, the matrix reflects a well-performing model with precise class separation. Fig. 12 illustrates that the model accurately detects floral waste, ritual waste, plastic wrappers, and plastic caps, performing reliably even in cluttered heaps and mixed waste, with precise bounding boxes and stable confidence scores.



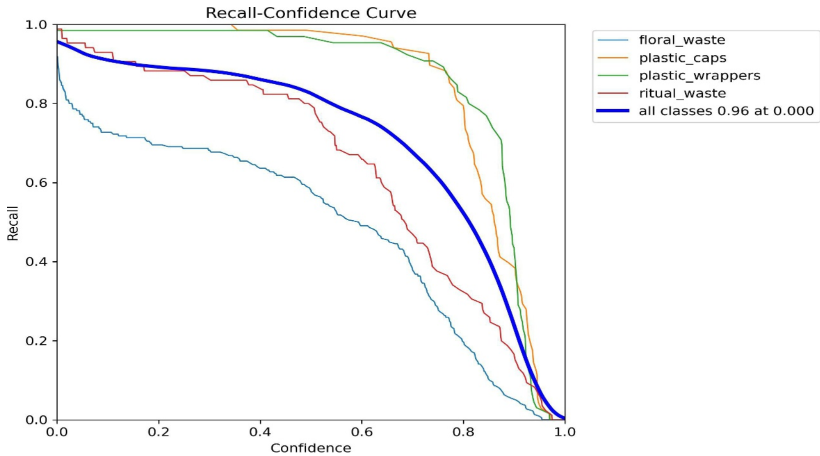
(a) Precision-Recall Curve



(b) F1-Confidence Curve



(C) Precision-Confidence Curve



(d) Recall-Confidence Curve

Fig. 10. Evaluation metrics curves for the model. (a, b, c & d)

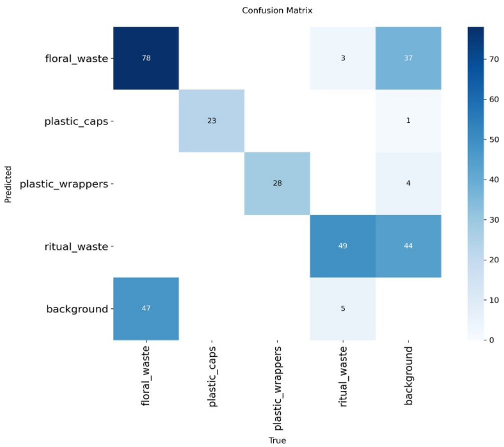


Fig. 11. Confusion Matrix

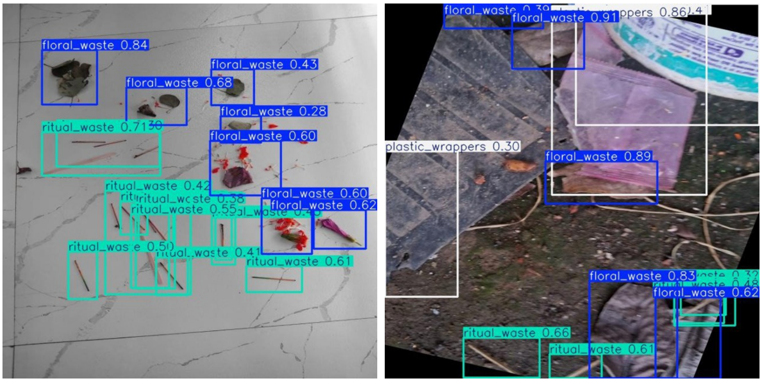


Fig. 12. Detecting micro waste in temple environment simultaneously.

5 Conclusion and future scope

The suggested YOLOv8-based model performed exceptionally well in identifying and categorizing micro- waste in various temple settings. Floral trash, plastic caps, plastic wrappers, and ritual waste are the four main waste categories that it correctly detected with high precision, recall, and F1-scores. Because of their asymmetrical shapes, color variations, and propensity to blend in with intricate temple backgrounds, flower and ceremonial debris were found to have somewhat poorer accuracy.

Conventional models like CNN, SVM, KNN, and Naïve Bayes were also assessed for comparison with YOLOv8. These models produced low precision and inconsistent predictions due to their severe difficulties with small object detection, overlapping trash items, and cluttered scenes. According to our comparative investigation, YOLOv8 is the most reliable and appropriate model for detecting micro-waste in actual temple settings.

All things considered, the YOLOv8 system offers a dependable baseline for automated and real-time temple trash monitoring, which immediately contributes to increased sustainability, quicker waste identification, and better cleaning.

To improve generalization, future work can entail adding more photos to the dataset that were taken in different temple sites, during different seasons, with crowds, and in varied lighting conditions. To make the system more complete, further trash classes like metal bits, incense sticks, biodegradable products, or mixed rubbish can be added. To improve accuracy for small and visually complex trash items, model improvements like as attention modules, transformer-based YOLO variations, or multi-scale feature fusion can be investigated. A fully automated waste management pipeline can be made possible by integration with robotic waste collectors, smart bins, and IoT-enabled camera networks. In difficult situations, ensemble learning using Vision Transformers, EfficientDet, or hybrid CNN-transformer models may also increase resilience and flexibility.

References

1. Rahmatulloh, Alam, Irfan Darmawan, Aldy Putra Aldya, and Firmansyah Maulana Sugiartana Nursuwars. ”WasteInNet: Deep Learning Model for Real-time Identification of Various Types of Waste.” Cleaner Waste Systems 10 (2025): 100198.
2. Nikouei, Mahya, Bita Baroutian, Shahabedin Nabavi, Fateme Taraghi, Atefe Aghaei, Ayoob Sajedi, and Mohsen Ebrahimi Moghaddam. ”Small Object Detection: A Comprehensive Survey on Challenges, Techniques and Real- World Applications.” arXiv preprint arXiv:2503.20516 (2025).
3. Surekha, S. S., DM Swarna Lakshmi, A. S. NithishBalaji, and N. S. Abinaya. ”Smart Monitoring and Prediction of Industrial Pollution Using IoT and ANN.” In International Conference on Recent Advancements and Moderni- sations in Sustainable Intelligent Technologies and Applications (RAMSITA 2025), pp. 926-941. Atlantis Press, 2025.
4. Biswas, Rajib. ”State of the art detection methods of microplastics as marine litter: a mini review.” Discover Oceans 2, no. 1 (2025): 24.
5. Williams, Wesley A., and Shyam Aravamudhan. ”Reliability Testing of Machine Learning Model Prediction Capability towards Unidentifiable Microplastic Spectral Data: Triple Battery and Colorant Investigation.” Mi- croplastics and Nanoplastics 5, no. 1 (2025): 1.
6. Moktar, Muhammad Hafizuddin, Hassan Mohamed, Sami Salama Hussen Hajjaj, and Mohd Zafri Baharuddin. ”Medical waste sorting machine development with IoT and YOLO model utilization.” Journal of Engineering and Applied Science 72, no. 1 (2025): 86.
7. Shankar, Kopanati, Pentakota Divya Gowri, Tannieru Hema Vardhan, Mohammad Hafizunnisa, Matha Venkat Krishna Mohan, and Nadipineni Venkata Siva Lokesh. ”Automated Data Driven Approach To Waste Manage- ment.” In International Conference on Computational Innovations and Emerging Trends (ICCIET-2024), pp. 1423-1434. Atlantis Press, 2024.
8. Sankhala, Somesh, Lipsa Dash, Sambhabi Patnaik, and Shreya Chatterjee. ”Artificial Intelligence as an Aid: Regulating Plastic and Microplastic Pollution.” In NDIEAS-2024 International Symposium on New Dimensions and Ideas in Environmental Anthropology-2024 (NDIEAS 2024), pp. 365-372. Atlantis Press, 2024.
9. Ni, Jianjun, Shengjie Zhu, Guangyi Tang, Chunyan Ke, and Tingting Wang. ”A small-object detection model based on improved YOLOv8s for UAV image scenarios.” Remote Sensing 16, no. 13 (2024): 2465.
10. Li, Mengxin, and Kunyan Zheng. ”Research on Cigarette Butt Small Target Detection Using an Improved YOLOv8s Algorithm.” In 2024 IEEE 7th International Conference on Information Systems and Computer Aided Education (ICISCAE), pp. 396-401. IEEE, 2024.
11. Ren, Yuanming, Yizhe Li, and Xinya Gao. ”An MRS-YOLO model for high-precision waste detection and clas- sification.” Sensors 24, no. 13 (2024): 4339.
12. Liu, Shenlin, Ruihan Chen, Minhua Ye, Jiawei Luo, Derong Yang, and Ming Dai. ”EcoDetect-YOLO: A lightweight, high-generalization methodology for real-time detection of domestic waste exposure in intricate en- vironmental landscapes.” Sensors 24, no. 14 (2024): 4666.
13. Fan, Zhipeng, Zheng Qin, Wei Liu, Ming Chen, and Zeguo Qiu. ”SS-YOLOv8: A Lightweight Algorithm for Surface Litter Detection.” Applied Sciences 14, no. 20 (2024): 9283.
14. Patil, Ravindra R., Mohamad Y. Mustafa, Rajnish Kaur Calay, and Saniya M. Ansari. ”S-BIRD:

A novel critical multi-class imagery dataset for sewer monitoring and maintenance systems.” Sensors 23, no. 6 (2023): 2966.
15. Zhang, Qiang, Qifan Yang, Xujuan Zhang, Wei Wei, Qiang Bao, Jinqi Su, and Xueyan Liu. ”A multi-label waste detection model based on transfer learning.” Resources, Conservation and Recycling 181 (2022): 106235.
16. Danı¸sman, Taner. ”Machine learning based cigarette butt detection using yolo framework.” (2022).