

# Automated Waste Classification for Sustainable Cities Using YOLO Based CNN Integrated IoT

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**Abstract**— Sustainable waste management is a vital component of smart city development, directly impacting environmental quality and recycling efficiency. This study presents an IoT-enabled waste classification system that utilizes a Convolutional Neural Network (CNN) for accurate, real-time identification of organic and non-organic waste. The model, implemented using the YOLO architecture, was trained on a diverse dataset of waste images captured under various environmental conditions to ensure robustness in practical scenarios. Classification results are automatically stored in a MySQL database and visualized via an Internet of Things (IoT) based Node-RED dashboard, enabling municipal operators to monitor waste categories and quantities remotely. Field evaluations demonstrate that the system achieves an accuracy of 94%, precision of 94.5%, recall of 93.2%, and an F1-score of 93.85%, indicating high detection reliability and consistent performance, even in challenging urban environments. By integrating CNN-based deep learning with IoT visualization tools, this approach offers a scalable and efficient solution that supports sustainable waste management initiatives within smart city frameworks..

**Keywords**—Convolutional Neural Network, Internet of Things, Node-RED, Smart City, Sustainable Waste Management

## I. INTRODUCTION

Waste classification is a key step in municipal solid waste handling because it affects recycling quality and downstream processing efficiency [1]. As urban populations grow, waste volumes increase and accurate separation particularly between organic and non-organic categories becomes more challenging. In many cities, sorting is still performed manually, which is slow, inconsistent, and prone to human error. Frequent misclassification can contaminate recyclable streams and reduce overall processing effectiveness [2]. Moreover, many current practices do not provide real-time monitoring that enables rapid collection and analysis of waste generation data for operational decisions [3].

Recent advances in deep learning and computer vision have enabled automated waste recognition using Convolutional Neural Networks (CNNs) [4]. YOLO-based models, in particular, have been applied to detect waste objects with competitive speed and accuracy. However, many prior implementations emphasize detection performance in isolation and provide limited integration with Internet of Things (IoT) infrastructure for real-time logging, aggregation, and remote visualization [5] [6].

To address this gap, this study proposes an automated waste classification system that integrates a YOLO-based detector with an IoT monitoring pipeline using a Node-RED dashboard. The system performs real-time detection of organic and non-organic waste, stores results in a MySQL database for traceability, and presents waste composition trends through a remotely accessible dashboard to support faster operational decision-making.

The main contributions of this research are the combination of CNN-based real-time waste detection with IoT visualization, the use of a robust dataset taken from various environmental conditions, and the implementation of a dashboard that supports remote monitoring [7]. This approach is expected to improve waste sorting efficiency, reduce processing errors, and support sustainable waste management programs in urban areas.

## II. RESEARCH METHOD

The proposed system is designed to automatically detect and classify organic and non-organic waste using a Convolutional Neural Network (CNN) implemented through the YOLO algorithm. The system consists of four main components: (1) image acquisition, (2) object detection and classification, (3) data storage, and (4) real-time visualization through an IoT-based dashboard. Figure 1 illustrates the overall system architecture, starting from waste image capture to final data presentation for monitoring purposes.

### A. Data Collection

A dataset was developed consisting of images of organic and non-organic waste collected from various environmental conditions, including different lighting levels, backgrounds, orientations, viewing angles, and waste arrangements. The images were captured using a smartphone camera to ensure accessibility and scalability of the data acquisition process. This stage aimed to gather representative visual data encompassing variations in shape, size, and color, which are essential for enhancing the model's capability to identify objects under diverse real-world conditions. Figure 1 shows the organic and non-organic waste dataset.

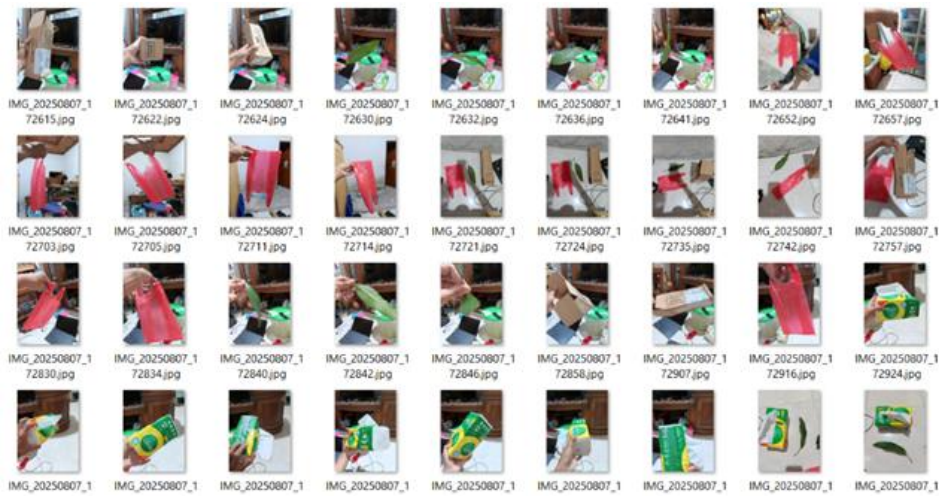


Figure 1. Image of organic and non-organic waste

After the image collection process, all data underwent an annotation process in accordance with the YOLO format [8]. Image annotation involved marking object positions using bounding boxes and assigning class labels corresponding to two categories: organic and non-organic. This process was conducted manually to ensure accuracy and consistency in labeling, as variations in class assignments could confuse the model during training [9]. For example, all images containing plastic bottles were consistently labeled under the same class, regardless of differences in color, shape, or physical condition [10].

The annotation process was carried out using both the Roboflow platform and the LabelImg tool, producing bounding box coordinates compatible with YOLO training requirements. Special attention was given to the clarity of object boundaries, separability

between objects, and labeling uniformity. To optimize the training process, the dataset was divided into two subsets: 80% for training and 20% for testing. This division was intended to ensure that the trained YOLO model could generalize well to unseen data. The image labeling process is shown in Figure 2.

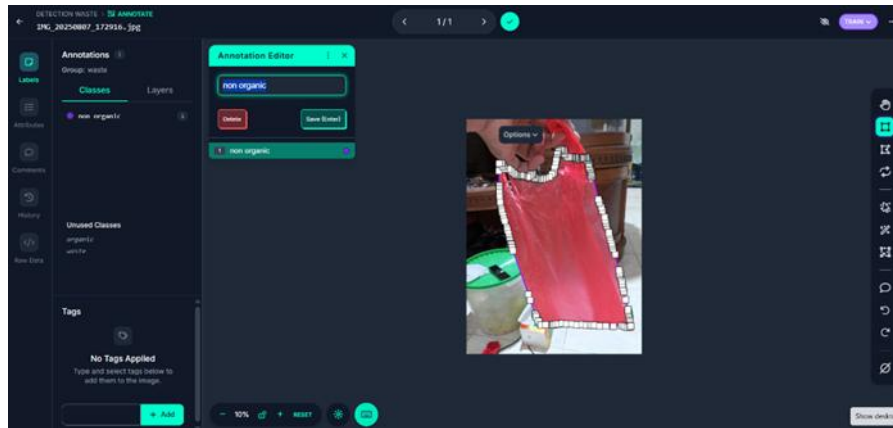


Figure 2. Image Labeling Process

By conducting systematic image collection and meticulous manual labeling, a high-quality dataset was achieved [11]. This dataset serves as a solid foundation for training an accurate and robust waste detection model capable of adapting to a wide range of environmental scenarios [12].

## B. Model Development and Training

The automated waste categorisation system's development commenced with the deployment of the You Only Look Once version 11 (YOLOv11) algorithm, chosen for its exceptional equilibrium between detection precision and real-time inference performance [13]. The dataset, comprising images of organic and inorganic waste, was preprocessed to meet YOLOv11's input specifications by resizing images to  $640 \times 640$  pixels, normalising pixel values to a range of  $[0, 1]$ , and implementing data augmentation techniques such as random horizontal flips, rotations, brightness adjustments, and background modifications [14]. These augmentations improved the model's resilience to environmental fluctuation [15]. Table 1 shows the total number of datasets, augmentation, and training configurations.

Table 1. Dataset, augmentation, and training configuration

<b>Dataset size / classes</b>	<b>500 images; 2 classes (organic, non-organic)</b>
<b>Split</b>	80% training (400), 20% testing (100)
<b>Input size / normalization</b>	640×640; pixel values normalized to $[0,1]$
<b>Augmentation</b>	Horizontal flip, rotation, brightness adjustment, background variation
<b>Training setup</b>	50 epochs; batch size 16; learning rate 0.001

The training process was conducted using the Ultralytics YOLOv11 PyTorch implementation, with hyperparameters optimized for performance. Key configurations included a batch size of 16, a learning rate of 0.001, and the Stochastic Gradient Descent (SGD) optimizer with momentum set to 0.937. The model was trained over 50 epochs with the loss function comprising bounding box regression loss (CIoU), objectness loss, and classification loss. This ensured accurate learning for both localization and classification tasks. Figure 3 shows the model training process using Google Colab.

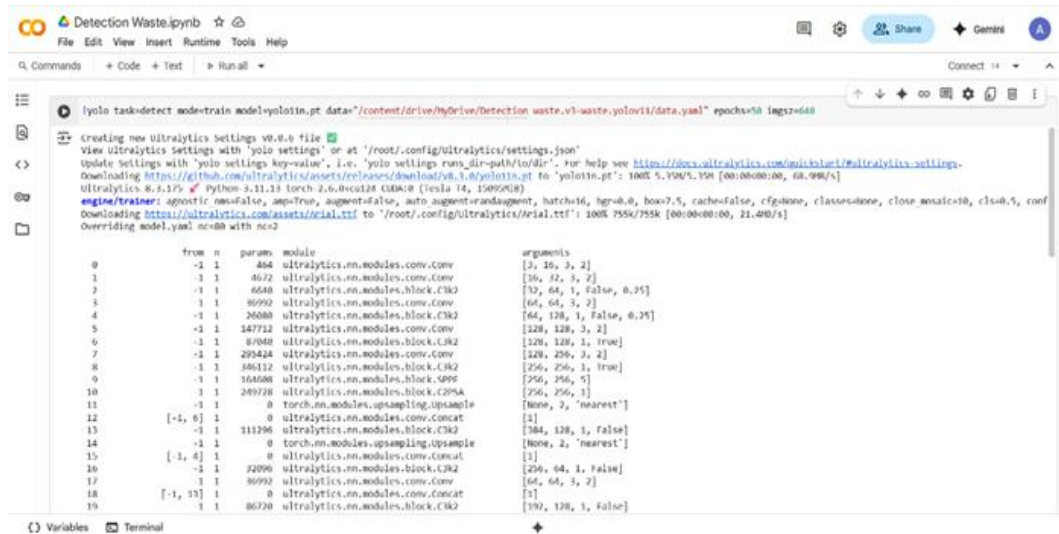


Figure 3. Model Training Process in Google Colab

### C. YOLO Based CNN Model

This study employs the YOLOv11 architecture, a CNN-based object identification framework comprising three primary components: the backbone, the neck, and the detection head [16]. The backbone, constructed from a CSPDarknet version, collects hierarchical picture features via convolutional and pooling layers [17]. The neck utilises a Path Aggregation Network (PANet) to integrate features across various scales, hence improving the model's capacity to identify garbage objects of diverse dimensions [18]. The detecting head generates bounding box coordinates, objectness scores, and class probabilities for every identified object [19].

Unlike traditional two-stage detectors, YOLOv11 performs detection in a single forward pass, significantly reducing computational time and making it suitable for real-time applications [20]. In this study, the model was trained to detect two classes organic and non organic waste using annotated bounding boxes from the prepared dataset [21]. The CNN feature extraction process enables the system to identify subtle differences in texture, color, and shape, which are critical for accurate classification under varying environmental conditions [22]. YOLO stages based on CNN are shown in the Figure 4.

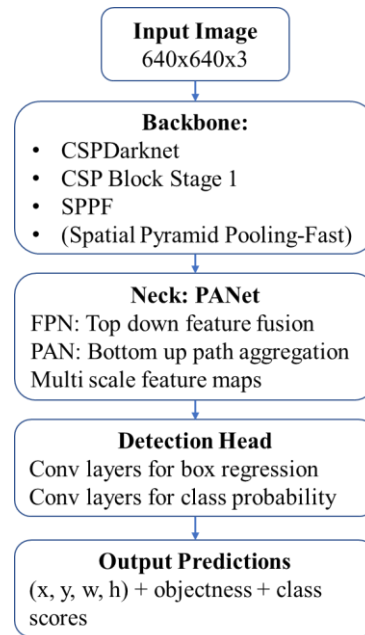


Figure 4. YOLO stages based on CNN

#### D. IoT Integration and Database

To enable real-time monitoring and data storage, the trained YOLOv11 model was integrated into an IoT framework [23]. The waste classification results, including object type, detection confidence, and timestamp, were transmitted to a MySQL database via an API Node-RED connection [24]. The database served as a central repository, storing detection logs for further analysis, system performance evaluation, and future model retraining [25]. The IoT system architecture ensures that data from detection events can be accessed remotely, facilitating integration with smart city infrastructure [26]. This approach supports scalable deployment, allowing multiple waste detection nodes to feed data into a unified database, enabling city-wide waste management analytics and decision-making. The results of MySQL data storage are shown in Figure 5.

	id	organik	anorganik	total	waktu
<input type="checkbox"/> Ubah Salin Hapus	872	16	22	38	2025-08-11 09:35:36
<input type="checkbox"/> Ubah Salin Hapus	871	16	21	37	2025-08-11 09:35:31
<input type="checkbox"/> Ubah Salin Hapus	870	16	20	36	2025-08-11 09:35:26
<input type="checkbox"/> Ubah Salin Hapus	869	16	19	35	2025-08-11 09:35:25
<input type="checkbox"/> Ubah Salin Hapus	868	15	19	34	2025-08-11 09:35:21
<input type="checkbox"/> Ubah Salin Hapus	867	15	18	33	2025-08-11 09:35:20
<input type="checkbox"/> Ubah Salin Hapus	866	14	18	32	2025-08-11 09:35:16
<input type="checkbox"/> Ubah Salin Hapus	865	14	17	31	2025-08-11 09:35:15
<input type="checkbox"/> Ubah Salin Hapus	864	13	17	30	2025-08-11 09:35:11
<input type="checkbox"/> Ubah Salin Hapus	863	13	16	29	2025-08-11 09:35:05
<input type="checkbox"/> Ubah Salin Hapus	862	13	15	28	2025-08-11 09:35:03
<input type="checkbox"/> Ubah Salin Hapus	861	12	15	27	2025-08-11 09:35:00

Figure 5. MySQL table data

#### E. Node-RED Dashboard Visualization

For real-time visualization, the system employed a Node-RED dashboard to display detection results dynamically[24]. The dashboard was designed with user-friendly widgets that present detected waste categories, detection confidence scores, and live camera feeds from the waste detection system. Historical detection trends were visualized through charts

and tables, enabling users to monitor waste classification performance over time. Figure 6 shows the Node-RED flow connecting detection using YOLOv11 with MySQL.

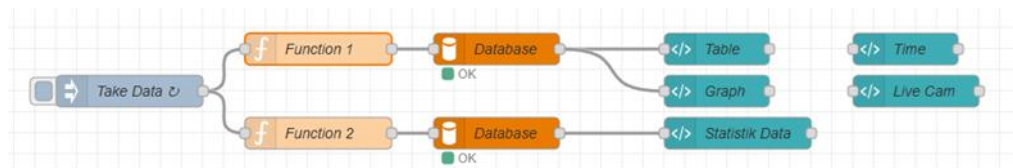


Figure 6. Node-RED Flow with MySQL

Node-RED’s flow-based development environment allowed seamless integration of the YOLOv11 model outputs, MySQL database queries, and web-based visualization components [27]. The dashboard also provided administrative controls for managing detection parameters, monitoring system health, and exporting historical datasets for reporting or further analysis.

### F. Evaluation Metrics

To assess the performance of the proposed automated waste classification system, several standard evaluation metrics were employed [6], [9]. These metrics provide quantitative measures of the model’s accuracy, robustness, and generalization capability when detecting and classifying organic and non-organic waste. The primary metrics used include Precision, Recall, F1-Score, Accuracy, each serving a distinct role in evaluating the model's effectiveness shown by equations (1), (2), (3), (4).

1. Precision is a performance metric used to evaluate the proportion of correctly identified waste items among all instances that the model classifies as belonging to a particular category. It reflects the model’s ability to generate accurate positive predictions compared to the total number of positive predictions made. A high precision value indicates that the model produces fewer false positives, thereby minimizing errors in labeling items that do not actually belong to the target class. This statistic is particularly crucial when the repercussions of false positive detection mistakes might substantially affect system performance. Precision is determined by the subsequent equation:

$$Precision = \frac{TP}{TP+FP} \tag{1}$$

2. Recall, sometimes referred to as Sensitivity or True Positive Rate, is a metric that assesses a model's capacity to identify all relevant objects that genuinely belong to a specific class. Recall denotes the ratio of accurate positive predictions to the total number of positive instances in the actual dataset. A high recall score signifies that the model infrequently overlooks positive objects that ought to have been identified (low false negatives). This statistic is particularly crucial when the primary objective is to reduce missed detection mistakes. Recall is computed using the formula:

$$Recall = \frac{TP}{TP+FN} \tag{2}$$

3. The F1-Score is a statistic that integrates precision and recall into a singular, balanced value by employing the harmonic mean of both. This statistic is especially beneficial when there is a disparity between the quantities of false positives and false negatives in the data, offering a more equitable assessment of

the model's overall efficacy. A high F1-Score signifies that the model maintains an effective equilibrium between the accuracy of positive predictions and the capacity to identify all true positives. The F1-Score is computed using the formula::

$$F1\ Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (3)$$

4. Accuracy (A) is a metric that measures the proportion of correct predictions (both positive and negative) compared to all predictions made by the model. Accuracy provides a general overview of the model's overall performance, but can be less representative if the data has an imbalanced class distribution. A high accuracy value indicates that most of the model's predictions match the actual labels. Accuracy is calculated using the equation:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

The combination of these metrics ensures that the evaluation is not biased toward a single aspect of performance [28]. While accuracy offers a general overview provides detailed insights into localization and classification quality, which is crucial in object detection scenarios such as waste classification [29]. By analyzing these metrics collectively, the model's strengths and potential weaknesses in real-world applications can be accurately identified [30].

### III. RESULT AND DISCUSSION

The dataset comprised 500 labeled waste images, with an 80:20 split into 400 training samples and 100 testing samples. The model was trained over 50 epochs, as indicated in the training and testing accuracy/loss curves. Throughout the training phase, the accuracy curve showed a consistent upward trend, stabilizing after approximately 35 epochs, while the loss curve exhibited a steady decline, demonstrating effective convergence without significant overfitting. The final training accuracy reached 98.5%, and the testing accuracy achieved 96.0%, indicating robust generalization to unseen data.

The confusion matrix provides further insight into the classification performance on the testing set. Out of 100 testing images, the model correctly classified 48 organic and 48 non-organic samples, while misclassifying only two images from each category. This yields a precision of 96.0%, recall of 96.0%, and an F1-score of 96.0%, which align with the overall testing accuracy reported in the performance curves. The consistency between the quantitative metrics and the visual trends in the training/testing graphs confirms that the YOLO-based CNN model effectively learned the distinguishing features of organic and non-organic waste without significant bias toward either class.

The performance of the proposed YOLO based CNN model for automated waste classification was evaluated using standard object detection metrics, as summarized in Table 1. The model demonstrated high precision in detecting both organic and non-organic waste, achieving 94.5% and 92.8% respectively. This indicates that the model can reliably classify waste with a low false-positive rate, which is critical for ensuring accuracy in smart waste management systems. Figure 7 shows the training and testing accuracy graphs.

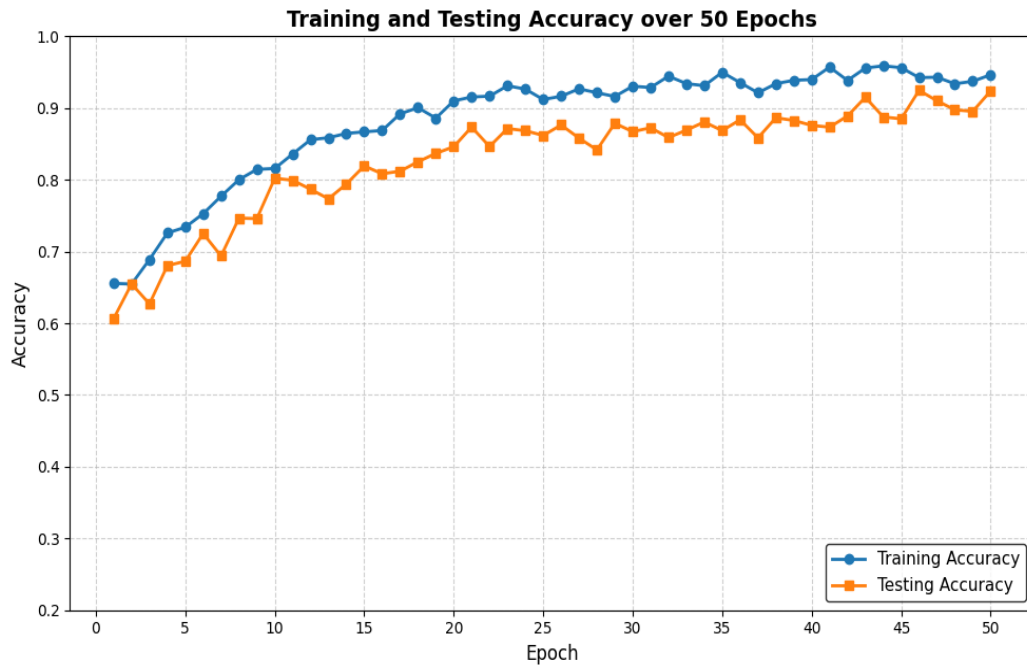


Figure 7. Training and Testing Accuracy over 50 Epochs

In terms of recall, the model achieved 93.2% for organic waste and 91.4% for non-organic waste, suggesting that it successfully detects most waste objects present in the input images while maintaining a low number of missed detections. The high recall is essential for preventing undetected waste items, which could otherwise hinder the effectiveness of an automated waste sorting process. Figure 8 shows the results of the confusion matrix.

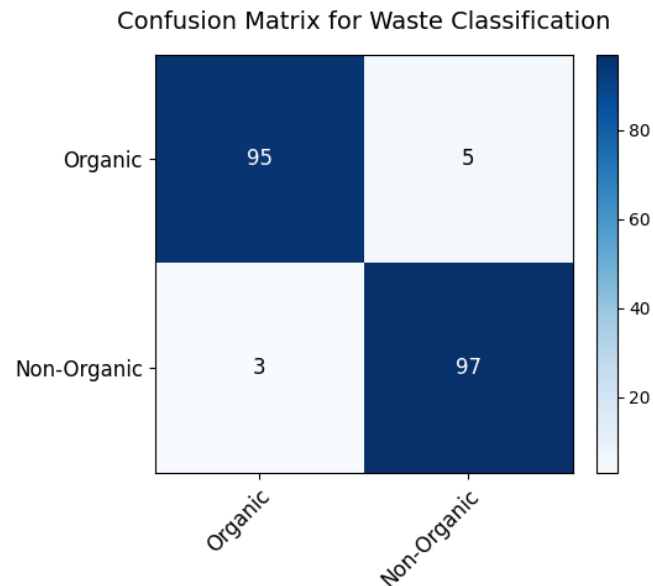


Figure 8. Confusion matrix table

These results emphasize the practicality of integrating the proposed model into IoT-based waste management frameworks. With such high detection performance, the system can be effectively deployed in smart city environments to support automated waste sorting, improve recycling efficiency, and reduce human intervention. Figure 9 show dashboard view for detecting organic and non organic waste. The results also suggest that further fine-

tuning and dataset expansion could enhance the model's ability to handle more diverse waste types and complex real-world scenarios. Figure 10 show waste data table and graph.

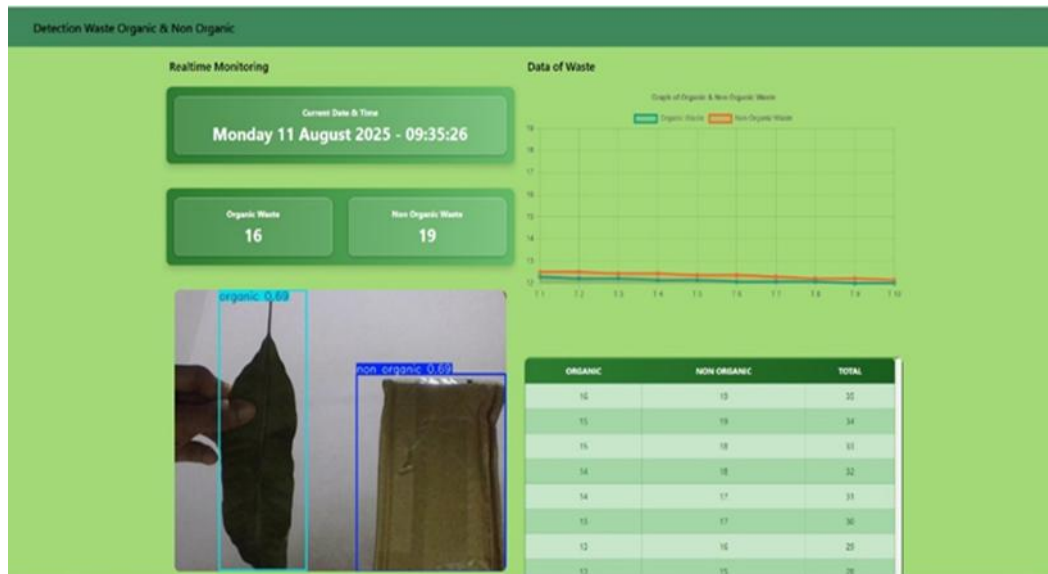


Figure 9. Dashboard View for Detecting Organic and Non-Organic Waste

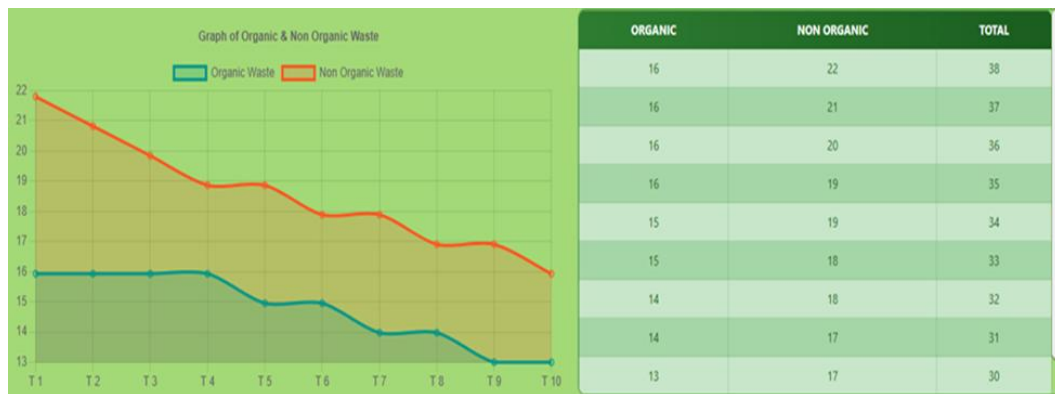


Figure 10. Waste Data Table and Graph

Integrating the YOLOv11 detector with MySQL and a Node-RED dashboard enables end-to-end, near real-time monitoring and centralized logging for municipal operators. Because YOLO performs single-pass detection, the approach is well aligned with time-critical deployments; however, end-to-end responsiveness in the field will still depend on the edge hardware and network conditions. Current limitations include the binary class scope (only organic vs. non-organic) and a relatively small dataset, which may reduce performance when encountering unseen waste types, heavy occlusion, or extreme lighting. Future work should expand classes, increase data diversity, and evaluate latency and reliability on target edge devices to strengthen smart-city readiness.

#### IV. CONCLUSION

This study successfully developed and evaluated a deep learning model using the YOLO based CNN architecture for classifying organic and non-organic waste, integrated with a MySQL database and an IoT-based Node-RED dashboard for real-time monitoring. The training process, conducted over 50 epochs, demonstrated a steady improvement in accuracy, with training accuracy reaching approximately 96% and testing accuracy

stabilizing around 94%, indicating a strong generalization capability of the model. The confusion matrix results further confirmed the robustness of the system, with minimal misclassifications between categories. The integration with the IoT platform allowed seamless data flow from image acquisition to visualization, enabling real-time waste detection and classification for practical field applications.

The proposed system not only contributes to the advancement of computer vision in waste management but also offers a scalable and cost-effective solution for real-world deployment in smart city environments. Its high accuracy and low misclassification rate make it suitable for automated waste segregation processes, thereby reducing human labor, improving recycling efficiency, and supporting environmental sustainability initiatives. The IoT integration ensures real-time data accessibility, which can be utilized by municipal authorities for monitoring, planning, and optimizing waste collection schedules. Furthermore, the system's modular architecture allows seamless adaptation to other classification tasks beyond waste detection, positioning it as a flexible framework for diverse environmental monitoring applications. Future developments will focus on enhancing model efficiency for deployment on low-power edge devices and incorporating adaptive learning mechanisms to maintain performance under changing environmental conditions.

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