

Implementation of YOLOv11 on a Rotating Mechanical System for Smart Waste Sorting

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Abstract: Waste management still faces limitations in efficiency and consistency in manual sorting. Hence, a computer vision-based smart waste-sorting system integrated with mechanical actuation is required. This study applies YOLOv11 for object detection and waste classification in a smart waste-sorting system integrated with a rotational mechanism that directs objects into organic and inorganic categories. The dataset comprised 17.231 waste images collected from multiple publicly available datasets on Kaggle, resized to 512×512 pixels, normalized, and augmented. The YOLOv11n model was trained for 100 epochs with a batch size of 16, an automatic optimizer configuration, and an initial learning rate of 0.01 to identify five classes: Organic, Paper, Glass, Plastic, and Metal. The system transmitted detection results from a laptop or mini PC to the ESP32 via UART to control the sorting mechanism using two servos. The five detection classes were mapped to two operational categories: organic and inorganic. Model evaluation resulted in an overall precision of 77.3%, recall of 67.9%, F1-score of 72.29%, mAP@50 of 78.2%, and mAP@50–95 of 59.1%. Physical testing yielded 178 successful trials out of 180 (98.89%). The average system response time was 1.78 ± 0.16 seconds, rotation movement time was 1.77 ± 0.03 seconds, and total processing time was 3.54 ± 0.17 seconds. The mechanism operated smoothly for objects weighing 2–159 grams during testing. The results indicate that integrating YOLOv11 with a rotational mechanism can support automated smart waste sorting under the tested conditions.

Keywords: Computer Vision; Object Detection; Rotational Mechanism; Smart Waste-Sorting; Waste Classification; YOLOv11

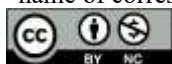
INTRODUCTION

Waste management is an evolving problem driven by population growth and human activity. Urbanization and consumption patterns increase waste generation, affecting the environment and health (Zhang et al., 2024; Kumar, 2025). In waste management, sorting by type, such as organic and inorganic, is crucial to effective recycling and the circular economy (Kumar, 2025). In practice, this process remains largely manual, resulting in low efficiency, a high potential for errors, and a decline in the quality of recyclable materials (Wilts et al., 2021; Meza et al., 2025). Additionally, workers face health risks from exposure to hazardous waste and less ergonomic working conditions (Zhang et al., 2024; Ahmed et al., 2023). An automated system is needed to improve waste-sorting efficiency, speed, and accuracy.

Developments in computer vision and Artificial Intelligence (AI) offer significant opportunities for smart waste-sorting systems based on real-time object detection. Various studies show that deep learning approaches, such as Convolutional Neural Networks (CNNs) and the YOLO family of algorithms, can improve classification accuracy and efficiency compared with conventional methods (Arishi, 2025; Sayem et al., 2024). As a one-stage detection algorithm, YOLO offers faster processing and can detect multiple objects simultaneously, making it widely used in automatic waste-sorting applications (Bawankule et al., 2023; Maity, 2023). Previous studies implementing YOLOv3, YOLOv5, and YOLOv8 show AI-based systems can achieve high accuracy and strong performance in image-based waste sorting (Ahmad et al., 2025; Nafiz et al., 2023; Ren et al., 2024).

Nevertheless, most prior research focuses on image classification and does not effectively integrate it with physical sorting systems. The literature shows many efforts stop at object identification in controlled environments, without implementing actuation capable of automatically separating objects in the real world (Lu & Chen, 2022; Arbeláez-Estrada et al., 2023). Systems that integrate physical sorting generally use conventional mechanisms

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such as conveyors with servo gates or simple actuators, offering limited flexibility and responsiveness to variations in object positions (Arbeláez-Estrada et al., 2023). This indicates a research gap in integrating AI-based detection systems with integrated physical sorting mechanisms to support automated sorting processes.

Moreover, previous research has rarely explored rotational mechanical systems as sorting mechanisms in depth. Most automatic sorting systems still rely on complex multi-actuator configurations, thereby increasing control requirements and implementation costs (Kiyokawa et al., 2024). In contrast, the rotation mechanism offers an alternative approach to direct objects to multiple output paths through coordinated actuation (Xu & Lu, 2024).

The present study offers two key innovations based on the identified issues and research gaps: using the YOLOv11 algorithm for object detection and developing a rotational mechanical sorting mechanism integrated with the detection results. This integration aims to support automated waste sorting by linking object detection to physical actuation. Previous research has integrated deep learning-based detection systems with mechanical actuators to support automatic sorting processes (Koskinopoulou et al., 2021; Almtireen et al., 2025; Raman et al., 2023; Thanh et al., 2023; Fadir et al., 2024).

This research aims to implement the YOLOv11 algorithm in an intelligent waste-sorting system integrated with an automatic rotation mechanism. This study focuses on designing a YOLOv11-based object detection system, developing a rotation-based sorting mechanism, and integrating both into a synchronized automatic sorting system. This research evaluates the system's performance in terms of detection accuracy and response time.

The research question focuses on designing and integrating a rotational mechanical system with YOLOv11-based object detection for automated waste sorting, and on applying YOLOv11 to detect and classify different waste types during operation. This study is expected to contribute to the development of automated waste-sorting systems that integrate object detection with mechanical actuation.

LITERATURE REVIEW

The development of artificial intelligence-based waste-sorting systems reflects a shift from conventional approaches to deep learning, particularly for object detection. YOLO has become a widely used approach because it integrates detection and classification in a single computational stage, offering faster inference than two-step methods such as Faster R-CNN (Demetriou et al., 2023; Vijayakumar & Vairavasundaram, 2024). In waste sorting applications, YOLO has shown responsive real-time performance with stable accuracy (Arishi, 2025; Kaburuan et al., 2024). The development of YOLO from YOLOv8 to YOLOv11 has focused on improving accuracy and computational efficiency, including low-latency implementation on edge devices (Hingmire & Pujeri, 2025; Nasien et al., 2025). However, these developments have not always included end-to-end integration between detection and physical actuation.

YOLO-CNN hybrid approaches can improve feature extraction and detection performance, but they also increase computational complexity and latency (Mustapha et al., 2025; Raza et al., 2025). From a mechanical perspective, waste sorting systems commonly rely on conveyor-based approaches with multiple actuators, such as servos or pneumatic systems. These systems direct objects based on detection results (Adebimpe et al., 2022; Konstantinidis et al., 2023), but synchronizing detection, conveyor movement, and actuation increases system complexity, energy consumption, and maintenance requirements (Rianmora et al., 2023; Choithwani, 2025).

Efforts to integrate object detection with mechanical systems have been reported, but most remain partial. Detection outputs are not always used directly as control signals for physical actuation, which can introduce latency between identification and actuation (Giel et al., 2025; Aberger et al., 2025). This indicates that the challenge is not only detection accuracy but also synchronizing classification results with physical actuation. As an alternative, researchers have developed rotation-based mechanisms for object distribution by changing rotation angles through a main actuator (Bianchi et al., 2024). However, integration between rotation-based mechanisms and deep learning-based detection, particularly YOLO, remains limited.

Although deep learning-based detection algorithms have advanced rapidly, end-to-end integration between object detection and physical sorting mechanisms remains limited. The main challenges include synchronizing detection results with actuation and reducing the complexity of conventional mechanical systems. Therefore, this study integrates YOLO-based detection with a rotational actuation mechanism to link classification results directly to the physical sorting process.

METHOD

This study proposes an integrated waste-sorting system that combines computer vision and mechanical actuation into a single system. The system uses the YOLOv11 algorithm to detect and classify objects during operation, along with a rotation-based sorting mechanism controlled by an ESP32 microcontroller. The classification results drive decision-making, directing the sorting mechanism to the appropriate position so detection, classification, and sorting can be carried out automatically in a single workflow.

The primary contribution of this method is directly mapping object classification results to mechanical rotation angles (θ). We group several object classes recognized by YOLOv11 into two sorting categories, organic and

inorganic, and map each to a specific rotation position. The classification results are sent to the ESP32 via UART serial communication using a USB connection. This approach directly connects computer vision results with physical actuation. Fig. 1 shows the research flowchart.

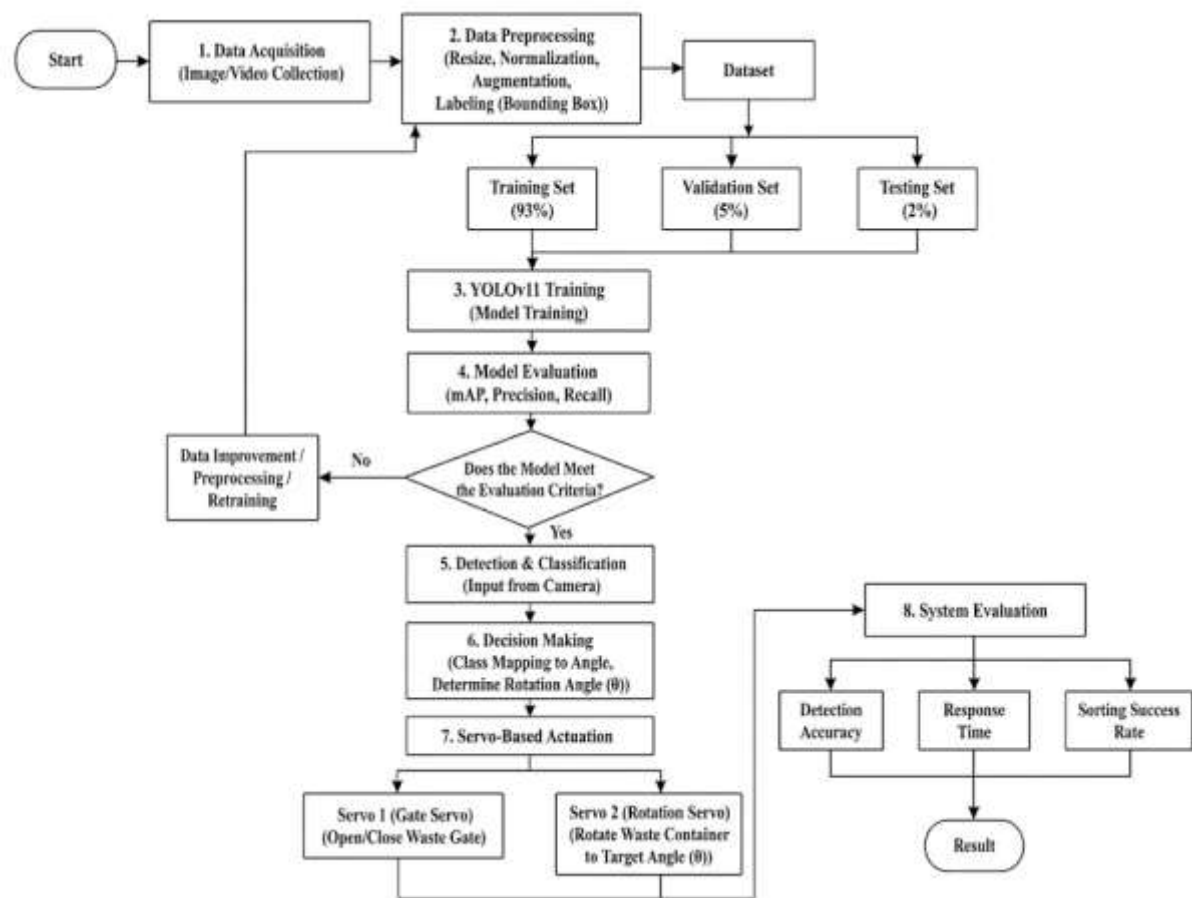


Fig.1 Research Flowchart

Dataset

The dataset comprises 17,231 waste images collected from multiple publicly available Kaggle datasets and organized using Roboflow. It includes five classes: Glass (3,034 images), Paper (3,937), Metal (3,166), Organic Waste (2,844), and Plastic (4,250). The images were manually annotated by the authors using bounding boxes and class labels. The dataset was split into training (93%), validation (5%), and testing (2%) sets using Roboflow. Potential data leakage was examined across the three subsets using SHA-256 hashing and perceptual hashing (pHash). Ten potentially similar images identified by pHash were manually inspected, confirming that images of the same physical object were not distributed across different subsets. Examples of the dataset used for waste detection are shown in Fig. 2.



Fig. 2 Dataset of Waste Images for Classification

Preprocessing Data

There are 17.231 images of garbage items in the dataset. To increase variance and reduce overfitting, we resize photos to 512×512 pixels, standardize them, and augment the data with rotation and brightness adjustments. Bounding boxes in YOLO format are used in the annotation process.

YOLOv11 Model Training

To identify and categorize waste objects, we preprocessed the dataset and annotated bounding boxes before training the YOLOv11 model. The YOLOv11n model was trained for 100 epochs with a batch size of 16, using the automatic optimizer configuration and an initial learning rate of 0.01. These settings were used as the training configuration for this study. We examined the training and validation curves to assess the model's learning progress. However, we did not conduct a dedicated hyperparameter ablation or sensitivity study; therefore, we do not claim that the selected settings are optimal. The model produced bounding boxes, class labels, and confidence scores. Its performance was evaluated using precision, recall, F1-score, mAP@50, and mAP@50-95.

Detection and Classification

The process begins when the camera (webcam) captures images of the waste object in real time. A Full HD 1080p webcam captures the images, positioned about 20 cm from the waste object under bright lighting conditions. The image is sent to a Mini PC/Laptop for inference using the YOLOv11 model. The detection results, presented as bounding boxes, class labels, and confidence scores, determine the sorting category.

System Integration and Communication

The integrated system architecture is illustrated in Fig. 3.

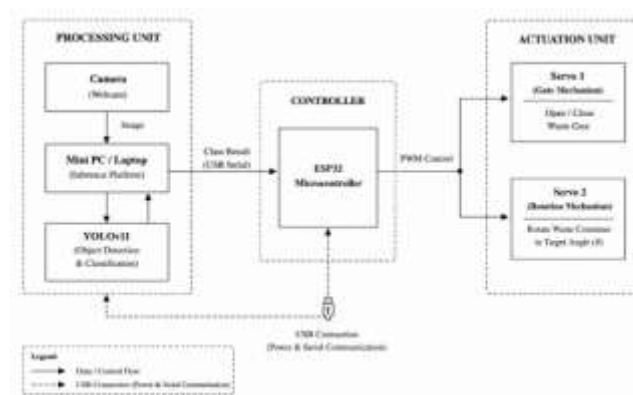


Fig.3 System Architecture

YOLOv11 classification results on the Mini PC/Laptop are sent to the ESP32 via UART serial communication over a USB connection. Although the model classifies several object classes, the actuation stage maps the results into two main categories: organic and inorganic. A five-class detector is maintained to preserve class-specific

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information and provide a basis for potential future expansion to more than two sorting categories. In the current system, the five detected classes are mapped to two operational categories: Organic at 0° and Paper, Glass, Plastic, and Metal at 180°. Multi-angle sorting beyond these two categories has not yet been implemented in this research. The relationship between object classes, sorting categories, and rotation angles is expressed as:

$$\theta = f(g(c)) \quad (1)$$

Where (c) is the object class, $g(c)$ is the function that groups the object class into organic or inorganic categories, and θ is the target rotation angle. The angle implementation includes 0° (organic) and 180° (inorganic).

The decision-making process uses a detection threshold of 0.7 and a minimum confidence of 0.6 for sending the classification result to the ESP32. If no valid object is detected, no classification command is sent, and the system remains idle. When multiple objects are detected simultaneously, the object with the highest confidence is processed. If the prediction fluctuates between frames, the system uses the detection with the highest confidence in the current frame, provided that it meets the sending threshold. Once a classification command is sent, a 4-second cooldown prevents another command from being sent immediately.

To validate the physical system, we tested the integrated sorting mechanism using nine representative waste objects: five organic and four inorganic. Each object was tested 20 times, resulting in 180 trials. The same objects were reused across trials, and the Glass class was excluded from physical testing due to the limited availability of representative glass objects.

Therefore, physical validation is limited to a narrow range of object variations and is not intended to represent the system's performance under various waste shapes, orientations, and lighting conditions.

Actuation Mechanism (Rotation System)

ESP32 controls two servos using PWM signals. Servo 1 is used to open and close the waste gate, while Servo 2 is used to rotate the waste container to the target angle (θ) based on the classification results. The actuation mechanism directs the object to the container based on the specified waste category.

System Evaluation

The model's efficiency in identifying and categorizing garbage objects was evaluated using precision, recall, F1-score, mAP@50, and mAP@50–95. Recall measures the model's ability to identify real objects, precision measures the accuracy of positive predictions, and F1-score balances precision and recall. These measures reflect the object detection evaluation methodology used in earlier research, including Langi and Fadlullah (2026) and Prasetyo and Nambo (2024).

The exactness model's positive predictions are determined using:

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

Recall is used to measure the model's ability to locate all positive objects and is calculated using:

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

The F1-score, computed using the harmonic mean of precision and recall, is used to assess how well the 2 metrics are balanced:

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

Where (TP) is True Positive, (FP) is False Positive, and (FN) is Undetected Positive. Given the correlation between precision and recall at a specific Intersection over Union (IoU) level, Mean Average Precision (mAP) assesses object-detection performance. This study assesses detection effectiveness at various levels of localization accuracy using mAP@50 and mAP@50–95.

RESULT

This section presents the test results and performance evaluation of the smart garbage sorting system. This section evaluates the YOLOv11 model's ability to identify garbage objects and the system's capacity to combine detection results with a rotation-based sorting mechanism. We assessed model performance during testing using precision, recall, F1-score, mAP@50, and mAP@50–95; physical sorting tests; system response time; and mechanism stability under varying object mass. The YOLOv11 model detects five classes, Organic, Paper, Glass, Plastic, and Metal, mapped to two sorting categories: Organic and Inorganic.

We trained the YOLOv11 model on a dataset of waste images that underwent preprocessing and bounding box annotation. Table 1 shows the model evaluation results for precision, recall, F1-score, mAP@50, and mAP@50–95.

Table 1 Results of YOLOv11 Model Evaluation

Class	Precision (%)	Recall (%)	F1-Score (%)	mAP@50 (%)	mAP@50–95 (%)
Organic	87.2	74.5	80.35	87.2	64.1
Paper	94.8	78.5	85.89	92.5	68.0

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Glass	95.5	84.0	89.38	95.4	70.9
Plastic	22.1	28.6	24.93	31.7	28.4
Metal	86.9	73.9	79.87	84.2	64.2
Overall	77.3	67.9	72.29	78.2	59.1

The model obtained 77.3% precision, 67.9% recall, 72.29% F1-score, 78.2% mAP@50, 59.1% mAP@50–95, according to Table 1. The YOLOv11 model's overall evaluation (all) yielded the precision, recall, mAP@50, and mAP@50–95 values in the Overall row. Equation (4) was used to calculate the harmonic mean between precision and recall, yielding an F1-score of 72.29%. By entering the recall value of 67.9% and the precision value of 77.3% into Equation (4), we get:

$$F1 - score = 2 \times \frac{77.3 \times 67.9}{77.3 + 67.9}$$

$$F1 - score = 72.29\%$$

The calculation results match the F1-score in the Overall row of Table 1. The Overall row represents the model's overall evaluation results, not the arithmetic mean across the five classes.

A recall of 67.9% shows the model's ability to identify objects in the data, while a precision of 77.3% shows how well the model generates positive predictions. An F1-score of 72.29% indicates a balance between recall and precision. Meanwhile, an mAP@50 of 78.2% and an mAP@50–95 of 59.1% show the model's detection performance at different localization precision levels. Research by Langi and Fadlullah (2026) and Prasetyo and Nambo (2024) uses precision, recall, F1-score, and mAP as object-detection evaluation metrics.

The Glass class achieved the highest performance: 95.5% precision, 84.0% recall, an F1-score of 89.38%, and an mAP@50 of 95.4%. The Paper, Organic, and Metal classes achieved mAP@50 scores of 92.5%, 87.2%, and 84.2%, respectively. Meanwhile, the Plastic class performed the worst, with a precision of 22.1%, recall of 28.6%, an F1-score of 24.93%, an mAP@50 of 31.7%, and an mAP@50–95 of 28.4%.

Across classes, Glass shows the highest detection performance, while Plastic shows the lowest. This difference indicates the model's ability to detect objects varies across each class.



Fig.4 Normalized Confusion Matrix of the YOLOv11 Model

The normalized confusion matrix further shows that the Plastic class is frequently confused with other waste classes, particularly Glass (0.43) and Metal (0.41), indicating difficulty in distinguishing Plastic from visually similar objects. This finding aligns with the Plastic class's relatively low detection performance, which achieved 22.1% precision and 28.6% recall in Table 1. The difference between the low Plastic detection performance and the 20/20 physical sorting result is attributed to limited physical testing that repeatedly used a single representative plastic bottle. Therefore, the 20/20 physical sorting result does not represent the robustness of Plastic detection across various waste forms. Further testing with plastic objects of different shapes, sizes, colors, and surface conditions is needed.

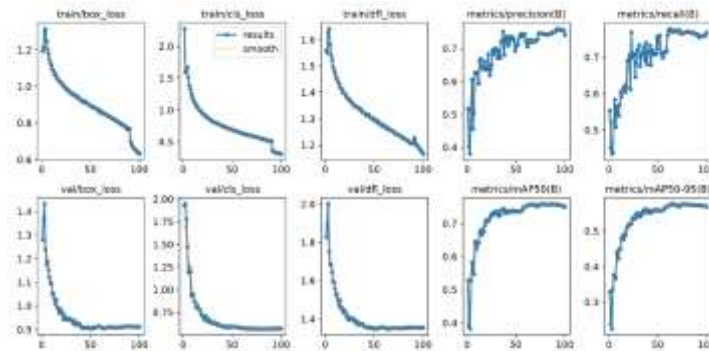


Fig.5 Results of training and validation of the YOLOv11 model

Figure 5 shows the YOLOv11 model's training and validation progress. Training losses, including box loss, classification loss, and distribution focal loss (DFL), gradually decreased throughout training. Validation losses also substantially decreased during the early epochs and then tended to stabilize in the later stages of training. The training and validation curves follow a similar downward trend with no significant deviations, indicating no clear signs of overfitting. Meanwhile, precision, recall, mAP@50, and mAP@50–95 increased during training and tended to stabilize toward the later epochs. This trend indicates that the model continues to learn effectively without clear signs of underfitting.

The YOLOv11 detection results serve as the basis for sorting decisions. The model's five classes are grouped into two categories based on the sorting-mechanism configuration. The Organic class maps to the Organic category, while Paper, Glass, Plastic, and Metal map to the Inorganic category. Table 2 shows the class mapping and rotation positions.

Table 2 Mapping of YOLOv11 Detection Classes to Sorting Categories

YOLOv11 Detection Class	Sorting Category	Test Object	Target Rotation Angle (°)	Goal
Organic	Organic	Fresh leaf, dried leaf, orange, rotten mango, rotten tomato	0	Organic
Paper	Inorganic	Cardboard, newspaper	180	Inorganic
Glass	Inorganic	—	180	Inorganic
Plastic	Inorganic	Plastic bottle	180	Inorganic
Metal	Inorganic	Beverage can	180	Inorganic

Based on Table 2, the Organic class is directed to a rotation position of 0°, while Paper, Glass, Plastic, and Metal are directed to 180°. The five classes at the detection stage do not require five different sorting mechanisms. The detection results are first converted into two sorting categories and used to actuate the mechanism.

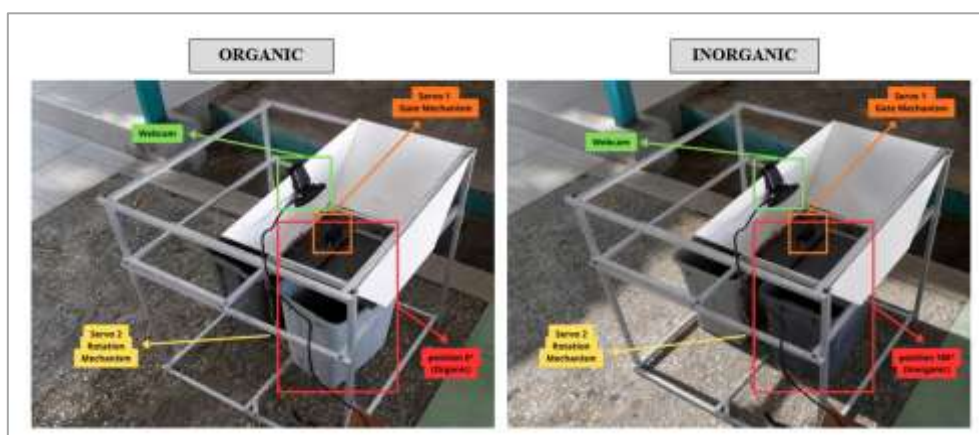


Fig.6 Position of the rotation-based waste sorting mechanism at 0° (organic) and 180° (inorganic).

During actuation, the YOLOv11 classification results on the inference platform are sent to the ESP32 via UART over a USB connection. The ESP32 controls two servos using PWM signals. Servo 1 opens and closes the

waste gate, while Servo 2 rotates the waste container to the target angle based on the detection category. This configuration translates detection results into physical sorting actions.

The physical sorting test assessed how well the system integrated detection results with the rotation-based sorting mechanism. The test used nine objects: five organic and four inorganic. Each object was tested 20 times, resulting in a total of 180 trials, as shown in Table 3.

Table 3 Results of Physical Sorting Success Testing

Category	Test Object	Experiment	Successful	Incorrect	Accuracy (%)
Organic	Fresh leaf	20	20	0	100
Organic	Dried leaf	20	19	1	95
Organic	Orange	20	20	0	100
Organic	Rotten mango	20	20	0	100
Organic	Rotten tomato	20	20	0	100
Inorganic	Beverage can	20	20	0	100
Inorganic	Cardboard	20	20	0	100
Inorganic	Newspaper	20	19	1	95
Inorganic	Plastic bottle	20	20	0	100
Average		180	178	2	98.89

Based on Table 3, 178 of 180 trials were categorized correctly, while two were categorized incorrectly. The percentage of successful sorting is calculated using the equation:

$$\text{Sorting Success Rate} = \frac{178}{180} \times 100\% = 98,89\% \quad (5)$$

Most objects achieved a 100% sorting success rate, while dried leaves and newspapers each achieved 95%. In the dried leaf test, one trial produced an incorrect sort after the system detected a change before making its final decision. In the newspaper test, one error occurred when the object's shape changed due to folding or stacking, making its appearance in the camera less consistent. The findings indicate sorting errors relate not only to mechanism movement but can be influenced by changes in the object's visual characteristics during detection. Objects with irregular shapes, or those that change shape, can produce different visual patterns than in their initial state, affecting the stability of detection results.

The results indicate that object presentation during detection is an important factor in maintaining sorting consistency. Objects with relatively stable shapes can be detected and sorted more consistently, while changes in shape or visible appearance may increase the possibility of an incorrect sorting decision.

This condition becomes relevant during the sorting operation, when decisions must be made while the object is moving or changing position. Only two trials failed out of 180, so the errors were limited to the tested conditions. The overall sorting success rate of 98.89% indicates that the integrated system performed consistently under the tested conditions. However, these results should be interpreted within the scope of the evaluation, which involved nine objects and excluded the Glass class from physical testing. Therefore, the reported success rate does not establish the system's performance across diverse waste types.



Fig.7 Bounding Box Detection Results.

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The detected bounding boxes reveal that YOLOv11 can identify object locations and predicted classes during system operation. This detection information serves as the basis for determining the sorting category before forwarding the actuation decision to the ESP32. The bounding box visualization illustrates the object detection stage and serves as input for the physical sorting process.

Subsequent testing measured the system's response time and the rotation-based sorting mechanism's movement time. The system's reaction time is calculated from detection and decision-making to issuing the actuation command, while the movement time is the time for the rotation mechanism to reach the target position. Table 4 shows the test results.

Table 4 System Response Time Test Results

Category	Test Object	System Response Time (s)	Rotation Movement Time (s)	Total Process Time (s)
Organic	Fresh leaf	1.79	1.79	3.58
Organic	Dried leaf	1.60	1.72	3.32
Organic	Orange	2.10	1.78	3.88
Organic	Rotten mango	1.89	1.79	3.68
Organic	Rotten tomato	1.60	1.78	3.38
Inorganic	Beverage can	1.65	1.75	3.40
Inorganic	Cardboard	1.88	1.76	3.64
Inorganic	Newspaper	1.64	1.77	3.41
Inorganic	Plastic bottle	1.86	1.75	3.61
Average		1.78	1.77	3.54

We measured response time with a stopwatch during each trial and validated it with video recordings to verify the recorded timing. Each of the nine test objects was evaluated in 20 trials, resulting in 180 measurements. The total process time was calculated as the sum of the system response time and rotation movement time. Based on Table 4, the average system response time was 1.78 ± 0.16 s (95% CI: 1.75–1.80 s), while the average rotation movement time was 1.77 ± 0.03 s (95% CI: 1.76–1.77 s). The average total process time was 3.54 ± 0.17 s (95% CI: 3.52–3.57 s). Across the 180 measurements, system response time ranged from 1.57 to 2.13 s, and total process time ranged from 3.27 to 3.93 s.

The fastest average processing time was for the dried leaf (3.32 s), while the longest was for the orange (3.88 s). The relatively small standard deviations, particularly for the rotation movement time, indicate consistent timing across repeated trials. The variation in response time may reflect differences in detection and decision-making between trials.

The system's response time is primarily influenced by detection, decision-making, and communication before actuation, not directly by the object's mass. Mass relates more to the load borne by the mechanism and actuator, so it is more relevant to the motor's movement time.

Mechanical testing assessed the stability of the rotation-based sorting mechanism with objects of different masses, as shown in Table 5.

Table 5 Results of Mechanical Load Testing

Category	Test Object	Mass (g)	Rotational Movement	Condition
Organic	Fresh leaf	5	smooth	Stable
Organic	Dried leaf	2	smooth	Stable
Organic	Orange	159	smooth	Stable
Organic	Rotten mango	42	smooth	Stable
Organic	Rotten tomato	31	smooth	Stable
Inorganic	Beverage can	10	smooth	Stable
Inorganic	Cardboard	30	smooth	Stable
Inorganic	Newspaper	9	smooth	Stable
Inorganic	Plastic bottle	13	smooth	Stable

The objects used ranged from 2 to 159 grams. All objects moved smoothly, and the mechanism remained stable during testing. The 159-gram object is the heaviest object used in the test, not the mechanism's maximum capacity.

DISCUSSIONS

The research results show that the developed system successfully integrates YOLOv11-based object detection with a rotation-based physical sorting process. The system transmits YOLOv11 outputs via UART to the ESP32 to control the waste gate and waste container position, forming a single automated sorting flow from detection and decision-making to actuation.

At the model level, YOLOv11 achieved an overall precision of 77.3%, recall of 67.9%, F1-score of 72.29%, mAP@50 of 78.2%, and mAP@50–95 of 59.1%. These metrics reflect overall detection performance and align with object detection evaluation approaches in prior research.

Performance varies clearly across classes: Glass achieved the highest mAP@50 at 95.4%, while Plastic had the lowest score at 31.7%. These differences may reflect the visual characteristics and variations of the objects in the dataset. In the Plastic class, variations in shape, size, color, orientation, and surface condition can increase object diversity, making detection more difficult.

Although the Plastic class achieved an mAP@50 of 31.7%, plastic bottle objects were successfully sorted in 20 out of 20 physical trials. This shows that model detection performance and physical sorting success are different aspects of evaluation. Model evaluation measures detection capability on the dataset, whereas physical testing measures how well the system directs objects to the appropriate category. Therefore, a lower mAP for a class does not directly indicate failure of the physical sorting mechanism.

Physical testing shows a sorting success rate of 98.89%, with 178 successes out of 180 trials. Errors only occurred with dried leaves and newspapers, each once. For dried leaves, changes in detection results made the actuation decision unstable, while for newspapers, changes in shape due to folding or stacking could affect how the object appeared to the camera. However, the 98.89% success rate should be interpreted within the tested conditions, as the physical evaluation involved only nine objects, each tested 20 times, and excluded the Glass class. Therefore, these results should not be generalized to all waste types.

Mapping the five detection classes into two categories is an important part of system integration. The Organic class is directed to a rotation position of 0°, while Paper, Glass, Plastic, and Metal are directed to a position of 180°. This approach allows the model to provide specific object information at the detection stage, while the actuation mechanism requires only two sorting decisions. In the current configuration, the rotation mechanism is used to handle the two operational categories through the same physical mechanism. The two servos divide the actuation functions: Servo 1 controls the waste gate, and Servo 2 adjusts the waste container position.

From a time perspective, the average system response time was 1.78 ± 0.16 seconds (95% CI: 1.75–1.80 seconds), while the rotational movement time was 1.77 ± 0.03 seconds (95% CI: 1.76–1.77 seconds), resulting in an average total processing time of 3.54 ± 0.17 seconds (95% CI: 3.52–3.57 seconds). The relatively small variation indicates consistent processing times under the tested conditions, with slightly greater variation in system response time than rotational movement time. Variation in time between objects shows that process duration depends on more than an object's mass. A dried leaf weighing 2 grams has a movement time of 1.72 seconds, while an orange weighing 159 grams has a movement time of 1.78 seconds. This difference indicates that the test data do not yet support a linear relationship between the object's mass and the mechanism's movement time. Response time relates more to detection, decision-making, and communication before actuation, while movement time can be influenced by actuator characteristics and the system's mechanical conditions.

Mechanical testing showed stable movement for objects weighing 2–159 grams. However, 159 grams is only the largest tested mass, not the mechanism's maximum capacity, because we did not conduct failure testing.

To compare this research with previous studies, Table 6 presents the model, object/class, model performance, physical testing, and system mechanism.

Table 6 Comparison of Previous Research with the Proposed System

Research	Model	Object/Class	Model Performance	Testing Result	Mechanism
Yasiri et al. (2025)	YOLOv5	Plastic bottle	Precision 89.8%; Recall 83.1%; mAP 89.2%	82–93% (image-based testing)	Detection system
Lahoti et al. (2024)	YOLOv5	4 waste categories	Precision 65%	80% (physical sorting test, 8/10)	3D-printed robotic arm
Arvio et al. (2024)		5 inorganic classes	Precision 99.63%; Recall 96.53%; F1 98.03%	98% (direct testing)	Real-time detection
This research	YOLOv11	5 classes → 2 categories	Precision 77.3%; Recall 67.9%; mAP@50 78.2%	98.89% (178/180, physical sorting test)	Rotation-based sorting mechanism, 0°–180°

Yasiri et al. used YOLOv5 to detect plastic bottles, achieving 89.8% precision, 83.1% recall, and 89.2% mAP, with test results on image data ranging from 82% to 93%. Meanwhile, Arvio et al. used YOLOv8 to detect five classes of inorganic waste and achieved 99.63% precision, 96.53% recall, an F1-score of 98.03%, and 98% direct test accuracy. Lahoti et al. used YOLOv5 in a waste-separation prototype with a 3D-printed robotic arm and achieved an 80% success rate in physical separation in a controlled test environment (8 successful trials out of 10).

The performance values in this study cannot be used to determine whether YOLOv11 is superior to YOLOv5 or YOLOv8 because the number of classes, object types, dataset composition, and testing scenarios differ. Yasiri et al. focus on plastic bottles, while Arvio et al. focus on five classes of inorganic waste. This study uses five classes, Organic, Paper, Glass, Plastic, and Metal, mapped into two categories: Organic and Inorganic. The mAP@50 of 78.2% should be interpreted in the context of the detection task and the system configuration used. The physical sorting results in this study cannot be directly compared with Lahoti et al. because the object types, number of trials, and sorting mechanisms differ.

This research's main contribution is integrating multi-class detection with a rotation-based physical sorting mechanism. The detection results do not stop at classification; they are mapped to two actuation decisions, 0° for Organic and 180° for Inorganic, and sent via UART to the ESP32. Unlike research that focuses on detection or classification performance, this study evaluates performance through physical sorting and achieves a 98.89% success rate over 180 trials.

This research has several limitations, including the lower performance of the Plastic class, limited variation in physical test objects and conditions, and mechanical testing within a mass range of only 2–159 grams. Future development can increase dataset quantity and diversity, particularly for the Plastic class, by varying shape, size, orientation, lighting, distance, and surface conditions. Physical testing can also be expanded to include more waste types and environmental conditions. Additionally, stepwise load testing up to failure conditions can determine the mechanism's maximum capacity, while measuring latency at the detection stage, UART communication, the waste gate, and waste container rotation can provide a more detailed time evaluation.

CONCLUSION

This research successfully implemented YOLOv11 in an automated waste-sorting system integrated with a rotation-based mechanical mechanism. The YOLOv11 model detected five waste classes: Organic, Paper, Glass, Plastic, and Metal, mapped to two operational categories: organic at 0° and inorganic at 180°. The model achieved an overall precision of 77.3%, recall of 67.9%, F1-score of 72.29%, mAP@50 of 78.2%, and mAP@50–95 of 59.1%. Integrating YOLOv11 with the ESP32 via UART communication enabled the system to translate detection results into mechanical sorting actions.

The physical testing achieved 178 successful trials out of 180, resulting in a sorting success rate of 98.89% under the tested conditions. The average system response time was 1.78 ± 0.16 seconds, rotation movement time was 1.77 ± 0.03 seconds, and total processing time was 3.54 ± 0.17 seconds. These results indicate that the proposed system can perform automated waste sorting using a rotational mechanism for the tested objects weighing 2–159 grams. However, physical testing involved only nine objects and excluded the Glass class due to the limited availability of representative glass objects for physical validation. Therefore, the reported success rate should not be generalized to all waste types. The main contribution of this research is integrating multi-class YOLOv11 detection with a rotational mechanical system that converts detection results into physical sorting actions.

The main limitations are the low detection performance of the Plastic class and the limited variation of objects and physical testing conditions. Future research should expand the dataset, particularly for Plastic, test more diverse waste objects and environmental conditions, and evaluate the mechanism under higher loads and failure conditions.

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