

Development of an AI-Based Waste Segregation System with Real-Time Object Classification and Automated Bin Sorting Mechanism

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ABSTRACT

Manual segregation of waste at its point of origin is labor-intensive, error-prone, and a persistent bottleneck in waste management. Advancements in artificial intelligence have produced accurate image-based waste classifiers, but many of these studies stay within controlled laboratory conditions. They rarely integrate classification with a physical sorting mechanism that can operate in practical, small-scale settings. The study proposes the development of an AI-based waste segregation system that combines real-time object classification with an automated bin sorting mechanism. The system will identify common waste materials, categorized as biodegradable, non-biodegradable, and recyclable, through real-time image recognition, then direct each item into its corresponding bin without manual intervention. The development process will focus on a low-cost, practical prototype that keeps classification and sorting delay within a reasonable real-time response. The system will be evaluated for classification accuracy and overall sorting performance under real-world testing conditions. The study aims to reduce human error, processing delays, and exposure to hazardous materials, while giving resource-constrained communities and organizations a feasible tool for cleaner waste streams and more effective recycling.

Keywords: Artificial Intelligence, Computer Vision, Raspberry Pi, YOLO, Waste Classification

SECTION I — INTRODUCTION (THE PROBLEM AND ITS SETTING)

1.1 Introduction

Waste management depends heavily on how well waste is separated at its source. When segregation is done manually, it is slow, inconsistent, and prone to human error. It also places a heavy burden on individuals and becomes a major bottleneck in the wider management process (Bharti et al., 2022). Mixed or misplaced waste lowers the quality of recyclable materials, so improving segregation at the point of disposal has value well beyond the bin itself.

Artificial intelligence, particularly deep learning and computer vision, has become a leading approach to automating this task. A systematic review found that deep learning and hybrid approaches dominate current waste classification research, with convolutional neural network (CNN) architectures and transfer learning showing especially promising results (Fotovvatikhah et al., 2025). Reported accuracy is consistently high. Smart bins using VGG16 have classified wet, dry, and electronic waste with up to 98% accuracy (Ruparel et al., 2024), and a CNN-based model reached 98.16% across twelve waste categories (Gonzales et al., 2025). Real-time detection has also been demonstrated, as in a YOLOv8 study that classified 17 types of household waste using a custom dataset of 3,775 images (Arishi, 2025). Interest in the field continues to grow, with computer vision-enabled waste sorting showing steady growth in academic output (Lu & Chen, 2022). Some work has moved

beyond classification to physical sorting. ConvoWaste classifies waste images with a deep convolutional neural network and places items into the corresponding bin using a servo motor-based mechanism, reporting 98% accuracy (Nafiz et al., 2023).

Most reviewed studies focus on either classification or detection, and few integrate them with an automated sorting mechanism in one deployable system (Latha et al., 2026). Models also tend to perform poorly on waste that differs from their training data (Yevle & Mann, 2025), and real waste is often cluttered and deformable in ways existing datasets seldom capture (Bashkirova et al., 2022). Many studies also rely on large or manually labeled datasets (Ogrezeanu et al., 2024; Zhalgas et al., 2026), which is a barrier for smaller, lower-budget implementations.

This study responds to these issues by developing an AI-based waste segregation system that unites real-time object classification with an automated bin sorting mechanism. It is designed as an affordable and practical solution for small-scale, non-industrial settings such as schools and small communities.

1.2 Background of the Study

Manual segregation and its consequences. Sorting waste by hand at the point of origin is labor-intensive, slow, and inconsistent, and it is a major obstacle to effective waste management (Bharti et al., 2022). Beyond the effort involved, reliance on people leaves room for human error and exposes workers to hazardous and chemical pollutants. Automation that removes people from the sorting step is therefore a sensible target for improvement.

Current directions in AI-based waste classification. Research on AI-based classification and sorting is active and growing. Computer vision-enabled waste sorting has seen steady growth in academic output, which reflects its increasing relevance (Lu & Chen, 2022). A systematic review concluded that deep learning and hybrid methods now dominate the field, with CNN architectures and transfer learning performing particularly well (Fotovvatikhah et al., 2025).

Reported results are high across a range of designs and category schemes:

- Single-architecture classifiers. Smart bins using VGG16 classified wet, dry, and electronic waste with up to 98% accuracy (Ruparel et al., 2024). A CNN-based model reached 98.16% accuracy across twelve waste categories (Gonzales et al., 2025).
- Comparative studies. Zhalgas et al. (2026) tested YOLOv8, DenseNet169, and ResNet50v2 on a six-category system, with accuracy of up to 92%.
- Detection-based approaches. Ogrezeanu et al. (2024) combined several classification models with YOLOv8-based detection on the WaRP dataset to handle cluttered, real-world conditions. Arishi (2025) applied YOLOv8 to detect and classify 17 household waste types in real time.
- Integrated classification and sorting. Nafiz et al. (2023) paired a deep CNN with a servo-driven mechanism that physically sorts waste, achieving 98% accuracy.

Persistent limitations in real-world deployment. Several problems limit how well these systems transfer beyond the laboratory:

- Generalization. AI models do not perform well on new waste data outside their training conditions (Yevle & Mann, 2025). Models trained on limited categories, such as the organic versus recyclable classification of Chhabra et al. (2024), may also fail to generalize to contaminated or visually similar materials.
- Cluttered and overlapping waste. Existing datasets largely ignore how cluttered and deformable waste is on a conveyor belt or in a bin, which limits how well trained models transfer to real segregation scenarios (Bashkirova et al., 2022). Accuracy also drops when items overlap or lighting varies (Ogrezeanu et al., 2024).
- Data requirements. Many studies depend on large or manually labeled datasets (Ogrezeanu et al., 2024; Zhalgas et al., 2026), a barrier for smaller, lower-budget implementations.
- Power dependence. Conventional smart recycling bins depend on a continuous plug-in power source, which restricts them to places with accessible electricity and hinders their use in household and street settings (Li & Grammenos, 2023).
- Laboratory versus field conditions. Investigations have focused mainly on classification accuracy under

controlled, laboratory-based conditions, not on the practical challenges of real-world deployment (Olawade et al., 2026). Most reviewed studies were also tested on public datasets or controlled laboratory setups rather than in low-resource environments such as schools and small communities.

Research gap. Recent studies have tackled waste classification or IoT-based automation separately. There is little research on a single end-to-end system, and most existing literature either concentrates on classification or detection without addressing deployability, or does not fully integrate classification with an automated, real-time sorting mechanism (Latha et al., 2026). This creates a need for an affordable system that classifies waste accurately and provides direct sorting assistance in real-world, non-industrial settings, with a simpler and more practical mechanism suited to small-scale environments. This study addresses that gap by developing an integrated classifier-and-sorter prototype and evaluating it under real-world testing conditions.

1.3 Objectives of the Study

- **General Objective:** To develop an AI-based waste segregation system capable of real-time object classification and automated bin sorting, in order to improve the efficiency and accuracy of waste management practices.
- **Specific Objectives:**
 1. To design and develop an AI-based waste classification model capable of identifying common waste materials (biodegradable, non-biodegradable, and recyclable) using real-time image recognition.
 2. To build and integrate an automated bin sorting mechanism that physically directs identified waste into its corresponding bin without manual intervention.
 3. To minimize classification and sorting delay so the system can process and sort waste within a reasonable real-time response.
 4. To evaluate the classification model and automated sorting system under real-world testing conditions to achieve above 95% accuracy. And;
 5. To evaluate the developed system using applicable characteristics and sub-characteristics of ISO/IEC 25010.

1.4 Scope and Limitation of the Study

- **Scope:**

The study covers the design, development, and prototype testing of an AI-based waste segregation system that integrates real-time image classification with an automated bin sorting mechanism.

The system classifies waste into three categories: biodegradable, non-biodegradable, and recyclable. The classification component uses a YOLO-based model trained on TrashNet dataset augmented to 3,000 images and runs on a Raspberry Pi 4 Model B (4GB/8GB) paired with a Raspberry Pi Camera Module v2. The sorting mechanism is servo-based and directs each item into one of three bins. The prototype is intended for small-scale environments such as households, schools, community facilities.

Evaluation covers classification accuracy, sorting accuracy, and classification-to-sorting response time, tested under real-world conditions.

- **Limitation:**

The system recognizes only the waste categories and item types represented in its training data. Items outside those categories, or those that differ substantially from the training conditions, may be misclassified, since it tends to drop on unfamiliar data. Item size and weight are restricted by the mechanical limits of the sorting mechanism and the 83-liter storage capacity, limited to maximum dimensions of 15 x 15 x 20 cm and a weight of 1 kg, with a cumulative threshold of 9 kg per bin.

The prototype is designed to process one item at a time. It is not intended to separate heavily cluttered or overlapping waste of the kind found on industrial conveyor belts. This system requires power that is connected directly to a permanent plug socket. Operation without accessible electricity is not covered. Hazardous waste (e.g., chemical, medical, or electronic) is outside the scope of classification and handling.

1.5 Significance of the Study

The study offers benefits to the following groups:

Households, schools, and offices. The system removes the effort of manual sorting at the source, which is a recognized burden on individuals (Bharti et al., 2022). It lets everyday waste be separated correctly without requiring users to know sorting rules.

Waste handlers and sanitation workers. Automated sorting lowers human error and reduces direct contact with hazardous and chemical pollutants. It also reduces processing delays associated with manual segregation.

Local government units and community organizations. The low-cost design gives resource-constrained communities a feasible prototype for small-scale segregation. It supports better-managed local waste systems and can serve as a base for scalable infrastructure at the local and municipal level.

The environment and recycling efforts. By preventing cross-contamination, precise sorting helps keep recyclables out of landfills and supports sustainable recycling practices. This aligns with SDG 12 (Responsible Consumption and Production) through improved material recovery, and with SDG 11 (Sustainable Cities and Communities) by improving waste management efficiency, reducing municipal transport emissions, and fostering cleaner urban communities.

Future researchers. The study contributes an integrated, end-to-end prototype evaluated under real-world conditions. This addresses a gap in the literature, where classification and automated sorting are often studied separately or only under laboratory conditions (Latha et al., 2026; Olawade et al., 2026). Future work can build on it to improve generalization, handle cluttered waste, or extend deployment.

1.6 Definition of Terms

The following terms are operationally and conceptually defined to have a better understanding of the study.

Artificial Intelligence (AI): Computer-based methods that let a system perform tasks such as recognizing and classifying objects without explicit manual rules.

Automated Bin Sorting Mechanism: The mechanical component that physically directs an identified waste item into its corresponding bin without human intervention.

Biodegradable Waste: Waste that naturally decompose, such as food residuals and plant matter.

Classification Accuracy: The proportion of waste items the model assigns to the correct category out of all items tested.

Computer Vision: The field of AI that enables computers to interpret visual information from images or video, used here to identify waste items from camera input.

Convolutional Neural Network (CNN): A type of deep learning model designed to learn visual features from images, commonly used for image classification.

Dataset: The collection of labeled waste images used to train and test the classification model.

Deep Learning: A branch of machine learning that uses multi-layered neural networks to learn patterns from large amounts of data.

Generalization: A model's ability to perform accurately on new data that differs from its training data.

Manual Labeling: The process of assigning categories or bounding boxes to images by hand so they can be used to train a model.

Non-Biodegradable Waste: Waste that does not readily decompose and is not suitable for recycling.

Real-Time Object Classification: Identifying the category of a waste item from a live camera image quickly enough for sorting to happen as the item is presented.

Recyclable Waste: Waste materials, such as certain plastics, paper, glass, and metals, that can be processed and reused.

Response Time (Sorting Delay): The time from when an item is presented to the system to when it is deposited in the correct bin.

Servo Motor: A motor that moves to a precise commanded position that is used here to drive the sorting mechanism.

Sorting Accuracy: The proportion of items physically placed in the correct bin out of all items processed.

Transfer Learning: Reusing a model pre-trained on one dataset as the starting point for a new classification task.

Waste Segregation: Separating waste into categories at the point of disposal to enable proper treatment, recycling, or disposal.

YOLO (You Only Look Once): A family of real-time object detection models, such as YOLOv8, that locate and classify objects in a single pass over an image.

SECTION II — LITERATURE REVIEW

2.1 Introduction to the Review

The study surveys the body of literature that underpins the development of an AI-based waste segregation system combining real-time object classification with an automated bin sorting mechanism. Four layers structure the discussion. The first layer covers global evidence on AI and computer vision applied to waste classification, establishing the dominant techniques, benchmarks, and persistent limitations documented in international research. The second layer narrows to regional and national contexts, with particular attention to Southeast Asian and Philippine implementations that reveal how resource constraints and local waste profiles shape system design. The third layer examines local prototypes from the Philippines, including solar-powered bins, YOLOv4-based systems, and multi-category smart sorters whose deployment conditions are closely analogous to the target environment of the present study. The last layer reviews end-to-end systems that integrate classification with a physical sorting actuator, the configuration most germane to the proposed prototype.

Across these layers, the review identifies recurring themes: the dominance of CNN architectures and YOLO-family detectors, the gap between laboratory accuracy and field performance, the scarcity of deployable sorter-classifier systems, and the marginalization of low-resource, small-scale deployment contexts in the published literature. These themes collectively motivate the design decisions and evaluation strategy of the current study.

2.2 Review of Related Literature and Studies

The section reviews the literature and studies related to the development of an AI-based waste segregation system with real-time object classification and an automated bin sorting mechanism. The sources are arranged from global to national, local, and focal works.

Global

Waste generation continues to strain waste management systems around the world. Khan et al. (2022) reviewed municipal solid waste management in eight of China's eastern coastal regions and found that waste generation was rising in some provinces, while most waste was still treated through landfill (52%) and incineration (45%), with only 3% composted. They concluded that the effectiveness of the country's waste management system must be improved. Bharti et al. (2022) added that manual segregation of waste at its point of origin is labor-intensive and burdensome for individuals, which makes it a major bottleneck in effective waste management. In response, Fang et al. (2023) reviewed the use of artificial intelligence for waste management in smart cities and noted that CNN models and transfer learning can be applied to waste classification.

A more recent systematic review by Fotovvatikhah et al. (2025) examines AI-based waste classification techniques across sensor modalities and learning paradigms. Surveying a large corpus of peer-reviewed articles, the authors conclude that deep learning and hybrid methods now dominate the field, with CNN architectures and transfer learning demonstrating particularly strong classification performance.

On the hardware side, Kiyokawa et al. (2022) noted that the demand for robot-based recycling is increasing because of the biological risks of manual sorting and persistent labor shortages. They observed that existing successful sorters were developed for waste of a targeted category, and argued that future robotic sorters must

handle highly mixed industrial waste. Because sorting highly mixed waste is very difficult for a single dedicated machine, they suggested a combined system of dedicated machines, robots, and a few human workers. Satav et al. (2023) similarly pointed out that manual sorting can cause serious health problems for workers, and that robots can sort materials such as glass, paper, plastic, and metals, which supports the production of secondary raw materials while conserving energy and production costs. They added that computer vision, artificial intelligence, and automation can increase both the efficiency and accuracy of waste sorting.

Many studies have tested deep learning models for waste classification. Musham et al. (2024) developed a smart garbage classification system using the VGG-16 model integrated with chatbot functionality, achieving a classification accuracy of 96% across 12 distinct categories of garbage using live video streaming and OpenCV. Li et al. (2022) proposed RWNNet, which applies transfer learning to ResNet models for recyclable waste sorting and reached about 88% accuracy across models, with 88.8% for the best one. Zhalgas et al. (2026) built a self-collected dataset of 2,790 images in six waste categories and compared YOLOv8, DenseNet169, and ResNet50v2. DenseNet169 was the most accurate at 92%, while YOLOv8 reached 91% and showed excellent real-time detection. The authors concluded that transfer learning and fine-tuning improve reliability on smaller datasets. Arishi (2025) used YOLOv8 to detect and classify 17 types of household waste in real time using a custom dataset of 3,775 images.

Other studies focus on the difficulty of realistic waste images. Bashkirova et al. (2022) introduced the ZeroWaste dataset because existing datasets largely ignore the cluttered and deformable nature of waste as it appears on conveyor belts or in bins. Riyadi et al. (2024) compared YOLOv5 and YOLOv8 on the Waste Recycling Plant (WaRP) dataset, which contains cluttered, overlapping, and deformed waste items from an industrial sorting plant, and found that YOLOv8 offered improved detection speed and resolution over YOLOv5, though detection accuracy remained uneven across object classes.

National

Within the context of the Philippines, solid waste management is governed mainly by Republic Act No. 9003, or the Ecological Solid Waste Management Act of 2000, which requires segregation at the source. Studies show that awareness and practice of the law are still uneven. Versoza et al. (2024) surveyed 399 households in coastal barangays of Mati City, Davao Oriental, and found only moderate awareness and practice of solid waste management, with low awareness of RA 9003 and weaker segregation practices. The National Solid Waste Management Commission (as cited in IPEN, 2023) reported that the country's annual solid waste generation rose from 13.48 million metric tons in 2010 to 18.05 million metric tons in 2020, with the DENR-EMB estimating a further increase to 23.6 million metric tons by 2025.

Philippine researchers have also applied technology to waste problems. Gonzales et al. (2025) developed a low-cost embedded vision system that uses a Raspberry Pi 4 and a convolutional neural network to classify food waste by moisture content (dry, optimal, or wet) and a motorized wiper to route it accordingly, in support of black soldier fly larvae bioconversion. Using about 500 labeled images, the CNN reached 98.16% accuracy during training but 85.04% on unseen validation images, and it maintained about 84-85% accuracy in pilot conveyor-belt trials while processing each frame in about 1.2 seconds. The authors noted that its robustness was limited by dataset size, controlled imaging conditions, and environmental variability.

These works are related to the proposed study because they show the need for easier source segregation in Philippine communities. Gonzales et al. also show that a low-cost Raspberry Pi 4 system that combines a CNN with a physical sorting actuator can work in real time, which is similar to the hardware and approach of this study. Their drop in accuracy on unseen images also supports the importance of a sufficient and varied dataset.

Local

At the community level, Vanguardia (2023) assessed the implementation of RA 9003 by the barangay officials of Butong, Cabuyao City, using a descriptive design and a checklist based on the law's implementing rules. The study found significant gaps in waste segregation and collection, materials recovery facility (MRF) establishment, and annual budget allocation, and noted a lack of fines for non-compliance despite available ordinances. Although an operational MRF existed, waste segregation was limited to residents near the main road, and only 7 to 10 percent of the barangay's natural resource management and environmental services budget went to the MRF.

Carmen, J. V. (2026) examined the awareness and compliance of residents and garbage collectors with RA

9003 in Cabanatuan City, Nueva Vizcaya. The study found that awareness of RA 9003 was generally very high, though noticeably lower for specific technical provisions. Compliance practices were also moderate to high overall, with the 3Rs (Reduce, Reuse, Recycle) the most consistently practiced behavior, while composting, selling recyclables, joining clean-up drives, and reporting violations were done only "Sometimes." Practices were strongly and positively correlated ($r = .778$, $p = .001$), indicating that greater knowledge of the law was associated with more responsible waste behavior rather than a disconnect between the two.

Sigongan et al. (2023) present GULP, a solar-powered smart garbage segregation bin equipped with SMS notification and machine learning-based image processing, designed for deployment in Philippine communities where power access may be intermittent. The system integrates a Raspberry Pi-based classifier with a solar energy subsystem to enable off-grid operation, and it adds SMS alerts to notify sanitation coordinators when bins approach capacity. GULP addresses the power dependency limitation documented in earlier smart bin research.

Focal

The following studies are the closest to the proposed system because they integrate classification with a physical sorting mechanism. Nafiz et al. (2023) built ConvoWaste, an automatic waste segregation machine that uses a deep convolutional neural network to classify waste images captured by a camera to place the waste in its bin, achieving 98% accuracy. Li and Grammenos (2023) presented a smart recycling bin that classifies waste images at the edge, and they noted that bins depending on continuous plug-in power restrict deployment to places with accessible electricity. The ConvoWaste system (Nafiz et al., 2023) and the GULP bin (Sigongan et al., 2023) represent the two closest published antecedents. The former provides proof-of-concept for a servo-driven classification-to-sorting pipeline achieving 98% accuracy; the latter demonstrates that such a system can be made portable and community-deployable. Neither system, however, combines a YOLO-based real-time detector with a three-category scheme and physical servo sorting evaluated under open-environment conditions.

Mortos et al. (2024) from the Technological Institute of the Philippines developed SMARTSORT, a household waste sorting system that uses YOLOv4, a Raspberry Pi camera, and an Arduino Mega to separate paper, plastic, and metal. It reached 96.67% detection accuracy, 100% segregation accuracy, and 98.34% overall accuracy, but the authors noted that it could process only one waste object at a time and recommended a higher-torque servo motor.

Latha et al. (2026) confirms that end-to-end systems combining AI classification with automated sorting remain underrepresented in the literature relative to pure classification studies, and that most existing integrated systems have been evaluated primarily in controlled laboratory conditions. To evaluate the system, ISO/IEC 25010 provides a product quality model with characteristics and sub-characteristics, such as functional suitability, performance efficiency, and usability, which can be used to assess software-intensive systems.

2.3 Conceptual Framework

The proposed system is guided by the Input–Process–Output (IPO) transformation model and identifies the theoretical constructs drawn from the reviewed literature. Figure 1 presents the framework as a staged workflow in which physical waste items are transformed into segregated, correctly binned materials through a sequence of perception, inference, actuation, and evaluation processes. Each stage is grounded in constructs established in the reviewed literature.

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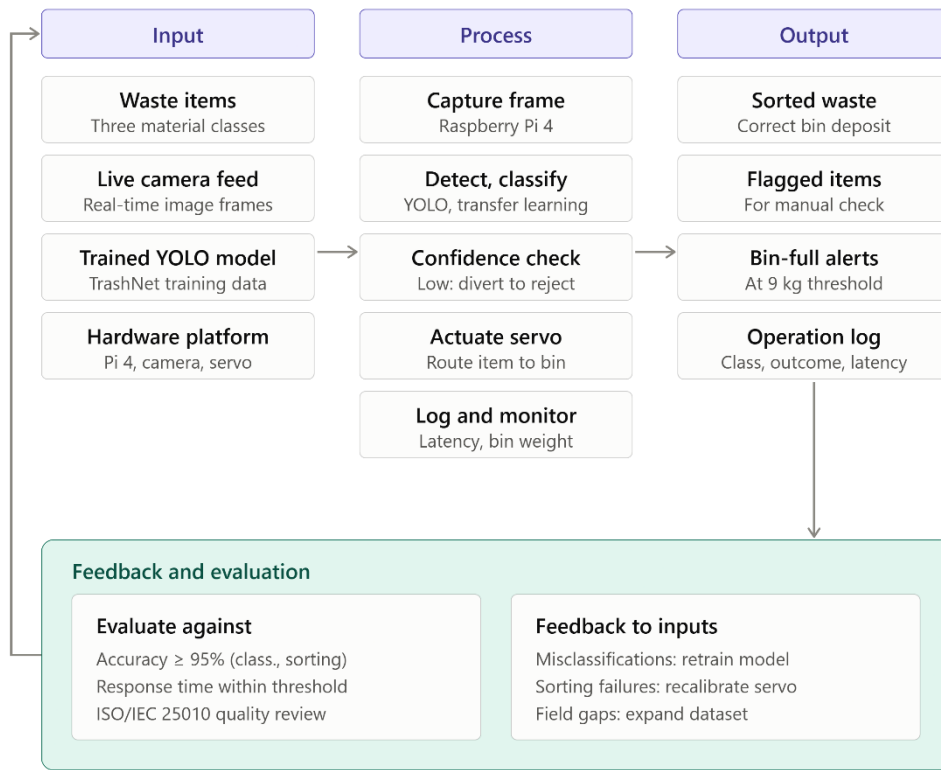


Figure 1. Input–Process–Output Model of the AI-Based Waste Segregation System.

INPUT: It encompasses the materials and data that enter the system. Physical waste items constituting the three target categories are the primary input, while the live camera feed provides the visual signal for classification. The augmented TrashNet dataset, assembled through image augmentation to 3,000 samples, provides the training foundation for the classifier. This layer is informed by the problem framing of Bharti et al., who established manual segregation inefficiency and occupational hazards as the conditions the system must ameliorate.

PROCESS: It represents the four-stage computational and mechanical pipeline. Image acquisition through the Raspberry Pi Camera Module v2 provides frames to the YOLO-based classifier, whose architecture reflects the dominance of CNN and detection-first approaches in the reviewed literature. The classification output triggers an actuation signal to a servo motor, which physically routes the item, which is a pipeline first demonstrated at high accuracy by Nafiz et al. in ConvoWaste and adapted to edge-computing constraints documented by Li and Grammenos. Response time management across the full pipeline is informed by the latency benchmarks reported in real-time detection studies.

OUTPUT: It specifies the measurable products of the system: correctly segregated waste items, classification and sorting accuracy at or above 95%, response time within a real-time threshold, and a quality profile assessed against applicable ISO/IEC 25010 sub-characteristics.

FEEDBACK: It captures the iterative relationship between output quality and system improvement. Misclassification cases are analyzed to guide dataset augmentation and retraining, addressing the generalization failure and the cluttered-scene obstacles. Mechanical sorting failures trigger servo recalibration. This feedback structure operationalizes the real-world evaluation protocol and provides a pathway for future development.

There are three theoretical constructs drawn from the literature. First, transfer learning enables a YOLO model pre-trained on large image datasets to be fine-tuned on the domain-specific TrashNet corpus, reducing data requirements while achieving competitive accuracy (Ruparel et al., 2024). Second, edge inference situates classification computation on the Raspberry Pi device rather than a remote server, eliminating network

dependency and making the system viable in connectivity-limited environments such as schools and community facilities (Sigongan et al., 2023). Third, servo-based actuation translates probability model outputs into mechanical motion, closing the loop between perception and physical waste placement (Nafiz et al., 2023). Together these creates define the chain from camera input to correctly binned output.

2.4 Synthesis

The reviewed body of literature yields four convergent findings that directly shape the design and evaluation strategy of the present study.

Deep learning classifiers, particularly CNN architectures and YOLO-family detectors, have achieved high accuracy on waste classification tasks, establishing that the classification component is technically feasible and that accuracy targets above 95% are achievable with current methods. The choice of a YOLO-based architecture is supported by evidence of real-time detection capability and successful deployment on resource-constrained hardware. However, there exists a consistent and well-documented gap between laboratory performance and field deployment performance. Model generalization is identified as the central unsolved problem, existing datasets systematically underrepresent the cluttered, deformable conditions of real sorting environments, and accuracy drops when items overlap or lighting varies. This finding motivates the use of real-world testing conditions as the primary evaluation context and the restriction of the prototype to single-item processing to reduce the influence of occlusion and clutter on classification performance.

The integration of classification with a physical sorting mechanism remains underrepresented in the published literature, as most computer vision waste sorting research focuses on classification in isolation. A few studies couple classification with an automated real-time sorting mechanism in a single deployable system, and existing relevant integrated systems were evaluated under controlled conditions and with limited category schemes. This scarcity of deployable prototypes evaluated under real-world conditions identifies a clear research gap.

There is an absence of an integrated, deployable classifier-and-sorter prototype evaluated in real-world, non-industrial Philippine conditions. Most existing studies evaluate either a classifier or a physical sorting mechanism but not both in a unified system tested under open-environment conditions. The reviewed studies report classification accuracy extensively but rarely measure end-to-end latency from item presentation to physical bin placement, and the mechanical delay introduced by servo actuation is not factored into existing evaluations. There is limited application of formal software quality evaluation frameworks, such as ISO/IEC 25010 quality characteristics, to embedded waste AI systems.

SECTION III — METHODOLOGY

3.1 Research Design

The study employed a developmental research design combined with a quantitative, experimental approach. Developmental research is appropriate because the study does not merely investigate a phenomenon but produces an integrated classifier-and-sorter prototype. It follows the IPO framework as a staged progression from problem analysis, to system design and implementation, to empirical testing and evaluation.

The quantitative-experimental component governs how the completed prototype was assessed. Rather than relying on descriptive observation alone, the study measured the system's performance through controlled, repeated trials under real-world testing conditions, generating numerical data on classification accuracy, sorting accuracy, and classification-to-sorting response time. These metrics were compared against the target thresholds set in specific objectives ($\geq 95\%$ accuracy) to determine whether the prototype met its design goals.

In addition, the study incorporated an evaluative design dimension through the application of ISO/IEC 25010 product quality characteristics (e.g., functional suitability, performance efficiency, reliability, usability). This approach aligns with waste-sorting systems that evaluate both classification performance and physical sorting performance and the framework was used to assess the system holistically as a software-hardware product.

3.2 System Development Methodology

The agile development life cycle is adopted for this study. The classification model, the actuation logic, and the mechanical sorter each require repeated cycles of build-test-refine before they can be evaluated together as one pipeline, a pattern already reflected in the feedback loop of the conceptual framework. The life cycle proceeds through the following iterative phases:

1. Planning and Requirements Analysis. Consolidating the objectives, scope, and limitations into the functional requirements.
2. Design. Translating requirements into the logical and physical design.
3. Implementation. Training/fine-tuning the classifier, wiring the actuation and servo logic, and integrating both on the Raspberry Pi 4, with each module revisited as issues surface.
4. Testing and Evaluation. Controlled and real-world trials measuring classification accuracy, sorting accuracy, and response time, and ISO/IEC 25010-based quality evaluation.
5. Review and Refinement. Feeding misclassification and sorting-failure data back into retraining/recalibration before the next iteration or final release, consistent with Figure 1.

Participant Sampling

Two distinct sampling needs arise from the study's objectives: (a) waste-item trials used to compute classification and sorting accuracy, and (b) respondent-based evaluation used to score the applicable ISO/IEC 25010 characteristics.

Waste-item trials: a purposive sample of waste items is drawn to represent the three target categories (biodegradable, non-biodegradable, recyclable) in proportions reflecting common environment waste streams, presented under the real-world conditions.

Quality-evaluation respondents: a purposive (non-probability) sample composed of (i) IT/technical evaluators able to assess functional suitability, performance efficiency, and reliability, and (ii) representative end users from the target deployment settings (e.g., students, faculty, or household members) able to assess usability.

Data Collection Methods

Trial logs: for each presented item, the system (or an observer) records the ground-truth category, the predicted category, the bin the item was actually deposited in, and the elapsed time between presentation and deposit. These records are aggregated to compute classification accuracy, sorting accuracy, and average/95th-percentile response time against the $\geq 95\%$ and real-time thresholds.

Structured evaluation questionnaire: a rating instrument mapped to the applicable ISO/IEC 25010 characteristics and sub-characteristics, administered to the evaluators.

3.3 Requirement Specification and Analysis

The study translates the objectives and its scope into explicit functional requirements and models the system's data movement and control logic using a context-level and Level-1 Data Flow Diagram (DFD) and an operational flowchart. The reviewed prototype does not have a relational database; therefore, an Entity-Relationship Diagram (ERD) is proposed for the minimal trial/log data the evaluation with a design proposal rather than a confirmed requirement.

ID	Functional Requirement	Description
FR-1	Image acquisition	The system shall continuously capture live video frames from the Raspberry Pi Camera Module v2 when a waste item is presented
FR-2	Real-time classification	The system shall classify each item into biodegradable, non-biodegradable, or recyclable using the YOLO-based model trained on the augmented TrashNet dataset.

FR-3	Confidence thresholding	The system shall withhold an actuation command and flag the item for manual handling if classification confidence falls below the defined threshold.
FR-4	Actuation signaling	The system shall convert a confirmed predicted class into a corresponding servo motor command.
FR-5	Automated bin sorting	The system shall physically route the item into its corresponding bin without human intervention, within the 15×15×20 cm / 1 kg item limit.
FR-6	Response-time management	The system shall record and minimize the elapsed time between item presentation and bin deposit.
FR-7	Capacity monitoring	The system shall track cumulative bin weight and flag a bin as full once the 9 kg per-bin threshold is approached.
FR-8	Performance logging	The system shall log classification outcome, sorting outcome, and response time for each trial to support accuracy computation.
FR-9	Quality evaluation support	The system shall expose the measures needed (accuracy, response time, failure counts) to score applicable ISO/IEC 25010 sub-characteristics.

Table 1. Functional Requirements.

Figure 2 presents the context-level (Level 0) DFD, showing the system as a single process exchanging data with its two external entities: the person presenting waste, and the sanitation coordinator/evaluator who reviews performance and configures evaluation trials.

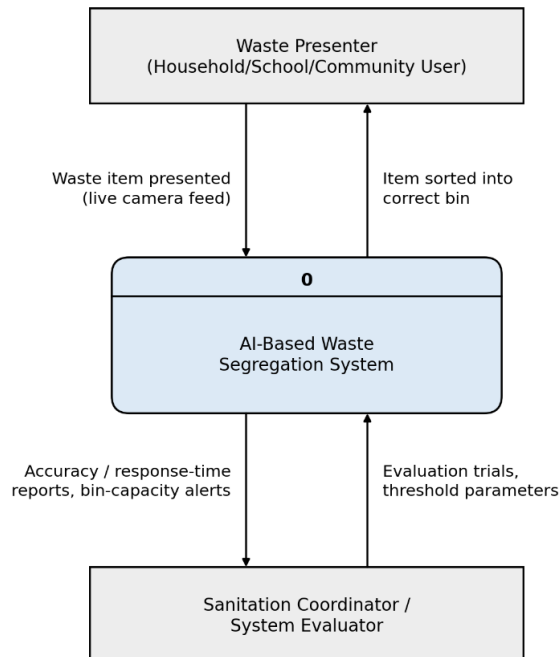


Figure 2. Context (Level 0) Data Flow Diagram of the AI-Based Waste Segregation System.

Figure 3 decomposes the system into its five processing stages, consistent with the IPO stages already defined in the conceptual framework: image acquisition, real-time classification, classification-to-actuation signaling, automated bin sorting, and response-time/accuracy logging. Two data stores are shown: D1, the trained YOLO-based model, and D2, the classification-and-sorting log used to compute the metrics.

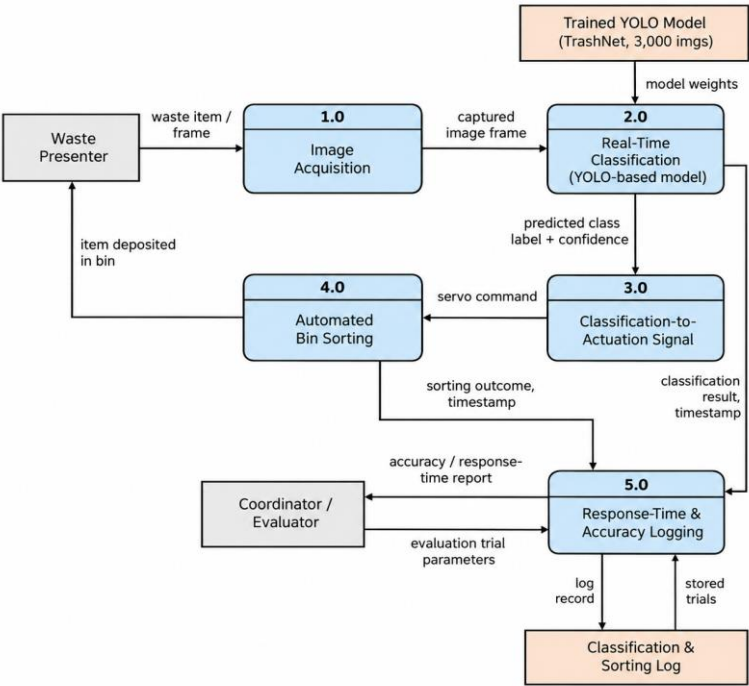


Figure 3. Level 1 Data Flow Diagram of the AI-Based Waste Segregation System.

Figure 4 proposes a minimal four-entity schema for this purpose: one row per presented item, its classification result, its sorting result, and quality-evaluation ratings collected from the respondents.

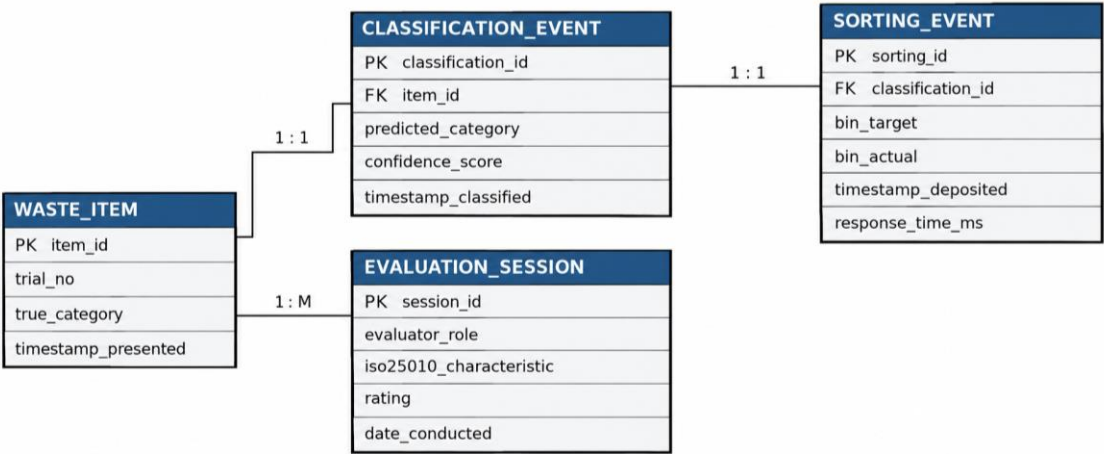


Figure 4. Proposed Entity-Relationship Diagram for trial and evaluation logging.

Figure 5 models the control logic of one end-to-end cycle, from idle capture through classification, confidence-gated actuation, bin deposit, logging, and capacity checking, implementing Stages 1-5 of the conceptual framework together with the confidence-handling and capacity-limit behavior implied by the limitations.

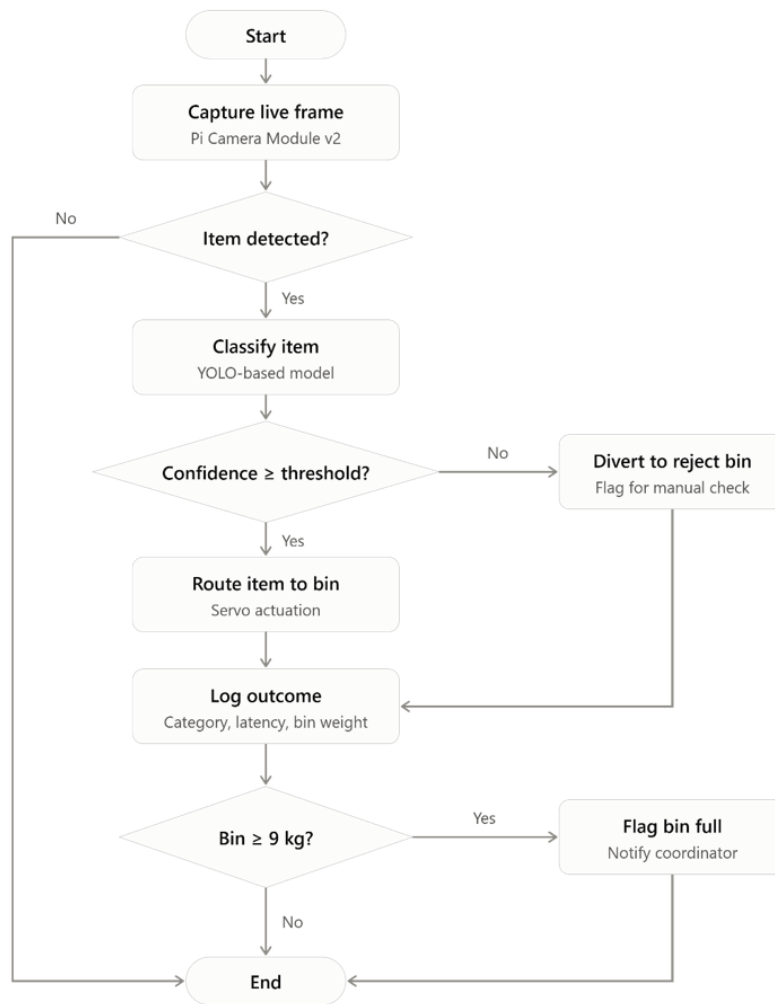


Figure 5. System Operation Flowchart, from item presentation to bin deposit and logging.

3.4 System Design Specification

The design is separated into a logical layer on how the software modules are organized and reasoned about, and a physical layer that serves as the concrete hardware and technology choices that realize that logic, consistent with the Scope of the study.

Logical Design

Module decomposition. The system logic is organized into four cooperating modules, mirroring the Level-1 DFD processes in Requirement Specification and Analysis:

- Image Acquisition Module - continuously polls the camera, applies basic pre-processing, and passes frames to the classifier only when a presence/motion trigger is detected.
- Classification Module - runs the YOLO-based model on the incoming frame, returns a predicted class and confidence score, and applies the confidence-threshold rule (FR-3).
- Actuation Control Module - maps a confirmed class to a servo position/command and monitors actuation completion before signaling the logging module.
- Logging & Evaluation Module - records each trial, aggregates running accuracy and response-time statistics, and raises the bin-capacity alert (FR-7).

User interface. The scope describes fully automatic operation "without manual intervention," and no end-user interface is named anywhere in the uploaded chapters. A coordinator-facing status view is nonetheless a natural extension of the capacity-alert requirement (FR-7) already implied by the Limitations. Minimal wireframe is therefore proposed below, strictly as a design recommendation:

- Status panel - current system state (Idle / Classifying / Sorting), last predicted category, and last response time.
- Bin-level indicators - three simple fill-level bars (Biodegradable / Non-biodegradable / Recyclable) that turn red when the 9 kg threshold is reached.
- Session summary - running classification accuracy and sorting accuracy for the current evaluation session.

Physical Design Specification

Table 2 separates the hardware and technology elements from those that need to be finalized by the research team.

Component	Specification	Proposed Information
Compute	Raspberry Pi 4 Model B, 4GB/8GB RAM	Exact RAM tier to be finalized; whether a cooling/heat-sink solution is used
Camera	Raspberry Pi Camera Module v2	Mounting distance/angle, frame resolution and FPS setting
Detection model	YOLO-based model, trained on TrashNet augmented to 3,000 images	Specific YOLO version (e.g., v5/v8), framework (Ultralytics/PyTorch), input resolution, confidence threshold value
Actuation	Servo motor-driven sorting mechanism, 3 bins	Number of servos and drive linkage (e.g., single rotating chute vs. gated multi-servo), torque rating, controller board (e.g., PCA9685/Arduino) and driver library
Storage / enclosure	83-liter total capacity; 9 kg cumulative threshold per bin; item limit 15×15×20 cm, 1 kg	Bin/chute material, structural mounting of camera and servos
Power	Continuous plug-in power (explicit limitation — no off-grid operation)	Supply voltage/current rating, surge protection
Software stack	Not stated	Programming language (commonly Python), inference library, servo-control library, OS (Raspberry Pi OS)
Data logging	Not stated	Proposed local log (see ERD, Fig. 4) — CSV/SQLite file on-device, or cloud logging if connectivity is available

Table 2. Physical Design Components, Specification, and Proposed Information.

3.5 Implementation

The prototype's software was organized around the five-stage pipeline established in the IPO conceptual framework: image acquisition, real-time object classification, classification-to-actuation signaling, automated bin sorting, and response time management. Structuring the codebase along these stages keeps each pipeline function (camera capture, inference, signal handling, servo control, and timing/logging) as a separable unit, which supports the unit-level testing described in testing and evaluation.

Integration followed the staged pipeline in Conceptual Framework Figure 1:

Stage 1 (Image Acquisition): The Raspberry Pi Camera Module v2 captures live frames, which are passed to the classification stage.

Stage 2 (**Real-Time Object Classification**): The YOLO-based model, trained on the augmented TrashNet dataset (3,000 images), processes each captured frame and outputs a predicted category (biodegradable, non-biodegradable, or recyclable).

Stage 3 (**Classification-to-Actuation Signal**): The predicted class label is converted into a command signal for the servo motor.

Stage 4 (**Automated Bin Sorting**): The servo-driven mechanism physically routes the item into the corresponding bin based on the received signal.

Stage 5 (**Response Time Management**): Timing is tracked across the pipeline to keep the classification-to-sorting delay within the real-time threshold targeted by the study's objectives.

The study describes a single-prototype developmental design rather than a system replacing an existing production system, "migration" in this context refers to the transition of the classification model from its training environment to the deployed edge device, consistent with the edge-inference construct. It involves:

- Training and validating the YOLO-based model on the augmented TrashNet dataset in a development environment.
- Transferring the trained model to the Raspberry Pi 4 (4GB/8GB) for on-device inference, consistent with the scope's specification of edge deployment rather than remote-server processing.
- Calibrating the classification-to-actuation signal and servo mechanism on the physical hardware to align the software output with the physical bin-sorting behavior.

3.6 Testing and Evaluation

The system combines a software classification component with a physical sorting mechanism, in which the following testing levels are applicable to this study:

Unit Testing. Each pipeline stage (image acquisition, classification inference, signal generation, and servo actuation) was tested individually to confirm it performs its designated function correctly in isolation before integration, consistent with the modular staged structure of the conceptual framework.

Integration Testing. The connected stages were tested together to verify that the classification output correctly and consistently triggers the corresponding actuation signal, and that the signal reliably drives the servo to the correct bin i.e., that Stage 2 output correctly maps to Stage 4 behavior end-to-end.

System/Real-World Testing. The completed prototype was tested as a whole under real-world conditions rather than only in controlled laboratory settings, since the reviewed literature identified the laboratory-to-field performance gap as a key limitation.

User Acceptance Testing (UAT). The scope names households, schools, and community facilities as intended deployment environments identifies these groups as direct beneficiaries. If the study involved actual end users (e.g., students, staff, or residents) interacting with the prototype and providing feedback on usability, this would justify including UAT as a testing protocol, since usability is also named as an ISO/IEC 25010 characteristic in research design.

The study evaluated the prototype using the following standard metrics:

Classification Accuracy - the proportion of waste items the model assigns to the correct category out of all items tested, targeted at $\geq 95\%$ under real-world conditions.

Sorting Accuracy - the proportion of items physically placed in the correct bin out of all items processed, also targeted at $\geq 95\%$.

Response Time (Sorting Delay) - the elapsed time from item presentation to the system to its deposit in the correct bin, evaluated against a real-time threshold as stated in the objectives.

ISO/IEC 25010 Quality Characteristics - the system was additionally evaluated against applicable characteristics and sub-characteristics of ISO/IEC 25010 (e.g., functional suitability, performance efficiency, reliability, usability).

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