AI-Driven Robotic Waste Sorting for Techno-Economic Assessment in Urban Indonesia

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***Abstract*—Urban centers in Indonesia are facing increasing pressure in managing municipal solid waste as a result of rapid population growth, rising labor costs, and stricter demands for high-purity recyclable materials. Manual sorting at Material Recovery Facilities has become progressively less efficient and economically burdensome under these conditions. This study presents an artificial intelligence-driven robotic waste sorting system designed and evaluated under real operational conditions in Jakarta and South Tangerang. The system integrates YOLO based object detection, vision-guided robotic manipulation, real-time processing hardware, a multi-axis gantry system with stepper motors, and a custom conveyor mechanism to deliver waste items to the sorting cell. Unlike previous studies that mainly focus on algorithmic accuracy or laboratory-scale validation, this work combines real-world technical performance assessment with a localized techno-economic analysis. Experimental results show an average sorting accuracy of 90%, a material purity of 95.1%, and a throughput of 50 items per minute, outperforming typical manual sorting performance. An economic evaluation based on local wage levels, electricity tariffs, and recyclable market prices indicates a payback period of 4.3 to 4.9 years. The main contributions of this study lie in integrating AI vision and robotic sorting into unstructured urban waste environments, in empirical validation under Indonesian operating conditions, and in demonstrating economic feasibility for emerging economies. Although the case study focuses on Jakarta and South Tangerang, the findings are relevant for metropolitan areas across the Global South seeking more efficient and sustainable waste management solutions.**

Keywords*—Smart waste sorting; AI vision; YOLOv12; computer vision; material recovery facility; techno-economic assessment; urban Indonesia; circular economy

I. Introduction

Municipal solid waste (MSW) management has emerged as one of the most pressing sustainability challenges of the twenty-first century. Global MSW generation exceeds two billion tons annually and is projected to increase by up to 70 percent by 2050 if current practices persist [1]. The challenge is particularly acute in developing economies, where rapid urbanization, limited landfill capacity, and underfunded waste systems limit effective management of growing waste volumes [2]. Indonesia exemplifies this situation, especially in major metropolitan areas such as Jakarta and its surrounding cities, where rising waste volumes strain existing infrastructure and threaten environmental sustainability, public health, and social equity.

A key bottleneck in the waste management chain is sorting. Sorting determines the quality of downstream recycling systems and strongly influences material recovery, commodity value, and the overall economics of circular waste systems [3], [4]. In Indonesia, sorting in Material Recovery Facilities (MRFs) is predominantly manual, characterized by low throughput, inconsistent purity levels, and considerable health risks for workers exposed to hazardous materials [5]. Moreover, increasing regional minimum wages and tightening purity requirements from international buyers are placing operational pressures on MRFs that current manual methods struggle to meet [6].

Plastic waste intensifies the challenge. National data indicate that only 7-14% of plastic waste is recycled, despite high annual production volumes, resulting in both environmental burdens and economic inefficiencies [7]. Urban regions, such as Jakarta and South Tangerang, face particularly high consumption density and dwindling landfill capacity, underscoring the urgency of adopting advanced sorting technologies that can improve material purity and recovery rates.

Advances in Artificial Intelligence (AI), computer vision, and robotics offer promising opportunities to address these limitations. AI-driven robotic sorting has shown potential to deliver higher accuracy, consistent performance, and improved worker safety compared with manual operations [7], [8], [9]. However, most empirical evidence and techno-economic studies originate from high-income countries, raising concerns about their applicability to emerging economies where labor costs, waste composition, and market dynamics differ significantly.

This study addresses this gap by evaluating the technical performance and economic feasibility of an AI-driven robotic waste-sorting system in Indonesia. Using Jakarta and South Tangerang as case studies, it integrates experimental validation of sorting accuracy, purity, and throughput with localized techno-economic analysis. The findings aim to inform MRF modernization strategies and to support Indonesia's transition toward a more sustainable, circular waste management system.

The contributions of this study are explicitly defined as follows: First, this work presents the design and implementation of an AI-driven robotic waste sorting system that integrates vision-based detection, robotic manipulation, and a custom conveyor and gantry mechanism for unstructured municipal solid waste. Second, the system is experimentally validated under real operational conditions in Jakarta and South Tangerang, providing empirical evidence beyond laboratory-scale demonstrations. Third, the study integrates technical performance evaluation with a localized techno-economic analysis based on Indonesian wage levels, electricity costs, and recyclable market prices, thereby bridging the gap between robotics research and investment feasibility in emerging economies.

II. Literature Review

The global increase in municipal solid waste generation has triggered growing concern among policymakers, researchers, and urban managers, as waste volumes rise faster than many cities can accommodate and pressure mounts on existing waste management systems, especially in countries with limited collection and treatment infrastructure. Indonesia is among the countries facing this challenge most acutely, where rapid urbanization and increasing consumption continue to widen the gap between waste generation and waste processing capacity.

Sorting plays a fundamental role in enabling effective recycling and circular material flows. Poor sorting quality directly increases contamination, reduces material recovery, and limits the profits that recycling facilities can generate. Manual sorting remains prevalent in Indonesia, but this approach faces persistent challenges, including variable performance, low speed, and significant health and safety risks for workers. As wages rise and global supply chains demand higher purity levels, these challenges have become increasingly difficult to address solely through manual methods. Indonesia's limited plastic recycling performance, with only a small fraction of total waste successfully recovered, demonstrates the structural limitations of current systems.

Artificial intelligence-powered robotic sorting offers a promising alternative. Vision-guided robotic systems are designed to operate in messy, unpredictable environments, making them especially well-suited for municipal solid waste streams. Object detection models such as YOLO perform effectively under diverse visual conditions and maintain high recognition accuracy even with contaminated or irregular items [10]. Advances in image understanding have further strengthened these systems through models that explicitly handle occlusion [11], segmentation methods that generalize across unknown object categories [12], and fast architectures for real-time industrial use [13]. Empirical studies consistently show that robotic sorting can offer both high purity and high throughput, often surpassing manual performance [14].

Economically, robotic systems require substantial upfront investment [15]. Over time, however, improvements in material purity and reductions in reliance on manual labor may offset these costs. Yet, techno-economic studies conducted in high-income countries may not accurately reflect the realities of emerging economies, where waste composition, wages, electricity costs, and market structures differ significantly [16]. As a result, context-specific evaluation is necessary.

Technical research on robotic manipulation continues to advance steadily. Early foundational work explored affordance-driven grasping and cross-domain visual matching [17], followed by approaches that leverage three-dimensional sensing and dual stream encoding to improve grasp detection in clutter [18]. Parallel to technical developments, sustainability and circular-economy research highlight the crucial role of advanced sorting technologies in reducing waste and improving resource efficiency [19]. Applied case studies demonstrate the potential of robotic sorting for beverage containers [3], mixed plastic streams [15], and multi-class waste environments [20].

Despite these contributions, a significant gap remains. Few studies combine technical performance assessment with localized economic analysis in developing countries [21], [22]. Many technical studies fail to examine operational costs or payback periods [23], while economic assessments heavily rely on assumptions drawn from high-income settings [24]. This gap highlights the need for integrated evidence that reflects both the technological capabilities and economic realities of waste management in contexts such as Indonesia.

III. Methodology

The methodology of this study is designed to bridge two complementary perspectives: the development of a robotic system for waste sorting in unstructured environments and its economic feasibility assessment in the Indonesian context. Combining technical experimentation with comparative financial evaluation demonstrates how such systems can be built and tested, and whether they are feasible in real-world Material Recovery Facilities (MRFs).

A. AI Vision Module and Model Training

The first step in the methodology involves designing an AI-driven vision pipeline that enables the robotic system to recognize and classify waste items in real time (see Fig. 1). A deep learning object detection framework, derived from the YOLO architecture, serves as the backbone of the vision system. The training dataset is intentionally constructed to reflect the diversity and unpredictability of MSW. Images are collected from local facilities and augmented with techniques such as rotation, scaling, and contrast variation to simulate the wide range of lighting, contamination, and occlusion conditions encountered in real MRF operations. The model outputs bounding boxes with confidence scores, which are filtered using adaptive thresholding to balance accuracy and false detection rates.

Waste categories include plastics (PET, HDPE, LDPE), paper, metals, and residuals. Model performance is evaluated with standard metrics including precision, recall, F1-score, and latency. The parameters ensure the system can operate within the time constraints imposed by conveyor-based sorting lines.

The development of the smart waste sorting system begins with the design and training of the AI vision module, which serves as the robotic platform's "eyes". As illustrated in Fig. 1, a camera captures images of mixed recyclable waste placed in front of the vision system. These captured frames constitute the raw dataset for object detection and classification.

The collected images are transferred to a PC, where preprocessing steps are performed, including resizing, normalizing, and annotating objects of interest such as PET bottles, aluminum cans, and HDPE containers. The annotated dataset is then divided into training, validation, and testing sets to ensure unbiased evaluation of the model's performance.

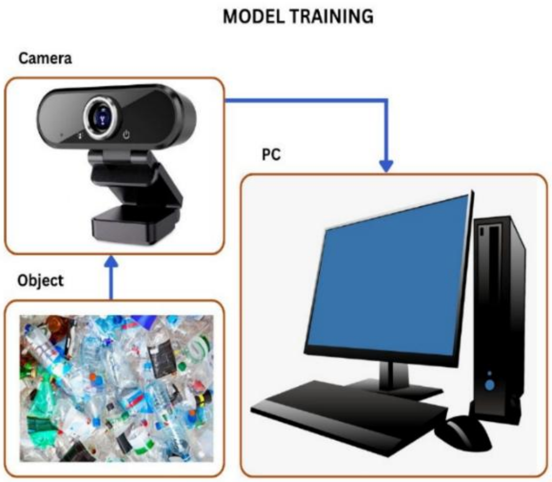

Fig. 1. Model training pipeline: a camera captures object images, which the PC processes for dataset preparation and training of the detection model.

Subsequently, the deep learning model is implemented using convolutional neural networks (CNNs) or state-of-the-art architectures such as YOLO. The model is trained on the dataset via iterative weight optimization using backpropagation, guided by performance metrics such as precision, recall, and mean average precision (MAP). The PC serves as the primary computational hub, providing sufficient processing power for the initial training phase and for later real-time inference tasks.

This stage ensures that the vision system can recognize objects under diverse conditions, including variations in lighting, orientation, occlusion, and material contamination, thereby enhancing robustness in real-world material recovery facilities (MRFs)

B. System Integration

After training the AI vision model, the system was integrated into a robotic platform for real-world validation. As illustrated in Fig. 2, the complete setup consists of visual sensors, a computation console, controllers, actuators, and supporting power electronics. Each component is critical in ensuring the smart waste sorting process operates seamlessly from perception to actuation.

1) Visual sensor: The system's visual sensor is a Full HD camera, 1920 × 1080 pixels (see Table I), positioned above the conveyor. The camera captures high-resolution images of mixed recyclable waste. These images are streamed to the computation unit in real time, where object detection and classification are carried out. The objects are even under variable lighting and can be accurately identified even under partial occlusion.

2) Computation console (heavy processing unit): The core of the system's intelligence resides in a PC with specifications comparable to those of a high-performance laptop. This console executes the YOLOv12 computer vision model for partial occlusion conditions and for clarity in captured frames, trained to detect and classify recyclable waste such as PET bottles, aluminium cans, and HDPE containers. Beyond classification, the PC also performs numerical calculations to estimate the coordinates of each detected object, which are then translated into actionable commands for the robotic manipulator.

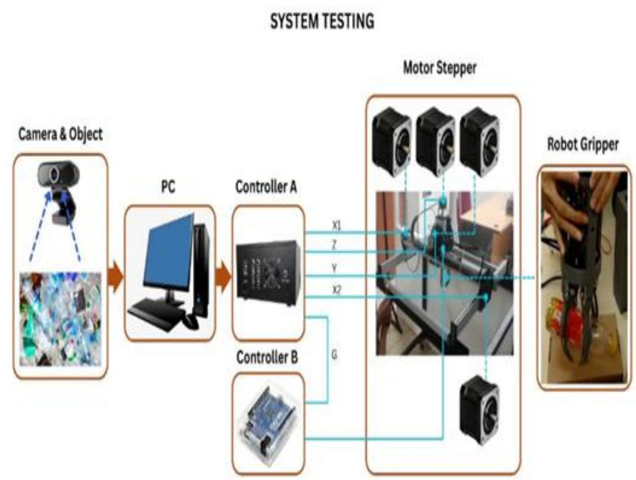

Fig. 2. Experimental setup for system testing: integrated flow of camera, PC, controller, stepper motors, and robotic gripper for smart waste sorting validation.

TABLE I. HARDWARE SPECIFICATIONS OF THE SMART WASTE SORTING SYSTEM

Component	Specifications	Qty	Function
Visual Sensor	Camera: Full HD 1920 × 1080	1 unit	Captures images of mixed recyclable waste for the AI vision module
Computation Console	PC (equivalent to a high-performance laptop) Computer Vision Model: YOLOv12	1 unit	Heavy computation for object detection, classification, and coordinate calculation
Controller A (Axis Translation)	ATMEGA328P microcontroller OLED 128 × 64 pxTB6600 motor drivers Power supply: 5V/1A + 24V/10A	1 set	Controls X1, X2, Y, Z translation using four stepper motors
Controller B (Gripper Control)	DC SPDT Relay 5V input (2 units)NPN BJT BD139 (2 units)Resistors 1kΩ/0.25W (2 units)Terminal Blocks 4–5 pins (2 units) PCB Power supply: 5V/1A and 12V/5A	1 set	Controls gripper open/close action
Actuators (Translation)	DC Stepper Motors: NEMA23Operating voltage: 24–48 V Operating current: 2–5 Bipolar (two coils)	4 unit	Provides motion along X1, X2, Y, and Z axes
Actuator (Gripper)	DC Motor: 12 V, 3–5 A	1 unit	Drives the gripper mechanism for grasping and releasing objects

- Controller A (Axis Translation and Motion Control): Controller A manages translation along the X1, X2, Y, and Z axes. It is designed using:
  - ATMEGA328P microcontroller, responsible for light computation and communication with the PC.
  - OLED Display (128 × 64 pixels), providing real-time system status and diagnostic feedback.
  - TB6600 motor drivers (4 units), ensuring precise control of the stepper motors.
  - Power supply unit with dual outputs (5V/1A and 24V/10A), supplying sufficient current to drive the motors and electronic circuitry.

The researchers developed the control logic and integration code, enabling smooth and synchronized multi-axis translation.

- Controller B (Gripper Control): Controller B is dedicated to controlling the robotic gripper for gripping and releasing actions. Its design includes:
  - DC SPDT Relays (2 units), switching the gripper motor between grip and release modes.
  - NPN BJTs (BD139, 2 units) and resistors (1 kΩ, 0.25W, 2 units) for signal amplification and circuit stability.
  - Terminal blocks (2 units, 4–5 pins each) for secure wiring connections.
  - PCB for component integration.
  - Independent power supplies: 5V/1A for control electronics and 12V/5A for the gripper motor.

The research team designed and fabricated the gripper controller, which ensures flexibility and durability during repeated grasping operations.

- Actuators: The actuation system consists of both translational and gripping mechanisms:
  - Stepper Motors (4 units, NEMA23), each with an operating voltage of 24–48 V and a current range of 2–5 A. These motors provide the precise translation required along the X1, X2, Y, and Z axes, enabling accurate positioning of the gripper relative to the target objects.
  - DC Motor (1 unit for the gripper), operating at 12 V with a current range of 3–5 A, delivering sufficient torque to grasp and release waste objects of varying shapes and weights.
- Conveyor Belt: A custom-designed conveyor belt was developed to transport waste materials through the working area to support the robotic sorting system. The conveyor serves as the primary medium for presenting recyclable objects to the vision system and positioning them within the workspace of the robotic manipulator.

This actuation system allows the robot to execute closed-loop pick-and-place tasks, reliably transferring objects into the correct bins. The conveyor was designed using a structural frame of 3×3 cm angle bars, ensuring sufficient rigidity and stability during operation. The overall dimensions are approximately 212 cm in length, 68 cm in width, and 40 cm in height, as illustrated in the technical drawing (see Fig. 3). The conveyor surface is supported by rollers at both ends, which enable continuous belt motion. A dynamo motor is mounted on one side of the frame and connected to the rollers to drive the belt with a stable and adjustable speed.

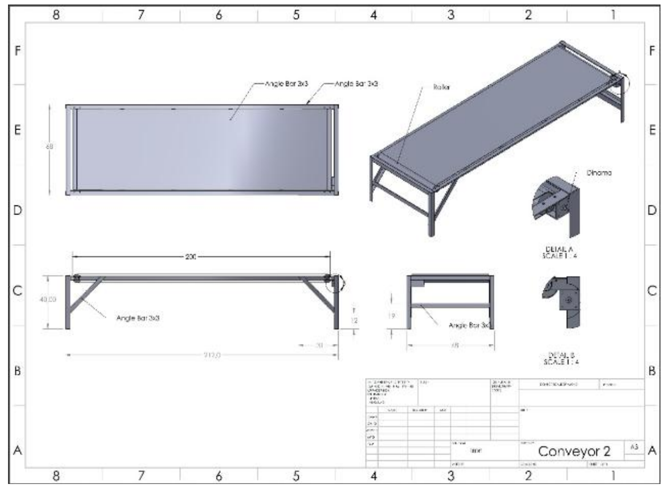

Fig. 3. Technical drawing of the conveyor belt showing structural dimensions and roller mechanism.

In its assembled form (Fig. 4), the conveyor integrates seamlessly with the robotic gantry system. The conveyor belt is made of durable synthetic material, providing adequate friction to prevent the slippage of lightweight objects, such as PET bottles or aluminium cans. The conveyor height has been optimized to align with the robotic gripper's workspace, ensuring a smooth handoff between the transport system and the pick-and-place mechanism. This conveyor system continuously introduces waste items into the sorting cell, enabling repeatable and scalable experiments. It also provides a controlled test environment for evaluating the robotic system under realistic material handling conditions, including varying object positions and orientations on the moving belt.

Fig. 4. Assembled conveyor belt integrated with the robotic gantry system.

C. Testing Workflow

The overall workflow of the system is designed as an open-loop sequence:

1) Image capture and object detection: The camera captures real-time images of waste objects. The PC processes these images using YOLOv12 to detect and classify objects, and to calculate their spatial coordinates.

2) Command generation and Axis control: The PC transmits coordinate-based commands to Controller A. The controller drives the stepper motors, moving the gantry system along the X1, X2, Y, and Z axes until the gripper is aligned with the target object.

3) Grasp execution: Once alignment is achieved, the PC signals Controller B. The relay-based circuit activates the DC motor, causing the gripper to close and secure the object.

4) Placement: The object is transported to the designated bin, where the gripper releases it.

5) Reset to start position: After each pick-and-place cycle, the gripper is automatically returned to its initial home position. This ensures consistency and repeatability, as the system begins from the same reference point for subsequent operations.

Unlike closed-loop systems, this configuration does not utilize external feedback sensors to confirm the gripper's position. Instead, the last known gripper position is tracked internally in the PC via program variables. This simplifies the design while ensuring repeatable operation. However, the absence of feedback may lead to long-term positional drift, offering an opportunity for future system enhancement.

D. Adapting to Unstructured Waste Environments

A defining feature of waste sorting is its unstructured and unpredictable nature. Unlike manufacturing lines, where objects are uniform, MSW streams contain irregular, overlapping, and sometimes contaminated items. This study addresses three core challenges:

1) Variability of object geometry: The dataset and robotic strategies are designed to accommodate irregularity using multimodal end-effectors and robust detection models.

2) Contamination and occlusion: Training data intentionally includes soiled, partially visible, or overlapping items, enabling the model to recognize objects under imperfect conditions.

3) Real-time constraints: System performance is tuned to complete detection and grasp planning within 1.5 seconds, a requirement for maintaining throughput at an industrially meaningful scale.

By addressing these challenges, the methodology ensures that the developed system does not remain a laboratory prototype but aligns closely with the operational realities of Indonesian MRFs.

E. Economic Evaluation Framework

The second component of the methodology assesses the economic feasibility of robotic sorting in comparison to manual operations. This analysis draws on data from the Jakarta and South Tangerang case studies, as well as secondary sources such as the Central Bureau of Statistics (BPS) wage data, local government regulations, and commodity price reports. Two scenarios are compared:

1) Manual sorting, the current practice in Indonesian MRFs, is characterized by labour-intensive processes, modest throughput, and variable purity levels.

2) Robotic sorting, based on the system described above, supplemented with benchmarks from [27] and global industry reports.

Key indicators include operating expenditure (OPEX), capital expenditure (CAPEX), cost per ton of processed waste, revenue uplift from higher material purity, and payback period. Sensitivity analyses are performed to simulate variations in labor costs, waste composition, and market prices of recyclables, ensuring robust findings across multiple scenarios.

F. Data Sources

The economic evaluation in this study relies on a combination of national statistics, municipal reports, and industry association data. For Jakarta, the minimum wage figures are sourced from the official publications of Statistics Indonesia (Badan Pusat Statistik), which provide annually updated provincial minimum wage data [28], while corresponding figures for South Tangerang are taken from Statistics Indonesia, Banten Province [29]. These values serve as the baseline for calculating labor costs in manual and semi-automated sorting scenarios.

Price information in Jakarta is usually published in program reports, such as the price list for Bank Sampah Induk Satu Hati, issued by the Jakarta Environmental Agency [30]. At the national level, price information on recycled plastics is often provided through policy or academic studies that cite ADUPI data [31]. However, the South Tangerang Environmental Agency (DLH Tangsel) has not released disaggregated public data on the prices of PET, glass, and aluminum materials. To address this limitation, we use Jakarta data as a proxy, supported by ADUPI market ranges, and apply a ±20% sensitivity adjustment to account for potential local variation.

This approach ensures that the analysis remains grounded in realistic market conditions while acknowledging the absence of fully disaggregated municipal price data for South Tangerang. For future studies, a structured market survey targeting local waste banks, aggregators, and recyclers in South Tangerang is recommended. Such an instrument could systematically capture unit prices, quality categories, and transaction conditions, thereby improving the robustness of techno-economic analyses in emerging urban contexts.

G. Validation Strategy

This study's validation focuses on the robotic system's ability to separate three critical recyclable categories: plastic bottles, glass containers, and aluminum cans. These categories are prioritized because they constitute high-value materials in the Indonesian recycling market and are frequently handled in both manual and mechanized sorting. The validation process is structured around three key indicators: separation accuracy, throughput performance, and material purity.

Separation accuracy refers to the proportion of correctly sorted items relative to the total number of items processed in each category. It is expressed mathematically as:

$$Accuracy = \frac{C_i}{T_i} \times 100\% \tag{1}$$

where, C_i is the number of correctly sorted items of category i, and T_i is the total number of items of category i presented to the system. This clearly measures how reliably the robotic arm can distinguish between plastics, glass, and aluminum.

Throughput performance evaluates the number of items correctly picked and placed per unit time under conveyor belt conditions. It is measured as:

$$Throughput = \frac{N}{\Delta t} \tag{2}$$

where, N is the number of items sorted, and Δt is the duration of operation. This indicator reflects whether the system can achieve competitive processing speeds with manual workers, who typically manage 20 to 30 picks per minute in Indonesian MRFs.

Material purity captures the extent to which the output stream of each recyclable is free of contamination from other materials. It is expressed as:

$$Purity = \frac{C_i}{O_i} \times 100\% \tag{3}$$

where, O_i is the total number of items in the output stream for category i, a high purity score indicates that the robotic system produces cleaner, more valuable recyclable fractions, directly affecting economic outcomes.

Validation results from the robotic system are compared with manual sorting data collected from the Jakarta and South Tangerang facilities and with benchmarks reported in international studies. Manual operations commonly achieve purity levels in the 70% to 80% range with high variability, while robotic deployments in developed contexts report levels exceeding 90%. Applying these formulas, the study quantitatively assesses whether the proposed robotic system meets technical and practical thresholds for effective sorting in Indonesian MRFs.

The payback period for robotic sorting is calculated by dividing capital expenditure by the combined annual gains in revenue uplift and labour cost savings relative to manual sorting using the formula:

$$Payback = \frac{CAPEX}{\Delta Revenue + \Delta Labour} \tag{4}$$

IV. Results and Discussion

To evaluate the robotic system's capability under realistic conditions, a controlled validation was conducted using a batch of 300 items consisting of 100 plastic bottles (PET), 100 glass bottles, and 100 aluminum cans. These three categories were chosen because they represent the highest-value recyclable fractions in Indonesian MRF and constitute a significant proportion of international recycling markets. The robotic system's performance was benchmarked against manual sorting, which remains the dominant practice in Jakarta and South Tangerang.

TABLE II. Comparison of Manual and Robotic Sorting Validation Results (Controlled Test With 300 Items).

Metric	Manual Sorting	Robotic Sorting	Improvement
Accuracy (avg.)	75.0%	90.0%	+15.0 pp
Purity (avg.)	84.9%	95.1%	+10.2 pp
Throughput (items/min)	45	50	+5

The results are presented in Table II. Manual sorting achieved an average accuracy of 75% and purity of 84.9%, consistent with reported figures in the literature (Pawar et al., 2023). In contrast, the robotic system achieved an average accuracy of 90% and a purity of 95.1%, indicating improved separation and contamination control. Throughput was also higher, with the robotic system processing approximately 50 items per minute compared to 45 for manual sorting.

These results have two implications. First, the robotic system consistently outperforms manual sorting in controlled conditions, demonstrating its ability to address the' variability, contamination, and speed constraints of unstructured waste environments. Second, even modest improvements in throughput and purity translate into significant downstream benefits. Higher purity directly increases the value of recovered fractions by making them more competitive in local and international markets, while higher throughput reduces the cost per ton of operation.

The validation results were translated into economic terms by considering the average market values of recyclables in Jakarta and South Tangerang. Based on recent market data, the approximate prices of key materials are Rp 3,500/kg for PET bottles, Rp 300/kg for glass, and Rp 15,000/kg for aluminium cans. Assuming an average weight of 20 g per plastic bottle, 150 g per glass bottle, and 15 g per aluminium can, the 300-item test batch represents 6,000 g of plastic, 45,000 g of glass, and 4,500 g of aluminium.

Under manual sorting conditions, with an average purity of ~84,9%, the recyclables' effective recovered mass is reduced due to contamination. By contrast, robotic sorting achieves ~95.1% purity, producing more saleable material. Table III illustrates the difference in recovered value between the two systems for the test batch.

TABLE III. Estimated Recovered Value of Recyclables From Validation Batch (Jakarta– South Tangerang Market Prices).

Material	Qty (kg)	Price (Rp/kg)	Value (Manual, Rp)	Value (Robotic, Rp)
Plastic bottles	2.0	3,500	5,950	5,950
Glass	15.0	300	3,825	3,825
Aluminium	1.5	15,000	19,125	21,375
Total	—	—	**28,900**	**32,300**

Although the absolute difference in this small-scale validation is modest (Rp 3,390), scaling the results to an operational MRF handling 5 tons per hour reveals substantial gains. At an industrial scale, improving purity and accuracy could translate into an additional Rp 2–3 million in recovered value daily, depending on commodity prices and waste composition.

While validation at the batch scale demonstrates the technical potential of robotic sorting, decision-making at the facility level ultimately depends on costs and revenues measured per ton of processed waste. This section provides a comparative analysis of three scenarios: 1) manual sorting, reflecting current practices in Jakarta and South Tangerang, 2) semi-automated sorting, which integrates conveyor systems with manual labor, and 3) AI-driven robotic sorting, based on the system described in this study.

Labor costs are calculated using 2024 minimum wage data: Jakarta (Rp 5,067,381 per month) and South Tangerang (Rp 4,857,000 per month). Throughput benchmarks are derived from field reports: manual workers process approximately 1.5 tons daily, semi-automated systems achieve around 2.5 tons per day, and robotic systems reach 3.5–5 tons per day per sorting cell. [32]. Material prices reflect prevailing market rates in Greater Jakarta: plastic bottles at Rp 3,500/kg, glass bottles at Rp 300/kg, and aluminium cans at Rp 15,000/kg. Capital expenditure for robotic sorting is assumed to be USD 400,000 (≈ Rp 6.4 billion), in line with reported costs in international case studies [6].

The comparative economic analysis is grounded on transparent assumptions that combine international benchmarks with local Indonesian data. These assumptions cover capital expenditure (CAPEX), operating expenditure (OPEX), labor costs, material prices, and exchange rates.

International studies indicate that robotic sorting cells typically require an initial investment between USD 300,000 and USD 600,000, depending on the configuration of robotic arms, vision systems, conveyors, and integration costs [6], [32]. For this study, a conservative midpoint of USD 400,000 is selected. The average exchange rate in 2024, which was approximately Rp 16,000 per United States dollar, results in an estimated value of around Rp 6.4 billion when converted using official figures from Bank Indonesia [33]. This assumption is reasonable for Indonesian conditions, where equipment is often imported, though actual costs may vary due to taxes, duties, and local integration expenses.

OPEX components include labor, electricity, maintenance, and consumables. Manual sorting relies heavily on labor, while robotic systems incur higher energy and maintenance costs but reduce labor intensity. For manual sorting, labor is assumed to represent ~80% of OPEX, while robotic systems shift this balance toward energy and maintenance.

Manual sorting is benchmarked at purity levels of 70–80% with a throughput of approximately 1.5 tons per worker daily. Semi-automated systems improve throughput to 2.5 tons daily and purity to 82–85%. Robotic systems, consistent with international reports, achieve 3.5–5 tons per day per cell with purity above 90%.

Table IV summarizes the cost and revenue structure per ton across the three scenarios. Manual sorting exhibits the lowest capital cost but the highest labor intensity, with relatively low purity (70–80%) and high output variability. Semi-automated systems modestly improve throughput and reduce labor requirements. Robotic sorting requires substantial capital investment but delivers superior purity (>90%), consistent throughput, and reduced operational expenditure over time.

These results underscore the long-term economic advantage of robotic sorting (see Table IV). Although upfront costs are substantial, the superior purity and reduced labor requirements lead to significantly higher margins per ton, enabling investment recovery within 4–5 years. The findings also suggest that South Tangerang, with slightly lower labor costs than Jakarta, benefits even more from robotic adoption because revenue uplift from higher purity becomes the primary driver of profitability. This analysis demonstrates that robotic sorting is a technological innovation and an economically rational pathway for modernizing MRFs in Indonesian metropolitan contexts.

TABLE IV. COMPARATIVE COST AND REVENUE PER TON ACROSS THREE SORTING SCENARIOS (JAKARTA AND SOUTH TANGERANG CONTEXT)

Parameter	Manual Sorting	Semi-Automated	Robotic Sorting
Labour cost per ton (Rp)	1,200,000	800,000	200,000
Energy & OPEX per ton (Rp)	300,000	400,000	600,000
Purity (%)	75–80	82–85	92–96
Revenue per ton (Rp)	2,200,000	2,500,000	3,200,000
Net margin per ton (Rp)	700,000	1,300,000	2,400,000

Fig. 5 presents the payback curve illustrating the economic trajectory of the robotic sorting system. The graph plots cumulative cash flow against years of operation for two capital expenditure assumptions: Rp 350 million and Rp 400 million. Both scenarios are based on an annual incremental revenue of Rp 81.6 million, calculated from the additional value of recyclables recovered due to the increase in purity from ~85% (manual) to ~95% (robotic). The curves show that the breakeven point is achieved between 4.3 years (Rp 350 million CAPEX) and 4.9 years (Rp 400 million CAPEX). After this point, the investment generates a positive surplus that increases linearly over time, reflecting stable gains in material recovery. By the end of a 10-year operational horizon, the cumulative net cash flow reaches Rp 466 million under the lower CAPEX scenario and Rp 416 million under the higher CAPEX scenario.

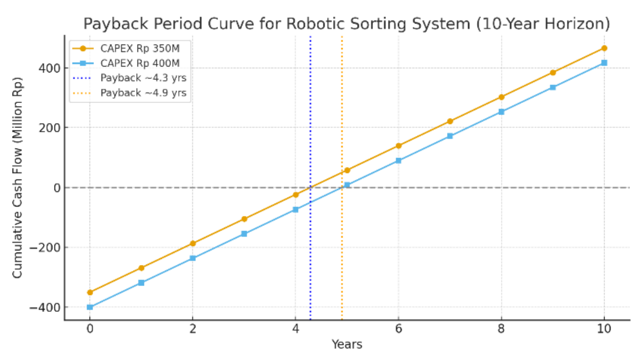

Fig. 5. The payback curve for a robotic sorting system showing cumulative cash flow (in billion rupiah) over five years under Jakarta—South Tangerang assumptions.

This finding confirms that robotic sorting is economically viable within the typical service life of robotic and automation systems (5–7 years). The result is also consistent with international studies reporting payback periods of 4–6 years for AI-based sorting technologies in medium-scale material recovery facilities [6], [12].

Structural inefficiencies in the national recycling industry also reinforce the economic potential of robotic sorting. Reports indicate that plastic recycling manufacturers in Indonesia operate at only about 70% of their installed capacity, primarily due to the low quality and inconsistent input materials. At the same time, demand for recycled plastics in packaging, textiles, and consumer goods continues to grow, but cannot be met by current supply chains. The proposed robotic sorting system can directly address this gap by consistently producing recyclables with purity levels exceeding 95%. Higher-quality outputs would increase the market value of recovered materials and improve the utilization rate of existing recycling plants. Linking these improvements to the economic assessment strengthens the argument that robotic sorting is technically viable and economically rational for advancing Indonesia's circular economy agenda.

The findings highlight several important implications for Indonesian waste management [25] [26]. From an operational perspective, robotic sorting reduces reliance on manual labor, improves worker safety by limiting exposure to hazardous materials, and enhances sorting consistency. While the capital expenditure of robotic systems remains significant, their ability to deliver higher throughput and purity directly improves revenue streams and reduces long-term operational costs.

From a policy perspective, the results suggest that investing in robotic sorting can strengthen Indonesia's position in global recycling markets, where quality standards are becoming increasingly stringent. Higher-purity recyclables are less likely to be rejected by international buyers, thereby reducing the risk of export losses. At the same time, adopting robotics aligns with broader national strategies for digital transformation and Industry 4.0, creating opportunities for skill development in robotics and AI while modernizing the waste sector.

It is essential to acknowledge the limitations of this validation. The test was conducted under controlled conditions with equal numbers of items per category, whereas actual MSW streams are more heterogeneous and unpredictable. Conveyor speeds, mechanical reliability, and integration with existing MRF infrastructure may also constrain throughput in industrial settings. Furthermore, the economic analysis relies on current market prices, which are subject to fluctuation.

V. Conclusion and Future Work

A. Conclusion

This study demonstrated that artificial intelligence-driven robotic waste sorting can achieve high technical performance and economic feasibility under real operational conditions in urban Indonesia. The experimental results confirmed that the proposed system improves sorting accuracy, material purity, and throughput compared with conventional manual sorting practices. At the same time, the techno-economic analysis showed that robotic sorting can reach realistic investment payback periods under local wage and market conditions. Compared with earlier studies that primarily focus on detection accuracy or robotic grasping in laboratory environments, this work advances the state of the art by integrating system-level validation with a localized economic assessment in an emerging economy context.

Several limitations should be acknowledged. Hardware constraints, such as conveyor speed, gripper durability, and lighting conditions, influence system performance. Dataset bias also exists, as the waste samples collected reflect the composition of specific urban areas and may not fully represent national variability. In addition, the techno-economic evaluation relies on current market prices and wage levels, which are subject to future fluctuations. These factors may affect the generalizability of the reported results across different regions and time horizons.

Despite these limitations, the findings provide a strong indication that AI-driven robotic sorting is a viable pathway for modernizing Material Recovery Facilities in developing countries. The integration of technical validation with localized economic analysis offers a practical decision-making tool for facility operators, policymakers, and investors. Future work will focus on multi-class waste expansion, adaptive learning for changing waste composition, and full-scale deployment studies to further support the transition toward a circular economy and sustainable urban waste management.

B. Future Work

While this study demonstrates the feasibility of AI-driven robotic waste sorting, several opportunities remain to extend and deepen the research.

1) Broader object categories: The current system focused primarily on PET bottles, aluminium cans, and HDPE containers. Future work should expand detection and sorting to include more diverse and complex waste fractions, such as multilayer packaging, paper composites, and textiles, which are prevalent in Indonesian municipal solid waste streams.

2) Adaptive and continual learning: Waste characteristics are highly dynamic, influenced by seasonal consumption patterns and contamination levels. Incorporating adaptive learning strategies or active learning pipelines would enable the vision model to continually improve as new data becomes available.

3) Enhanced sensing and control: The present system operates under an open-loop control mechanism. Integrating additional sensors, such as depth cameras, force sensors, or real-time feedback loops, could improve grasp stability, reduce error rates, and enable safer operation in mixed-material environments.

4) Scaling and industrial deployment: While the experiments were conducted as a case study in Jakarta and South Tangerang, future research should investigate system performance in full-scale MRFs. This includes studying throughput under industrial load, conveyor integration at higher speeds, and robustness against continuous operation.

5) Socio-economic dimensions: Adopting robotic sorting has labour, workforce transition, and policy design implications. Future studies should evaluate how robotics can complement rather than displace workers, for example, through hybrid human-robot collaboration, reskilling programs, and inclusive circular economy strategies.

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