

AI-POWERED SUSTAINABLE WASTE MANAGEMENT IN UZBEKISTAN: A VISION-LANGUAGE APPROACH TO SMART SORTING

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Abstract

Uzbekistan generated 14.8 million tonnes of household waste in 2024, but only 900,500 tonnes (6.1%) were processed by specialized enterprises [2]. At the same time, the country's Third Nationally Determined Contribution targets 60–65% recycling of solid household waste by 2028 [3]. This paper proposes EcoBin, a camera-first smart recycling MVP for PET bottles and aluminium cans. The design uses a Raspberry Pi 5 controller [9], Camera Module 3 [10], controlled LED chamber, trigger sensor, servo-based three-way gate, Telegram Bot API [11], and hybrid edge/cloud vision-language inference. Unlike fill-level-only smart bins, EcoBin performs item-level acceptance, rejection, routing, reward messaging, and metadata logging. The paper contributes a buildable hardware/software specification, an explicit cycle workflow, and a costed B2G/B2B/CSR pilot model grounded in Uzbekistan's waste-policy context [2], [3], [8], [16].

Index Terms—smart waste management, vision-language model, edge AI, Raspberry Pi, recycling, circular economy, Uzbekistan.

I. INTRODUCTION

Global municipal solid waste is projected to increase from 2.01 billion tonnes in 2016 to 3.40 billion tonnes by 2050 [1]. For Uzbekistan, the problem is operational: official data report 14.8 million tonnes of household waste in 2024, while only 900,500 tonnes were processed by 292 specialized enterprises, equivalent to 6.1% [2]. The policy target is much higher: Uzbekistan's Third NDC specifies a 60–65% recycling level for solid household waste by 2028 [3]. This gap indicates that the constraint is not only collection capacity but also clean source separation.

Existing smart-bin systems are useful for route optimization and fill monitoring, but smart-waste reviews show that many systems do not perform item-level classification [4]. Computer-vision waste classification can solve this gap, yet industrial-grade reviews show that real waste scenes are difficult because objects are damaged, dirty, occluded, or poorly illuminated [5]. VLMs are attractive because they can classify waste in zero-shot or few-shot settings, reducing the need for a custom dataset in the MVP stage [6], [7].

EcoBin is proposed as a constrained and buildable source-separation unit. The MVP processes one item at a time, accepts PET beverage bottles and aluminium cans, rejects unsupported items, and communicates with users through Telegram instead of a custom mobile app. This narrow scope lowers risk while preserving the core research value: integrating sensing,

lighting, VLM inference, rule logic, mechanical actuation, and business deployment.

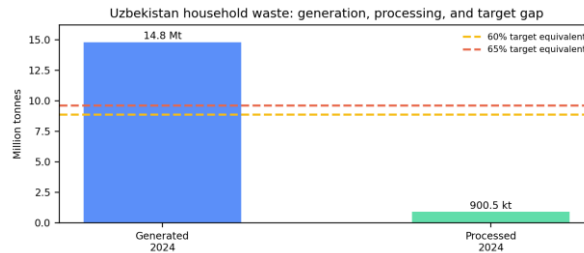


Fig. 1. Uzbekistan household waste generated and processed in 2024; dashed lines show the 60–65% recycling target equivalent for the same annual waste volume [2], [3]

II. RELATED WORK AND DESIGN GAP

A. Smart Waste Management and IoT:

Smart-waste literature commonly emphasizes fill-level sensing, routing, collection efficiency, and smart-city dashboards. Smart Waste Management 4.0 reviews position IoT, automation, and digital monitoring as core technologies for waste systems [5]. Recent IoT bin systems also use sensors to monitor fill levels and support optimized collection [6]. These systems improve logistics, but most of them do not solve the item-level sorting problem: they can report that a bin is full, but not whether the inserted item is a clean PET bottle, an aluminum can, a contaminated bottle, or an unsupported object.

B. Computer Vision Waste Classification:

Computer vision has been used for domestic waste detection and sorting. Li et al. proposed a multi-model cascaded convolutional neural network combining DSSD, YOLOv4, and Faster R-CNN, and reported a large-scale waste image dataset with 30,000 images and 52 categories [7]. However, recent reviews stress that industrial-grade waste classification **C.VLM for Low-Data Recognition:**

Vision-Language Models are relevant because they can map images to natural-language categories. CLIP demonstrated that visual concepts can be learned from natural-language supervision and applied to classification by providing category names [9]. Ranjbar et al. examined VLMs for zero-shot and few-shot plastic-waste classification, noting that labeled datasets are difficult to compile and that VLMs can generalize to unseen classes through natural-language descriptions [10]. Funk et al. evaluated MLLMs and VLMs for adaptive waste classification in zero- and few-shot settings and highlighted CLIP-based feature extraction, GPT-4o, and LLaVA-OneVision as useful approaches [11]. Mewada et al. tested OWL-ViT and OpenCLIP for municipal waste and reported 76.30% average accuracy without task-specific retraining, while also noting prompt sensitivity [12].

These results support EcoBin’s MVP strategy:

a first version can use pretrained LVLMs with structured prompts instead of collecting and labeling a local dataset before deployment. This does not remove the need for evaluation; it changes the evaluation from model training metrics to system feasibility, failure handling, and operational reliability.

D. Reverse Vending and Incentive Systems:

Reverse vending machines are a mature model for bottle and can recovery. TOMRA reports that AI and deep-learning technologies are being integrated into sensor-based sorting for mixed

waste, metal, and wood applications [13]. Recent circular-economy research describes deposit-return schemes and reverse vending machines as important recycling tools, but also notes that they remain underexplored in academic circular-economy literature [14]. Behavioral research on recycling vending machines indicates that perceived usefulness, ease of use, and perceived value influence adoption [15]. EcoBin uses this insight by combining QR/Telegram interaction with immediate feedback and rewards.

III. PROPOSED ECOBIN MVP

A. System Boundary and Target Items

The MVP accepts only two item groups: 1) PET beverage bottles and 2) aluminium cans. All unsupported or contaminated items are routed to reject. This scope follows the project concept deck, which defines the initial EcoBin as a can/plastic-bottle collection device with a reward mechanism [16]. Restricting accepted classes lowers sensing and logic complexity and aligns with high-frequency beverage-container waste. The chamber is designed for one item at a time, and the controller blocks the next cycle until the current item is logged and the gate returns to neutral.

B. Hardware Architecture

The controller is a Raspberry Pi 5 because it provides a quad-core 2.4 GHz Cortex-A76 CPU and up to 16 GB LPDDR4X memory [9]. Image acquisition uses Raspberry Pi Camera Module 3, which provides a 12 MP IMX708 sensor with HDR and phase-detection autofocus [10]. The camera is mounted inside an enclosed inspection chamber with diffuse 5600 K LED strips or ring lighting. A simple IR break-beam or proximity sensor triggers the cycle when an object crosses the inlet. An optional load cell can detect abnormal mass or multiple inserted objects, but it is not the primary classifier. Routing is performed by a servo flap or motorized chute with three outputs: plastic, metal, and reject.

The controller stack is intentionally hybrid. Raspberry Pi 5 is sufficient for device control, image capture, preprocessing, local caching, and network communication, but large multimodal models are still impractical for low-latency fully local inference on this hardware. The initial MVP therefore uses edge orchestration with cloud VLM inference: the Pi captures and pre-processes the image, sends a compact request to a VLM endpoint, receives JSON output, applies local rules, and actuates the gate.

TABLE II
BUILD-SPECIFIC HARDWARE AND SOFTWARE SELECTION FOR THE MVP

Module	Selected implementation	Specification / tool	Role in system	Ref.
Controller	Raspberry Pi 5	Quad-core Cortex-A76 @ 2.4 GHz; up to 16 GB RAM	Device logic, local API, logging, actuation	[9]
Camera	Camera Module 3	12 MP IMX708, HDR, autofocus	Captures item in inspection chamber	[10]
Lighting	Diffuse LED ring/strip	5600 K white LED, fixed chamber illumination	Reduces lighting variance and shadows	Design

Module	Selected implementation	Specification / tool	Role in system	Ref.
Trigger sensor	IR break-beam / proximity	Digital trigger only	Starts capture cycle when item enters	Design
Actuator	Servo flap or motorized chute	3-way routing: plastic / metal / reject	Routes item to target bin	Design
Device software	Raspberry Pi OS + Python 3.11	OS and runtime	Host environment for services and control logic	Design
Capture stack	libcamera / Picamera2 + OpenCV	Frame capture and preprocessing	Selects sharp frame, crops ROI, exports image	[10]
Inference interface	Hosted VLM API	Structured JSON response	Classifies item and returns metadata	[6], [7]
User interface	Telegram bot	HTTP-based Bot API	Session start, result message, reward display	[11]
Local data store	SQLite	On-device queue and event log	Stores events if network fails	Design

Fig. 2. EcoBin MVP architecture. Device control and rules run on the Raspberry Pi; recognition is performed by a VLM endpoint in the initial MVP.

C. Software and Control Logic

The software pipeline is deterministic. First, a QR code opens the Telegram bot, which creates a session ID and returns “ready for insertion.” Second, the trigger sensor detects an inserted item and locks the chamber for single-item processing. Third, the camera captures two frames; OpenCV computes a blur score such as variance of Laplacian and selects the sharper frame. Fourth, the selected image is sent to the VLM using a fixed prompt that requests JSON fields: `item_type`, `material`, `color`, `condition`, `contamination`, and `action`. Fifth, local rules map the response to a routing decision. Sixth, the gate actuates, the event is stored in SQLite, and the Telegram bot returns the result to the user.

The rule set is explicit because VLM output alone is not sufficient for actuation. The MVP accepts to plastic if material is PET and contamination is “none” or “low”; accepts to metal if material is aluminium and contamination is “none” or “low”; rejects if the item is not one of the two supported classes; and re-captures once if the returned material or action is uncertain. A compact event record stores `<session_id, timestamp, class, contamination, action, image_hash>`.

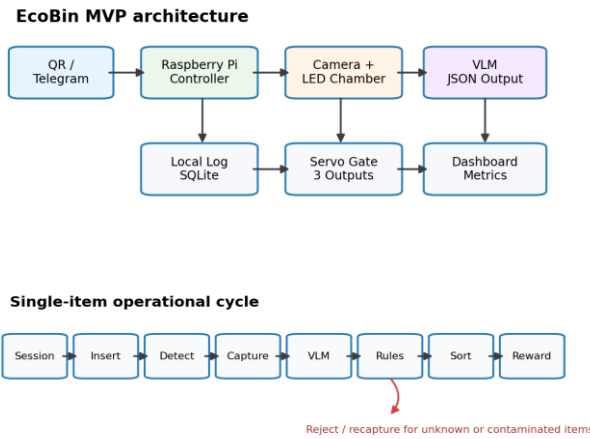


Fig. 3. Operational flow of one EcoBin cycle. The reject path is triggered for unsupported or contaminated items.

IV. FINANCIAL, BUSINESS, AND MARKET MODEL

A useful MVP must be technically buildable and commercially interpretable. The cost baseline from the EcoBin concept deck is: frame US\$415, electronics US\$200, software US\$82, battery and solar US\$42, and camera US\$12, for a total prototype BOM of approximately US\$752 [16]. This figure is a pilot engineering estimate rather than a manufacturing quote, but it supports first-order unit-economics reasoning.

At the concept selling price of US\$1,200 [16], the gross margin over BOM is approximately 37.3%. If 15% is added for assembly, testing, and installation, the landed prototype cost becomes about US\$865 and the contribution margin becomes about 27.9%. The business logic is therefore not only selling a bin once; it is deploying a service node that captures clean recyclables, user events, and venue-level sustainability data.

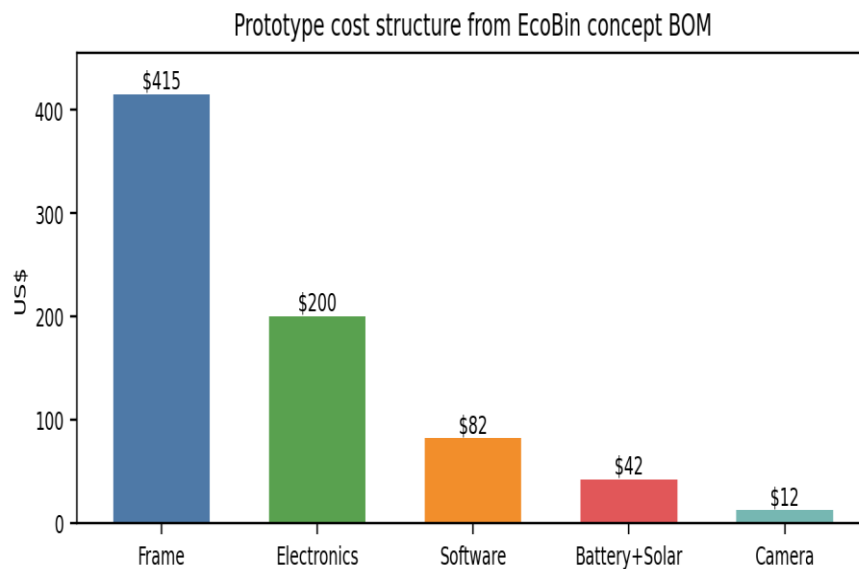
TABLE III
PILOT COMMERCIAL MODEL AND UNIT ECONOMICS

Element	Proposed model	Reasoning	Basis
Core product	EcoBin unit for PET/aluminium capture	Narrow scope lowers technical risk in pilot.	[5]–[7], [16]
Primary customers	Municipalities, universities, malls, offices	Venues have repeated beverage-container flow and visible sustainability needs.	[2], [3], [8], [16]
Revenue 1	Hardware sale or lease	Enables institutional deployment without full capex purchase.	[16]
Revenue 2	Annual software/support fee	Covers dashboard, bot maintenance, remote monitoring, and updates.	Design
Revenue 3	CSR-sponsored rewards	Sponsors can fund points/cashback for ESG visibility.	[12], [16]

Element	Proposed model	Reasoning	Basis
Revenue 4	Material recovery partnership	Separated PET and aluminium are cleaner than mixed waste operationally.	[2], [12]
Prototype BOM	≈ US\$752 per unit	Frame 415 + electronics 200 + software 82 + battery/solar 42 + camera 12.	[16]
Illustrative price	US\$1,200 per unit	Concept price from project deck; supports pilot margin.	[16]

Fig. 4. Prototype cost structure based on the EcoBin concept bill-of-materials [16].

The market case follows the waste-policy case. Uzbekistan is already investing in waste infrastructure, including a US\$120 million EBRD package for western Uzbekistan [8]. EcoBin should therefore be positioned as a source-separation front end for the broader recycling chain. The practical market entry is B2B/B2G rather than direct consumer sales. Recommended pilot sites are university campuses, office complexes, shopping centres, and residential compounds where beverage-container volumes are high and maintenance is manageable [16]. The reward model should be treated as an engineering feature, not only as marketing. OECD analysis shows that deposit-refund systems can influence consumer behaviour and reduce littering [12]. EcoBin can implement this through eco-points, venue-specific vouchers, or cashback through local payment partners. For pilots, non-cash rewards are preferable because they simplify settlement and compliance while still testing whether immediate feedback increases usage.



V. DEPLOYMENT VALUE, LIMITATIONS, AND SUSTAINABILITY

EcoBin aligns with Uzbekistan's waste and climate policy. The current 6.1% processing level [2] and the 60–65% recycling target [3] imply that source separation must improve. EcoBin contributes at the point of disposal, where contamination is still preventable. It also aligns with

smart waste-management literature that emphasizes digitalization and more intelligent waste flows [4]. From a sustainability perspective, the strongest linkage is SDG 12, while SDG 11 is supported through cleaner and more measurable urban services [14], [15].

The main limitation is inference reliability. Reviews of industrial-grade waste classification emphasize that real waste is difficult to classify robustly [5]. EcoBin mitigates this by narrowing the class set, using a chamber rather than open-scene vision, and rejecting unsupported items. The second limitation is compute: Raspberry Pi 5 is a strong edge controller [9], but the initial MVP should not assume full local large-model inference. The third limitation is operations. Public devices require regular bin emptying, cleaning, and actuator maintenance; therefore, the first pilot should be placed in indoor or covered environments with accountable facility staff.

VI. CONCLUSION

EcoBin is viable as a technically specific MVP because it reduces the problem to a buildable set of decisions: one item at a time, two accepted classes, one controlled imaging chamber, one structured inference interface, and one rule-based actuator controller. The design is not a generic AI waste bin; it is a defined system that can be built with a Raspberry Pi 5, Camera Module 3, chamber lighting, Telegram bot control, local event logging, and hybrid VLM inference. Financially, the concept BOM of approximately US\$752 and concept sale price of US\$1,200 [16] support a pilot business model with B2G/B2B/CSR channels. For Uzbekistan, where official waste generation is high and recycling targets are ambitious [2], [3], the value of EcoBin is cleaner source separation plus auditable recycling data.

REFERENCES

- [1] S. Kaza, L. Yao, P. Bhada-Tata, and F. Van Woerden, *What a Waste 2.0: A Global Snapshot of Solid Waste Management to 2050*. Washington, DC, USA: World Bank, 2018.
- [2] Ministry of Ecology, Environmental Protection and Climate Change of the Republic of Uzbekistan, “Waste recycling in Uzbekistan: a step towards a ‘Green’ future,” Mar. 1, 2025. [Online]. Available: <https://gov.uz/en/eco/news/view/38417>
- [3] United Nations Framework Convention on Climate Change, “Uzbekistan Third Nationally Determined Contribution,” 2025. [Online]. Available: <https://unfccc.int/sites/default/files/2025-11/Uzbekistan%20Third%20NDC.pdf>
- [4] D. Kannan, S. Khademolqorani, N. Janatyan, and S. Alavi, “Smart waste management 4.0: The transition from a systematic review to an integrated framework,” *Waste Management*, vol. 174, pp. 1–14, Feb. 2024, doi: 10.1016/j.wasman.2023.08.041.
- [5] P. Thielmann, Y. Zhou, B. Mirbach, D. Stricker, and J. Rambach, “A Review of Computer Vision for Industrial-Grade Waste Classification,” *IEEE Access*, vol. 13, pp. 137611–137632, 2025, doi: 10.1109/ACCESS.2025.3603903.
- [6] I. Ranjbar, Y. Ventikos, and M. Arashpour, “Zero-shot and few-shot multimodal plastic waste classification with vision-language models,” *Waste Management*, vol. 202, Art. no. 114815, Jul. 2025, doi: 10.1016/j.wasman.2025.114815.
- [7] D. Mewada, E. M. Grua, C. Eising, P. Denny, P. Van de Ven, and A. Scanlan, “Zero-Shot Learning for Sustainable Municipal Waste Classification,” *Recycling*, vol. 10, no. 4, Art. no. 144, 2025, doi: 10.3390/recycling10040144.
- [8] European Bank for Reconstruction and Development, “EBRD improves solid waste management in western Uzbekistan,” Mar. 28, 2022. [Online]. Available: <https://www.ebrd.com/home/news-and-events/news/2022/ebrd-improves-solid-waste-management-in-western-uzbekistan.html>

- [9] Raspberry Pi Ltd, “Raspberry Pi 5 Product Brief,” Apr. 2026. [Online]. Available: <https://pip.raspberrypi.com/documents/RP-008348-DS-raspberry-pi-5-product-brief.pdf>
- [10] Raspberry Pi Ltd, “Raspberry Pi Camera Module 3 Product Brief,” Jun. 2024. [Online]. Available: <https://pip-assets.raspberrypi.com/categories/786-raspberry-pi-camera-module-3/documents/RP-008151-DS-1-camera-module-3-product-brief.pdf>
- [11] Telegram, “Telegram Bot API,” 2026. [Online]. Available: <https://core.telegram.org/bots/api>
- [12] F. Laubinger, A. Brown, P. Börkey, and M. Dubois, “Deposit-refund systems and the interplay with additional mandatory extended producer responsibility policies,” OECD Environment Working Papers, no. 208, Dec. 2022, doi: 10.1787/a80f4b26-en.
- [13] Ministry of Ecology, Environmental Protection and Climate Change of the Republic of Uzbekistan, State of the Environment: National Report on the Republic of Uzbekistan, Illustrative Summary, 2023. [Online]. Available: https://ecochem.uz/upload/iblock/425/2ru0eqnsdao9gb0s108dq3jkkwbsgmdj/UZB_eco_report_2023_EN_web.pdf
- [14] United Nations, “Goal 12: Ensure sustainable consumption and production patterns.” [Online]. Available: <https://sdgs.un.org/goals/goal12>
- [15] United Nations, “Goal 11: Make cities and human settlements inclusive, safe, resilient and sustainable.” [Online]. Available: <https://sdgs.un.org/goals/goal11>
- [16] EcoBin Project Team, “EcoBin smart recycling network for Uzbekistan,” internal project pitch deck, 2026.