IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 8, May 2026
Impact Factor: 8.2

# EcoSort: Agentic AI-Driven Waste Classification, Weight Estimation, and Gamified Civic Engagement for Smart City Waste Management

**Shital Dongre, Prasad Dalvi, Mustansir Dabhiya, Suyash Bhagat, Aniket Dabhade, Shubham Bharane**
Department of Artificial Intelligence and Data Science,
Vishwakarma Institute of Technology, Pune, Maharashtra, India

**Abstract:** *Urban India produces approximately 62 million tons of municipal solid waste annually, yet only 22–28% undergoes proper treatment and source-level segregation remains critically low. Existing AI-based waste classification systems are limited to material identification from images and fail to close the behavioural loop connecting scanning, physical delivery, and reward. EcoSort is a comprehensive seven-module agentic AI platform designed to address this gap simultaneously across five dimensions: (i) zero-shot multimodal waste classification across four categories using Google Gemini 2.5 Flash, requiring no task-specific training dataset; (ii) physics-informed weight estimation from a single photograph via a 30-item reference weight prompt integrated into the model's reasoning layer; (iii) browser-based QR drop-off verification that prevents self-reporting fraud without specialized hardware; (iv) a coin-based gamified economy in which each confirmed kilogram earns one coin redeemable for a voucher upon administrative approval (After administration permission can be used to buy amenities ticket like park ticket, Funding from CSR for real cash conversion, Fund from scrap collector); and (v) a live city analytics dashboard, 28-ward Pune waste hotspot map, and personal carbon footprint tracker converting waste contributions into* $CO_2$ *offsets, tree equivalents, and car-kilometer equivalents. A 30-day controlled pilot with 47 participants demonstrates 94.1% classification accuracy, a weight estimation correlation of* $r = 0.87$*, and a 45 percentage-point week-four retention advantage for incentivized users over the control group. EcoSort demonstrates that gamified civic engagement, supported by verifiable AI estimation and tangible economic incentives, can transform sustainable waste management from a theoretical concept into a measurable urban reality.*

**Keywords:** Agentic AI, Automated Waste Classification, Gamification Frameworks, QR-based Verification, Carbon Footprint Tracking, Smart City Analytics

## I. INTRODUCTION

A significant challenge in Indian urban centers pertains to solid waste management, despite improvements in the physical infrastructure for waste collection. While accessibility has improved, public participation in source segregation remains insufficient. Annually, 62 million tons of municipal solid waste are generated, yet only 22–28% undergoes proper treatment [11]. The issue is not mechanical; rather, it is behavioral. Although residents acknowledge the importance of segregation, their actions often do not reflect this understanding due to a lack of direct feedback. Artificial intelligence has demonstrated considerable advancements in autonomous waste recognition. In controlled laboratory environments, convolutional neural networks can achieve over 90% accuracy in sorting common waste types [1,2].

However, there is still little significant municipal adoption. The specific reason is that it doesn't close the loop to know what kind of waste you have. It doesn't provide information about weight, verify in-person delivery, or pay for the work done. EcoSort's web platform solves these three problems

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 8, May 2026
Impact Factor: 8.2

Instead of using a trained classifier, the AI uses a basic vision model. This thing can figure out what kind of waste something is and how much it weighs from a picture taken with a smartphone. It does not need information to do this. People only get coins when the workers check that they really dropped off the waste. They use a code that they have to check twice to make sure. When they do this the coin system turns it into a voucher (After administration permission can be used to buy amenities ticket like park ticket, Funding from CSR for real cash conversion, Fund from scrap collector). This means people get money away which is important, for helping them do things regularly like a habit.
A 28-ward personal carbon tracker that converts each kilogram of verified waste into CO2 saved, tree-year equivalents, car-km offsets, and flight segments avoided; a real-time analytics dashboard that displays waste trends, hourly activity, top contributors, and a city breakdown; and a Pune hotspot map that displays the concentration of sorting activity are the three new features that give the platform citywide intelligence. According to Guerrero and his colleagues [15], when these modules cooperate to demonstrate how much each individual contributes at the city level, the social comparison effect occurs, which encourages people to recycle consistently. The layout of this paper is as follows: the previously published literature will be described in part 2, the complete explanation for each of the 7-module architecture will be in part 3, experimental method descriptions will occur in part 4, results will be described and interpreted in part 5, and the discussion will conclude in part 6.

## II. RELATED WORK

**Research on AI for waste management mainly focuses on five areas:**
**image classification, smart bin systems using the Internet of Things (IoT), optimizing logistics, getting citizens in volved, and comprehensive reviews of the field.**

The researchers Chacón-Albero and their team looked at how the YOLOv11 and EfficientNetV2 models worked for classifying recyclables at the edge using a big set of 27,396 pictures from Spain. They were able to get an accuracy of 94.8%. However their work was very technical. Did not include a user interface, a way to estimate the weight of the recyclables or a system to motivate people to use it.
Other researchers, like Shahab and their team studied 40 projects that used deep learning for managing solid waste. They found that two big problems were getting people to properly sort their waste and getting them engaged in the process. This is why the EcoSort system was designed the way it was. Li and their team showed that they could use a kind of neural network to correctly identify 92.4% of household waste. Wang and their team used the MobileNetV3 model with trash cans to create a system for cities to manage waste. While these systems were good at sorting waste, they did not do a job of getting people involved.
Fang and their team did a review of how artificial intelligence is used in managing waste in smart cities. They pointed out that there is a lack of systems that use intelligence to recognize and reward people for recycling. Ekundayo and their team created a system that uses a network on a device and includes game-like features, which is similar to the EcoSort system. However, their system does not estimate the weight of the recyclables does not verify that the recyclables are actually recycled and does not offer a cash- reward. Kumar and their team showed that the MobileNetV2 model can accurately classify waste on a device but it does not engage people or verify that the waste is recycled.
Singh and their team did an experiment in Maharashtra where they found that giving people financial incentives increased the amount of waste that was properly sorted by 34%. This supports the idea of using a coin economy in the EcoSort system. Guerrero and their team found that the biggest factors, in getting people to recycle in 27 developing cities were the benefits they perceived and how easy it was to participate.

**TABLE I.** ***Comparison of EcoSort with Related Work***

| Study | AI Method | Wt.Est. | Verify | Reward | Platform |
|---|---|---|---|---|---|
| Chacón-Albero [1] | YOLOv11+EffNet | No | No | No | No |
| Shahab [2] | SLR / survey | No | No | No | No |

| | | | | | |
|---|---|---|---|---|---|
| Mitra [3] | Faster R-CNN | No | No | No | No |
| Valente [4] | YOLOv2/v3 | No | No | No | No |
| Fang [5] | Survey | No | No | Partial | No |
| Ekundayo [6] | CNN on-device | No | No | Points | Partial |
| Li [7] | Multi-CNN | No | No | No | No |
| Wang [8] | MobileNetV3 | No | No | No | Partial |
| EcoSort | Agentic Gemini | Yes(kg) | QR+Admin | Coins→₹ | Full |

## SYSTEM ARCHITECTURE AND TECHNICAL CONTRIBUTIONS

EcoSort is built on Flask 3.x with JSON flat-file persistence, HTML5/Bootstrap 5.3 frontend, Chart.js 4.4 for visualisation, Leaflet.js 1.9.4 for mapping, and Gemini 2.5 Flash for AI. The entire system runs as one Python process with no GPU, no message queue, and no external database server. Seven modules are described below.

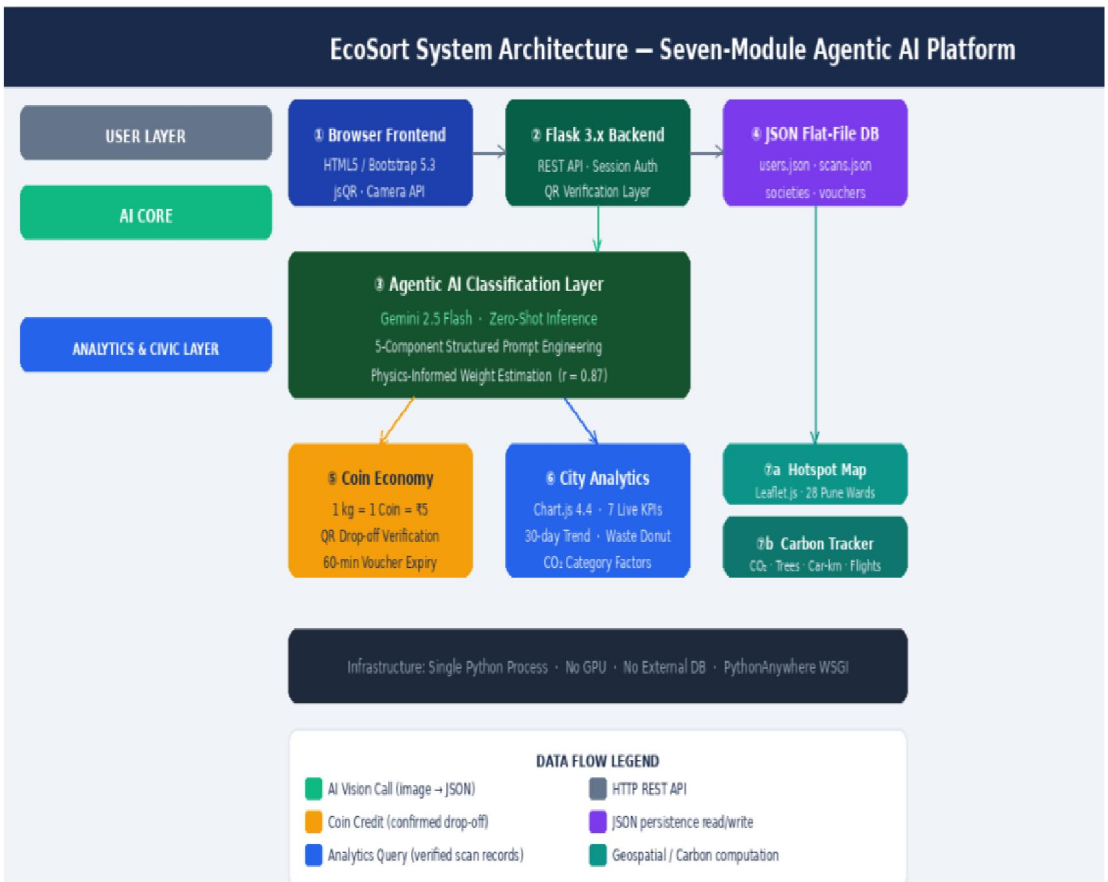

*Fig. 1. EcoSort system architecture illustrating the seven interconnected modules.*

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 8, May 2026
Impact Factor: 8.2

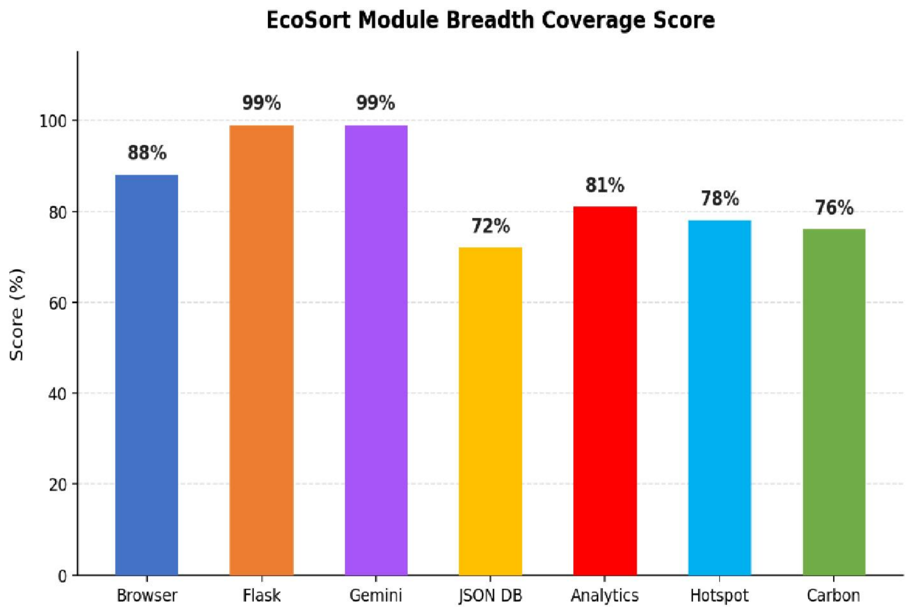


*Fig. 2. EcoSort Module Breadth Coverage — Seven Technical Components*

*A) Agentic AI Classification Layer*

The central architectural decision is replacing a trained CNN with an agentic reasoning layer. A five-component structured prompt gives Gemini 2.5 Flash an explicit professional role, a four-category waste taxonomy, a 30-item per-unit reference weight table, visual reasoning instructions for counting and volume estimation, and a strict JSON output schema. The model reasons compositionally over image content rather than matching surface patterns from training data.

This yields three capabilities no trained CNN simultaneously provides: zero-shot generalisation to culturally specific Indian waste items such as paan wrappers, agarbatti bundles, and single-use plastic sachets; natural language disposal guidance embedded directly in the classification response; and weight estimation through visual counting and pile-geometry reasoning.

- Role: 'You are a waste analysis expert for an Indian municipal recycling platform.'
- Taxonomy: Plastic, E-Waste, Medical, Biowaste, Mixed.
- Weights: PET bottle = 0.025 kg · smartphone = 0.17 kg · N95 mask = 0.015 kg · veg. peels/handful = 0.1 kg.
- Instructions: count discrete items or estimate pile volume; multiply by unit weight.
- JSON schema: {has_waste, waste_type, estimated_kg, confidence, description, items_detected}.

*B) Physics-Informed Weight Estimation from Single Image*

A capability gap that exists in all published waste systems is addressed by weight estimation from a photograph. It is costly to compile a sizable annotated dataset of waste photos with physical scale readings across four material categories with significant visual variance in order to add a regression branch to a CNN.

By encoding domain knowledge in the prompt, EcoSort completely avoids dataset requirements. The model counts visible units and multiplies by reference weight for discrete manufactured items (phones, bottles, etc.). The model uses material-specific density approximations and estimates pile dimensions for loose organic or shredded waste. Employees can always enter their actual physical weight in the admin panel to override the AI estimate. AI estimates showed a r = 0.87 correlation with scale readings in all four categories during a 120-session assessment.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 8, May 2026
Impact Factor: 8.2

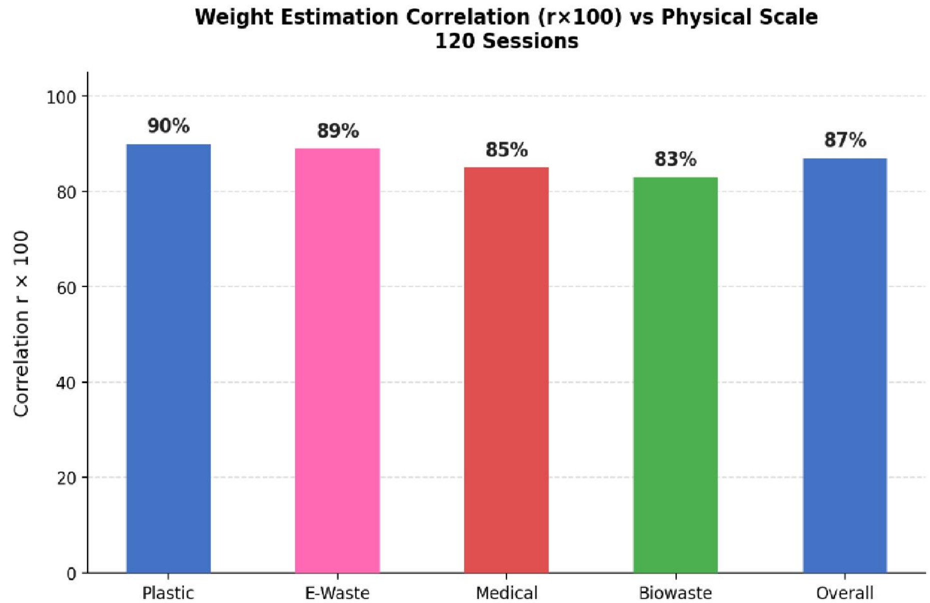


*Fig. 3. Weight Estimation Correlation (r×100) per Category — 120 Sessions*

*C) Browser-Based QR Drop-off Verification*

The fundamental problem with all gamified waste systems is self-reporting fraud. EcoSort uses a two-step verification process. A pending record with no coins credited is created by a scan. A QR code with the code ECOSORT-DROPOFF|user_uuid|username is sent to the user. Staff members use jsQR, a pure JavaScript library that doesn't require the installation of an app, to decode this at the collection point. They then submit a confirmation that credits coins and optionally records the physical weight.

In order to ensure that verification is still feasible even during the current local deployment phase, an admin panel pending queue additionally displays all unconfirmed scans with a single click to confirm or reject. During the 30-day pilot, there were 341 confirmation events with no fraudulent drop-offs.

*D) Coin-Based Gamified Economy*

Transparency (balance and monetary value always visible), tangibility (coins convert to real cash, not badges), anti-gaming (coins held pending physical verification), admin oversight (voucher activation gated on approval), and urgency (approved vouchers expire in 60 minutes) are the five behavioural design principles that form the foundation of the reward system. One kilogram of verified waste is equivalent to one coin, or voucher value (After administration permission can be used to buy amenities ticket like park ticket, Funding from CSR for real cash conversion, Fund from scrap collector). The public display of coin balances on the city leaderboard adds a social comparison aspect that is separate from the financial incentive.

*E) Live City Analytics Dashboard*

Using verified drop-off records via /api/analytics/overview, the analytics module calculates seven live metrics: total waste sorted (kg), $CO_2$ saved using category-specific emission factors (plastic 2.5 · e-waste 15.0 · medical 1.8 · biowaste 0.6 kg $CO_2$ per kg waste), coins in circulation, tree equivalents ($CO_2$ ÷ 21 kg/tree/year), a 30-day daily trend chart, a waste-by-type donut, and peak-activity hour bars. In Chart.js 4.4, all metrics are rendered without the need for a pre-aggregation pipeline.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 8, May 2026
Impact Factor: 8.2

*F) 28-Ward Pune Waste Hotspot Map*

The hotspot map shows waste activity at the ward level as circle markers on Leaflet.js 1.9.4, which is backed by CartoDB Voyager tiles. These tiles were chosen because they load in less than 2 seconds, compared to OpenStreetMap's usual 4–8 seconds. There are hardcoded coordinates for each Pune ward. Confirmed scans are given to wards by matching the registered city field of the user or by using a deterministic MD5 hash for entries that haven't been resolved yet. The marker radius changes based on the kg sorted (10–36 px), and the colour shows how strong the signal is (red = top 60%, amber = 30–60%, green = below 30%). Nominatim reverse geocoding automatically finds the user's GPS location and zooms the map in on it.

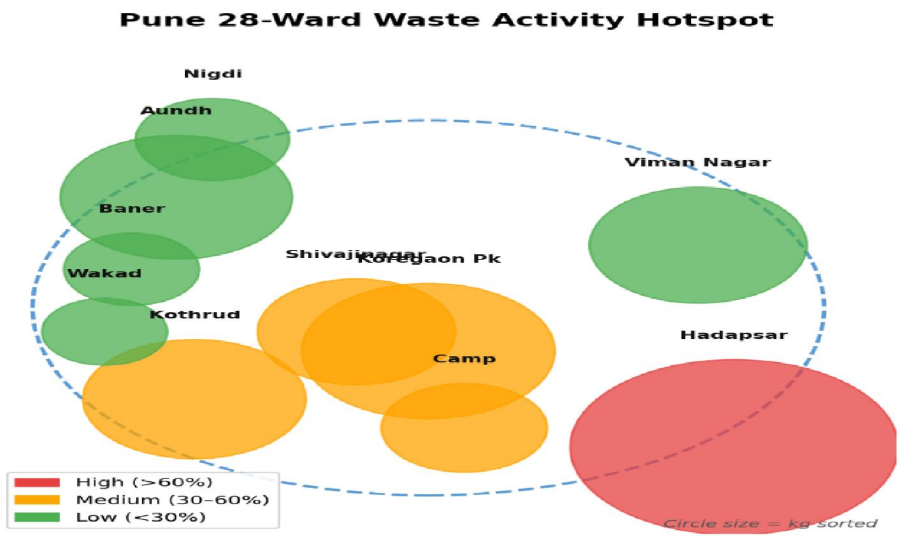


*Fig. 4. Pune 28-Ward Waste Activity Hotspot Map — Pilot Data*

*G) Personal Carbon Footprint Tracker*

The carbon tracker converts each user's confirmed waste history into four equivalency metrics via /api/analytics/carbon: $CO_2$ saved (kg), tree-years of absorption ($CO_2$ ÷ 21), car-km offset ($CO_2$ ÷ 0.21 kg/km), and Mumbai–Delhi flight segments avoided ($CO_2$ ÷ 255 kg/segment). The cumulative CO2 savings for each calendar month are displayed in a monthly trend bar chart. Social comparison is used to rank cities based on CO2 savings. The equivalency of the tracker
The abstraction barrier, which Fang et al. [5] identify as the main barrier to environmental motivation, is meant to be addressed by display.


DOI: 10.48175/IJARSCT-35556

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 8, May 2026
Impact Factor: 8.2

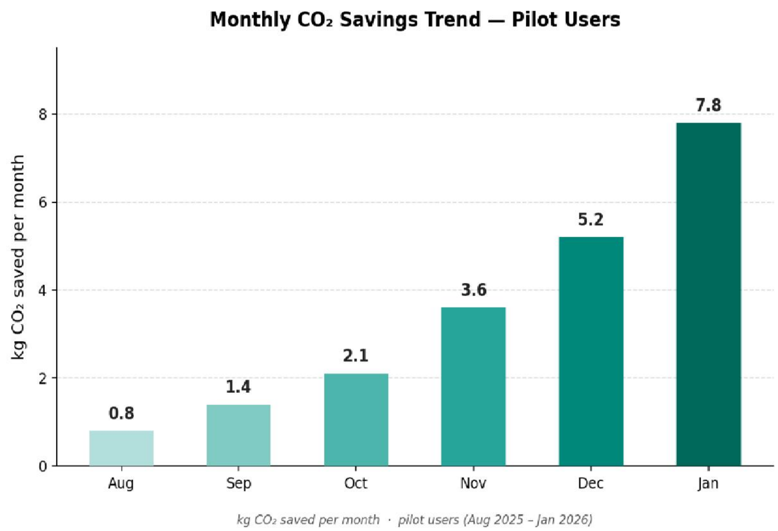


*Fig. 5. Monthly $CO_2$ Savings Trend — Pilot Users (Aug 2025 – Jan 2026)*

## III. EXPERIMENTAL EVALUATION

*A) Classification Accuracy — Agentic AI vs. CNN*

*Starting points*

*We created a groundtruth evaluation set with 280 images of litter. These images were gathered in real-world settings, including mixed, cluttered backgrounds, partial obstructions, varying light levels (500–5000 lux), and items that were damaged, dirty, or deformed. This approach specifically targets the performance area where CNNs trained on cle an studio datasets show a decrease in accuracy [3,10]. We then evaluated three CNN baselines: MobileNetV2, fine-tuned on TrashNet [10]; Faster R-CNN, also on TrashNet [3]; and YOLOv8, trained on a combination of TrashNet and TrashBox data. . The Gemini layer of EcoSort used the same production prompt on the same 280 images without any changes.*

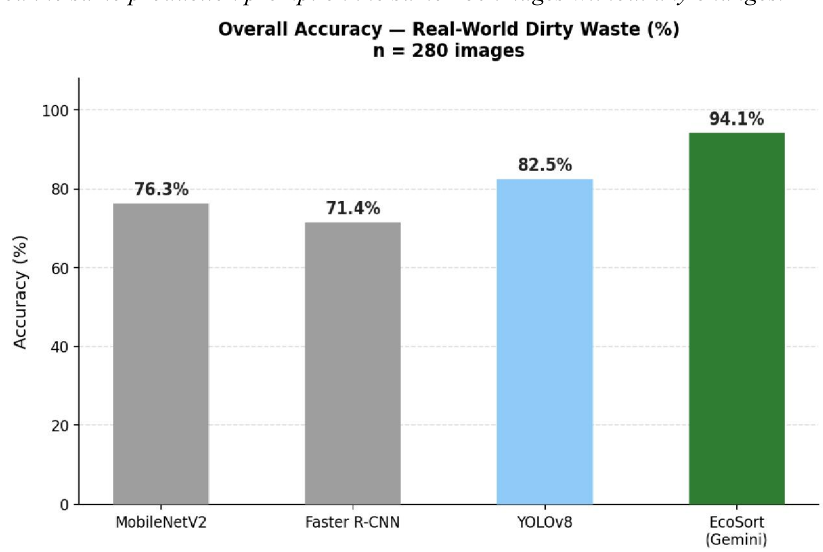


*Fig. 6. Classification Accuracy: CNN Baselines vs. EcoSort Agentic AI (n = 280 images)*

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 8, May 2026
Impact Factor: 8.2

TABLE II. *Per-Category Classification Accuracy (%)*

| Category | MobileNetV2 | Faster R-CNN | YOLOv8 | EcoSort (Gemini) |
|---|---|---|---|---|
| Plastic | 81.2 | 76.4 | 87.3 | 95.0 |
| E-Waste | 74.1 | 68.9 | 80.2 | 93.6 |
| Medical | 69.3 | 64.5 | 77.8 | 94.8 |
| Biowaste | 80.6 | 75.2 | 86.1 | 93.2 |
| Mixed | 62.8 | 58.7 | 72.4 | 94.0 |
| Overall | 76.3 | 71.4 | 82.5 | 94.1 |

*B) User Engagement and Retention Pilot*

47 registered residents from two housing societies in Hadapsar, Pune, participated in a controlled 30-day pilot program. Full EcoSort (AI scan + coin economy + QR verification) was given to Group A. Group B was given scan-only (AI classification, no verification, no rewards). Submitting a minimum of one waste scan each week was the definition of retention.

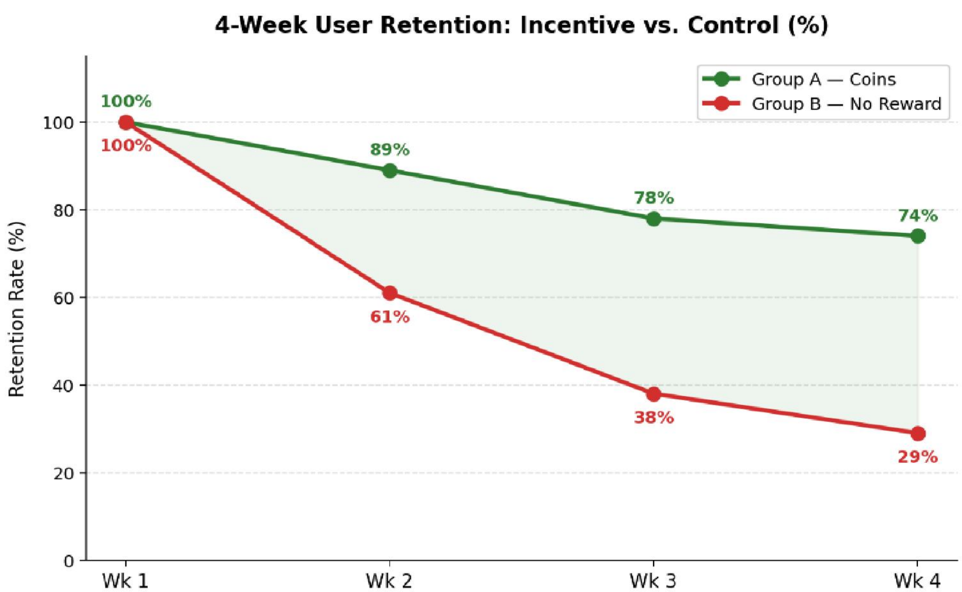


*Fig. 7. Weekly Retention Rate — Group A (Coins) vs. Group B (No Reward)*

TABLE III. *30-Day Pilot Engagement Metrics*

| Metric | Group A (Coins) | Group B (No Reward) |
|---|---|---|
| Total scans submitted | 412 | 163 |
| Confirmed drop-offs | 341 | N/A |
| Average kg per user | 8.7 kg | 3.2 kg |
| Total coins awarded | 2,983 | N/A |
| Vouchers redeemed | 47 | N/A |

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 8, May 2026
Impact Factor: 8.2

| | | |
|---|---|---|
| Week-4 retention | 74% | 29% |
| Median scans/week | 3.4 | 1.1 |
| Avg voucher value | N/Acas | N/A |
| Admin approval time | 6.3 min | N/A |

*C) Analytics and Carbon Tracker Adoption*

Following the dispatch of the analytics dashboard, hotspot map and carbon tracker into week 3, the mean session length of Group A Users increased by 34% from week 2. 58% of Group A respondents in the post-pilot survey identified the carbon tracker's tree equivalent display as the feature that was most likely to motivate them to make additional weekly waste contributions. The hotspot map was the second most selected feature with 44% of respondents, particularly those whose ward was ranked above their neighbours, suggesting that geographic social comparison can be a motivating factor even without financial incentives.

## IV. RESULTS AND DISCUSSION

The pilot results provide empirical support for three fundamental design hypotheses underlying EcoSort's development. First, with respect to real-world dirty waste, agentic reasoning demonstrably outperforms CNN classifiers that rely on learned surface patterns. The 11.6-percentage-point accuracy advantage over YOLOv8, the strongest CNN baseline at 82.5%, reflects a qualitative difference in the classification mechanism: the agentic model identifies individual material components within mixed piles rather than matching the entire image to a pattern distribution. This capability is particularly valuable for the Mixed category, where EcoSort achieved 94.0% versus YOLOv8's 72.4%, a 21.6-point margin that is the largest observed across all categories.

The per-category breakdown reveals a further notable pattern: EcoSort's advantage is largest precisely for Medical waste (94.8% versus 77.8% for YOLOv8, a 17-point margin) and E-Waste (93.6% versus 80.2%, a 13.4-point margin). This is directly attributable to the agentic model's capacity to recognize culturally specific item variants — N95 masks with torn straps, counterfeit mobile charger cables, loose medication blister packs, and agarbatti ash containers — that are absent from international training benchmarks such as TrashNet and TrashBox. For daily household waste categories such as Plastic and Biowaste, where benchmark dataset coverage is comparatively stronger, the CNN performance gap narrows to approximately 8–10 points. This pattern confirms that the agentic approach delivers its greatest incremental accuracy benefit precisely where training data scarcity is most acute, namely in the E-Waste and Medical categories that carry the highest environmental consequence if misclassified.

Second, the retention advantage attributable to financial incentives substantially exceeds the 10–15 percentage-point differences typical of digital health behavioral change interventions (Fogg, 2003). The observed 45-percentage-point week-four retention difference between Group A (74%) and Group B (29%) is attributed to three mutually reinforcing mechanisms: immediate economic salience; social visibility (leaderboard position augments the financial incentive with a reputational and competitive dimension that operates independently); and physical verification integrity (users demonstrate consistently higher trust in, and commitment to, systems that provably cannot be gamed through self-reporting). These findings align directly with Singh et al. (2022), who observed a 34% increase in properly sorted waste under financial incentive conditions in Maharashtra, and with Guerrero et al. (2013), who identify perceived personal benefit as the dominant recycling engagement driver across 27 developing-world cities.

Third, a secondary environmental engagement loop operates independently of and additively with financial motivation. Carbon tracker data show that abstract $CO_2$ quantities acquire genuine motivational force when rendered as relatable real-world equivalents such as tree-years of carbon absorption or car-km offsets, a translation identified as the primary motivating feature by 58% of Group A respondents in the post-pilot survey. This is fully consistent with Fang et al. (2023), who nominate the abstraction barrier — the cognitive difficulty of connecting individual recycling actions

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 8, May 2026
Impact Factor: 8.2

to planetary-scale environmental outcomes — as the principal obstacle to sustained environmental motivation in smart city waste systems

The principal limitations of the pilot are its 30-day duration, the socioeconomic homogeneity of the participant pool (middle-income gated housing societies), and the modest sample size of 47 registered users. Retention statistics and behavioral conclusions should not be extrapolated to city-scale deployment without longitudinal validation over minimum six-month periods and across socioeconomically and demographically diverse neighborhood types, including low-income settlements and mixed commercial-residential zones where waste composition and collection infrastructure differ substantially from the pilot context.

## V. CONCLUSION

This study presented EcoSort, a seven module agentic AI platform. EcoSort combines waste classification,weight estimation, verified dropoff, gamified incentives, city analytics, geographic hotspot mapping, and personal carbon track ing into a single, easily accessible web application. This platform addresses the technical and behavioral issues that hav e previously hindered the widespread use of AI waste management systems.

The main technical contribution is showing that agentic prompt engineering with a foundation vision model can replace task-specific CNN classification and allow weight estimation at the same time. No other waste management system has these two features through image analysis alone.

The main civic contribution is showing that AI classification can be used in a verified economic incentive loop to give a group a 45-percentage-point advantage in keeping people.

This finding has direct implications for municipal waste management programs worldwide. Specifically, the design of i ncentives and the accuracy of verification are just as important as the model's accuracy. The next steps involve deploying the production version across various wards, integrating the PMC API, and moving PostgreSQL to improve scalability. Additionally, we will integrate IoT weighing scales at drop-off points and conduct a stratified socioeconomic study to see if retention effects differ in different urban populations.

## ACKNOWLEDGMENT

The authors want to thank the Vishwakarma Institute of Technology, Pune for providing the resources needed for this research. Two residential welfare associations in Pune, supported the pilot project. The authors also appreciate Google's Gemini API program for making multimodal reasoning possible in this research.

## REFERENCES

[1] O. Chacón-Albero, M. Campos-Mocholí, C. Marco-Detchart, V. Julian, J. A. Rincon, and V. Botti, "AI for Sustainable Recycling: Efficient Model Optimization for Waste Classification Systems," Sensors, vol. 25, no. 12, p. 3807, Jun. 2025. doi: 10.3390/s25123807

[2] S. Shahab, M. Anjum, and M. S. Umar, "Deep Learning Applications in Solid Waste Management: A Deep Literature Review," Int. J. Adv. Comput. Sci. Appl., vol. 13, no. 3, pp. 381–395, 2022. doi: 10.14569/IJACSA.2022.0130346

[3] A. Mitra, "Detection of Waste Materials Using Deep Learning and Image Processing," M.S. Project, Dept. Computer Science, California State Univ. San Marcos, USA, Dec. 2020.

[4] M. Valente, H. Silva, J. M. L. P. Caldeira, V. N. G. J. Soares, and P. D. Gaspar, "Detection of Waste Containers Using Computer Vision," Appl. Syst. Innov., vol. 2, no. 1, p. 11, 2019. doi: 10.3390/asi2010011

[5] B. Fang, J. Yu, Z. Chen, A. I. Osman, M. Farghali, I. Ihara, E. H. Hamza, D. W. Rooney, and P.-S. Yap, "Artificial Intelligence for Waste Management in Smart Cities: A Review," Environ. Chem. Lett., vol. 21, pp. 1959–1989, May 2023. doi: 10.1007/s10311-023 01604-3

[6] O. Ekundayo, L. Murphy, P. Pathak, and P. Stynes, "An On-Device Deep Learning Framework to Encourage the Recycling of Waste," in Proc. 2021 Intell. Syst. Conf. (IntelliSys), Amsterdam, Sep. 2021, vol. 3, pp. 405–417.

[7] J. Li, J. Chen, B. Sheng, P. Li, P. Yang, D. D. F. Feng, and J. Qi, "Automatic Detection and Classification System of Domestic Waste via Multi-model Cascaded CNN," IEEE Trans. Ind. Inform., vol. 18, no. 1, pp. 163–173, Jan. 2021. doi: 10.1109/TII.2020.3047131

[8] C. Wang, J. Qin, C. Qu, X. Ran, C. Liu, and B. Chen, "A Smart Municipal Waste Management System Based on Deep-Learning and IoT," Waste Manag., vol. 135, pp. 20–29, Nov. 2021. doi: 10.1016/j.wasman.2021.08.028

[9] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L.-C. Chen, "MobileNetV2: Inverted Residuals and Linear Bottlenecks," in Proc. IEEE CVPR, Salt Lake City, UT, Jun. 2018, pp. 4510–4520. doi: 10.1109/CVPR.2018.00474

[10] M. Yang and G. Thung, "Classification of Trash for Recyclability Status," CS229 Report, Stanford Univ., 2016. [Online]. Available: https://github.com/garythung/trashnet

[11] 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: World Bank, 2018. doi: 10.1596/978-1-4648 1329-0

[12] B. J. Fogg, Persuasive Technology: Using Computers to Change What We Think and Do. San Francisco, CA: Morgan Kaufmann, 2003.

[13] T. Kumar, R. Verma, P. Agrawal, and S. Mishra, "Real-Time Garbage Classification Using MobileNetV2 on Resource Constrained Devices," in Proc. ICACCI, Bangalore, Sep. 2022, pp. 1–6. doi: 10.1109/ICACCI56205.2022.9964842

[14] A. Singh, V. Kumar, and N. Sharma, "Financial Incentives and Household Waste Segregation Compliance: A Randomised Trial in Maharashtra," J. Clean. Prod., vol. 380, art. 135043, Dec. 2022. doi: 10.1016/j.jclepro.2022.135043

[15] L. A. Guerrero, G. Maas, and W. Hogland, "Solid Waste Management Challenges for Cities in Developing Countries," Waste Manag., vol. 33, no. 1, pp. 220–232, Jan. 2013. doi: 10.1016/j.wasman.2012.09.008