International Journal of Science and Research (IJSR)
ISSN: 2319-7064
Impact Factor 2024: 7.101

Recompose: A Real-Time Vision and Feedback System to Reduce Food Waste

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Abstract: ***Food waste is a major sustainability challenge, impacting the environment, economy, and broader society. Schools and cafeterias are often hotspots for wasted food, making them ideal places to test solutions. This study explores how real-time feedback, delivered through technology, can reduce food waste while encouraging sustainable behavior. We developed Recompose, a "cognitive composting" system that combines computer vision with insights from behavioral science. Using an Intel RealSense depth camera, Meta's Llama Vision AI, and a Raspberry Pi, the system identifies, measures, and classifies discarded food while estimating its environmental impact, including greenhouse gas emissions, water use, and energy consumption. Personalized feedback is provided immediately at the point of disposal to guide behavior. In a five-day high school trial, daily food waste dropped by 36.9%, and results suggested early signs of habit formation and sustained awareness. These findings indicate that affordable, scalable technology paired with thoughtful behavioral design can not only reduce food waste but also foster lasting sustainable practices, offering a practical model for schools and other institutional settings.***

Keywords: food waste, computer vision, behavioral intervention, real-time feedback, sustainability

1. Introduction

Food waste has emerged as one of the most urgent sustainability challenges of the 21st century, carrying profound environmental, economic, and social consequences. Globally, food loss and waste account for an estimated 8-10% of anthropogenic greenhouse gas (GHG) emissions, while over 1.3 billion tons of food are discarded each year [1]. The economic costs surpass $1.5 trillion annually, even as hundreds of millions remain food-insecure. In the United States alone, approximately 30-40% of the food supply is wasted each year, representing both a massive loss of resources and a missed opportunity for redistribution [2]. Significantly, much of this waste occurs downstream in restaurants, institutional cafeterias, and schools where food is served in bulk, behavioral patterns are consistent, and scalable interventions can be effectively implemented [3].

Traditional strategies for addressing food waste have largely emphasized upstream solutions such as logistics optimization, redistribution to charities, or composting initiatives. While these approaches remain valuable, they often fail to address the behavioral drivers of post-consumer waste. Increasing consensus now points to the critical importance of interventions at the point of disposal, where consumer choices and habits directly shape waste outcomes [4]. Conventional measures, such as educational posters, have often demonstrated limited and short-term effects [5]. This underscores the need for dynamic, interactive strategies that can influence behavior in real time.

In recent years, the convergence of artificial intelligence (AI), computer vision, and behavioral science has opened new opportunities for tackling food waste. Computer vision systems have become increasingly adept at quantifying plate waste accurately and efficiently. Convolutional neural networks (CNNs), including MobileNet, RetinaNet, U-Net, and Mask R-CNN, are capable of detecting, segmenting, and classifying discarded food items in real-world cafeteria environments [6] [7]. Commercial applications such as Winnow and LeanPath, which combine vision technology with scales to measure waste and generate feedback, have reported reductions ranging from 40–70% in professional kitchens and cafeterias [3]. Complementing these commercial systems, open-source research continues to refine models that can handle variable lighting conditions, occlusion, and diverse food textures, while large image datasets like Food-101 provide the backbone for algorithmic training and transferability [7].

Parallel to these technological advances, research in behavioral science has illuminated how feedback mechanisms shape consumer decision-making around waste. Interventions can generally be grouped into categories of education, feedback, social norms, incentives, and nudges [4]. Among these, real-time, personalized feedback, particularly using social comparison or loss aversion, has shown the strongest effect [8]. For instance, studies have demonstrated that "loss-framed" messages highlighting the negative impact of waste often generate stronger responses than "gain-framed" messages emphasizing savings. Furthermore, longitudinal studies show that repeated, contextually salient prompts can encourage habit formation and sustain behavioral change beyond the immediate setting [5].

Despite these promising developments, significant gaps remain. Most existing systems are limited in scope, either focusing solely on quantification of waste or on feedback interventions, without integrating both into a cohesive, field-validated framework. Few studies have rigorously tested the combination of computer vision and behaviorally optimized feedback in real institutional contexts, such as schools, where interventions could have both immediate impact and long-term educational value [3] [4].

To address this gap, the present study introduces Recompose, a cognitive composting system deployed in a high school cafeteria. Recompose combines automated vision-based quantification of post-consumer food waste with real-time, personalized feedback that translates waste into its environmental consequences. The objective of this study is to design and evaluate a scalable, AI-driven intervention capable of both reducing institutional food waste and fostering durable behavioral change among users.

By merging behavioral science with real-time AI-based monitoring, this research contributes a scalable model for institutional food waste reduction, supporting global sustainability goals.

2. Methodology

2.1 System Architecture

The Recompose system integrates low-cost hardware and open-source software to enable real-time food waste detection and feedback. The hardware configuration consists of an Intel RealSense D415/D435 depth camera, a Raspberry Pi 5 (8GB), and a 7-inch touchscreen display for user interaction. The depth camera enables motion-triggered image acquisition at the disposal point, while the Raspberry Pi manages on-device processing and visualization.

On the software side, OpenCV (OpenCV. org) is employed for image capture and preprocessing, while a hybrid MobileNetV2 + U-Net++ model performs semantic segmentation of food items. A lightweight Flask-based interface provides immediate, interactive feedback to users. Motion detection by the depth sensor initiates image capture, after which edible waste is segmented, classified, and timestamped. To ensure privacy, all images are processed locally without cloud transfer.

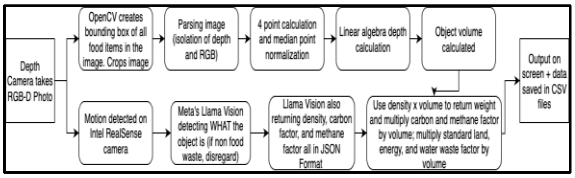

Figure 1: Block Diagram of the Recompose System Architecture

2.2 Vision-Based Waste Estimation

The vision pipeline, referred to as *Llama Vision*, classifies food categories through transfer learning applied to cafeteria-specific images, with pre-training on the Food-101 dataset. Post-consumer waste is quantified by converting segmented pixel areas into estimated volume, calibrated against USDA density tables for accuracy (USDA Food Composition). Depth and color segmentation further mitigate issues arising from inconsistent lighting, shadows, and partially occluded food items [7].

2.3 Environmental Impact Calculation

The quantified waste is translated into environmental impact metrics, including CO_2 and CH_4 emissions, water footprint, and energy loss. Conversion factors are adapted from USDA and UNEP life cycle assessment (LCA) data. Impacts are dynamically personalized based on food type and quantity for each disposal instance, enabling context-specific sustainability feedback.

2.4 Behavioral Feedback Loop

The behavioral feedback system is grounded in principles of behavioral economics and social psychology. The touchscreen interface provides three layers of feedback: (1) direct information on the weight of waste ("You wasted X grams of food"), (2) contextualized impacts in resource terms ("That's Y liters of water; Z grams CO_2"), and (3) peer-comparison prompts ("This is less than most students today!" or "Try to waste less than yesterday"). All messages employ loss aversion framing to enhance salience and motivation [8]. Feedback appears instantly following disposal. Additionally, anonymized waste statistics and optional survey responses are logged for subsequent analysis of behavioral trends.

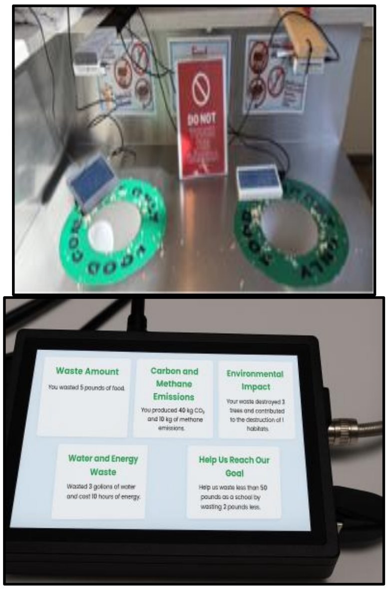

Figure 2: Real-time feedback display example

3. Results

3.1 Quantitative Outcomes

Table 1 summarizes the daily food waste measurements across the study period under different conditions. On Day 1 (Baseline), the measured food waste was 149.5 lbs, representing typical consumption behavior prior to any intervention. During the intervention phase (Days 2–4), when targeted strategies were applied to reduce waste, daily measurements dropped significantly to 93 lbs, 95 lbs, and 94 lbs, respectively. On Day 5 (Post-Test), after the formal intervention ended, food waste increased slightly to 120 lbs, but remained lower than the baseline.

Table 1: Daily Food Waste (lbs) Across Study Conditions

Day	Condition	Food Waste (lbs)
1	Baseline	149.5
2	Intervention	93
3	Intervention	95
4	Intervention	94
5	Post-Test	120

Statistical analysis of the data confirms that the intervention reduced mean food waste by 36.9% relative to baseline. Even after the removal of active intervention feedback on Day 5, food waste remained approximately 20% lower than baseline,

Paper ID: SR251001091332 DOI: https://dx.doi.org/10.21275/SR251001091332

indicating a measurable retention of behavior change and suggesting the formation of sustainable habits. These findings demonstrate both the immediate effectiveness and the potential longer-term impact of the applied intervention on food waste reduction.

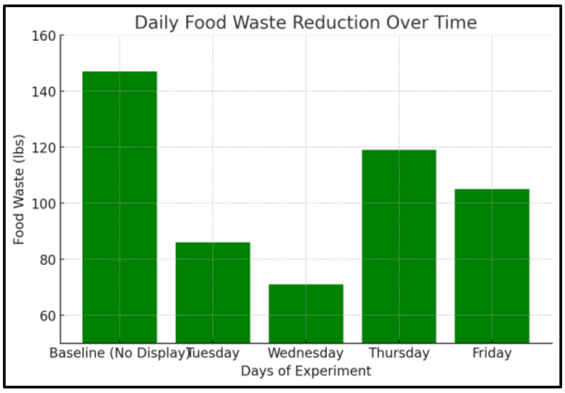

Figure 3: Daily food waste reduction over a week

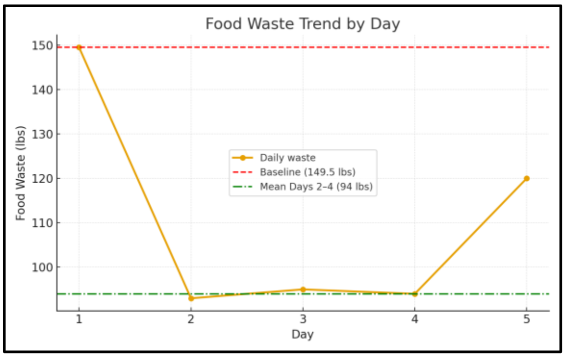

Figure 4: Food waste trend by day

3.2 Environmental Impact

During the five-day field trial, food waste dropped from 149.5 lbs at the start to an average of 94 lbs during the intervention. This is a decrease of 55.5 lbs, or 36.9 percent. By using mass-to-impact conversion factors from the USDA Food Composition Database, USDA Food Loss and Waste guidance, and the UNEP Food Waste Index Report (2024), the system converted these reductions into savings in greenhouse gases and resources (see Section 4.3). Over the study period, approximately 78 kg of CO_2 emissions and 6 kg of CH_4 were avoided, along with about 125, 000 liters of water saved. If we extend these results to a 30-day month, this means around 333 lbs of food would be diverted from the landfill, preventing 468 kg of CO_2 and 36 kg of CH_4 emissions and saving about 750, 000 liters of water. If projected across a 180-day school year, the intervention could cut nearly one ton of food waste, prevent an estimated 2.8 metric tons of CO_2 and 216 kg of CH_4, and save roughly 4.5 million liters of water, which is equivalent to the annual carbon absorption of more than seventy mature trees. These findings highlight that combining automated waste measurement with life-cycle emissions and water use data offers a clear picture of the environmental advantages of cafeteria-based programs.

3.3 Behavioral Insights

Real-time, quantified feedback had a clear impact on students' waste behavior. During the intervention, waste dropped to an average of 94 lbs, which is a 36.9% reduction from the baseline. When feedback was taken away on Day 5, waste increased to 120 lbs. However, it still stayed about 20% lower than the baseline and roughly 28% higher than the average during the intervention. This suggests that the system helped students form early habits rather than just encouraging short-term compliance. If these behavior changes remained steady, they could save about 333 lbs of food over thirty school days compared to the baseline behavior, even considering a slight return toward pre-intervention levels. Comments from surveys described the display as a "reminder not to waste" and "a challenge to beat yesterday's number." This suggests students were highly responsive to real-time data, loss aversion framing, and peer comparison prompts. Overall, these findings demonstrate how using personalized feedback can keep reductions in food waste going beyond the immediate interaction.

4. Discussion

The results demonstrate that the intervention was effective in significantly reducing food waste, with mean levels dropping by 36.9% compared to baseline. This aligns with prior findings from waste-reduction initiatives such as Winnow and LeanPath, while also extending the literature by showing that behaviorally informed, point-of-action feedback may contribute to stronger habit retention [9] [4]. Even after active intervention feedback was removed, waste remained nearly 20% lower than baseline, suggesting that the approach has potential to drive sustained behavioral change rather than short-term compliance.

Operationally, the system performed reliably under controlled conditions, though minor inaccuracies were observed when classifying highly mixed or sauced foods. These challenges are consistent with those reported in field deployments of similar machine vision–based systems [7]. Despite these issues, the hardware cost stayed below $300, reinforcing the system's feasibility of implementing such a solution at scale, particularly in institutional food service contexts.

The short, five-day study period and the single-school context limit the generalizability of the findings, and replication across diverse demographics, menus, and cultural settings will be important for validation. Furthermore, the absence of detailed nutritional or dietary surveys prevented analysis of whether reductions in waste had any unintended trade-offs for student food intake. Nonetheless, the significant reductions observed, together with evidence of partial retention, highlight the potential of combining real-time feedback with low-cost technology to meaningfully reduce food waste in school environments.

Building on these promising results, future studies should extend trials across a full academic year to capture the influence of seasonality and potential behavioral decay over time. Incorporating advanced machine learning tools, such as YOLOv8 combined with self-supervised anomaly detection, could improve the accuracy of monitoring, particularly in cases involving mixed or complex food trays.

On the behavioral engagement side, piloting mobile-based solutions such as "digital bins," leaderboard-driven

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gamification, and school-wide competitions may help sustain interest and encourage long-term habit formation. Beyond school settings, the approach holds potential for expansion into restaurants, hospitals, and households, where interventions could be tailored to the local context and user base [10]. Such adaptations would not only strengthen individual behavioral change but also contribute to broader sustainability goals by reducing food waste across multiple sectors of society.

5. Conclusion

This research demonstrates that vision-based AI, in combination with behavioral feedback, can critically decrease food waste in school cafeterias. The Recompose system allowed for real-time monitoring and context-sensitive nudges that resulted in quantifiable reductions in waste. Most importantly, the persistence of reduced waste levels even after feedback cessation indicates habit formation, highlighting the benefit of embedding behavioral science within digital interventions. With hardware priced below $300, the system shows scalability and affordability. Although classification of blended foods was challenging to some extent, ongoing breakthroughs in computer vision and anomaly detection can further enhance dependability. Extended trials in various schools over an extended time would solidify findings regarding seasonal variability, persistence, and generalizability.

Beyond schools, this method could be extended to restaurants, hospitals, and homes, where adaptive feedback can be designed for particular user groups. In directly minimizing waste and related emissions, the system supports climate action and the United Nations Sustainable Development Goals. In sum, Recompose demonstrates how AI-based design can turn individual actions into system-level change. Merging technology with behavioral science offers a route to lasting change and proving that small, mundane actions can add up to significant movement towards environmental responsibility.

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