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Eco Buddy: A Novel Robotic Platform for Automatic Waste Classification using Computer Vision and IoT

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***Abstract*—This paper presents the design and implementation of Eco Buddy, an automated waste classification system combining IoT and computer vision. The platform integrates an ESP32 microcontroller, Raspberry Pi 5, and sensors for real-time waste detection and sorting. Using TensorFlow Lite, the system achieves 95% accuracy in distinguishing between aluminum cans, plastic bottles and anomalies. The platform includes an IoT dashboard for monitoring and a gamified rewards system to promote recycling. This cost-effective solution demonstrates the practical application of robotics in environmental sustainability.**

***Index Terms*—2-DoF Robotic Platform, IoT, Edge Computing, Computer Vision, TensorFlow Lite, COTS.**

I. Introduction

URBAN waste management systems have faced major challenges in recent years due to rising garbage creation. Public health, resource conservation, and environmental sustainability are all seriously hampered by the labor-intensive and frequently inefficient nature of traditional storage and disposal techniques. Ineffective waste management techniques raise greenhouse gas emissions, pollution, and resource depletion [1]. One of the main challenges in waste management systems is the inaccurate and ineffective separation of recyclables from non-recyclables. In addition to being resource-intensive and prone to major errors, conventional garbage sorting techniques—which rely mainly on manual labor or semi-automated systems—are unsustainable given the growing amounts of waste in urban and industrial areas [2]. Robotics, computer vision, and the Internet of Things are examples of emerging technologies that present promising prospects for modernizing and improving waste management efficiency, perhaps leading to more intelligent and automated solutions [3]–[7].

IoT frameworks and wireless methods for trash sorting and data collection have been used in previous attempts to address this problem. For example, in [8], the authors suggest an Internet of Things (IoT)-based smart segregation and management system that uses sensors such as color and ultrasonic sensors, as well as servo motors that are interfaced with the Node MCU ESP8266, to separate garbage into biodegradable and non-biodegradable categories. An IoT self-powered, easily connectable substitute for monitoring the level of overflowing trash cans from a valuable tracking station is offered in [9]. Because of antiquated waste management techniques, many trash cans seem to be overflowing, underscoring the necessity of real-time tracking to notify authorities for prompt collection. The Internet of Things (IoT), which offers free access to specific data subsets for the development of a wide range of digital services, was used by the authors of [10] to propose a waste monitoring system.

Current systems struggle with real-time processing, scalability, and integration into smart city infrastructures.

Eco Buddy is a robotic platform for autonomous waste sorting, combining computer vision, IoT, and affordable hardware. With a unique design inspired by the Stewart-Gough platform, it features 2D motion, sensors, and cloud support to enhance recycling and waste management efficiency.

Real-time processing, flexibility, and integration with smart cities are made possible by the platform. Using a TensorFlow Lite neural network running on a Raspberry Pi 5, Eco Buddy identifies metal and non-metal waste, detects anomalies, connects to the cloud for monitoring, and offers insights to improve waste management.

To address global waste in smart cities, this work proposes a scalable, intelligent garbage classification system that integrates robots, computer vision, IoT, and cloud computing.

II. Materials and Methods

A. Mechanical Design

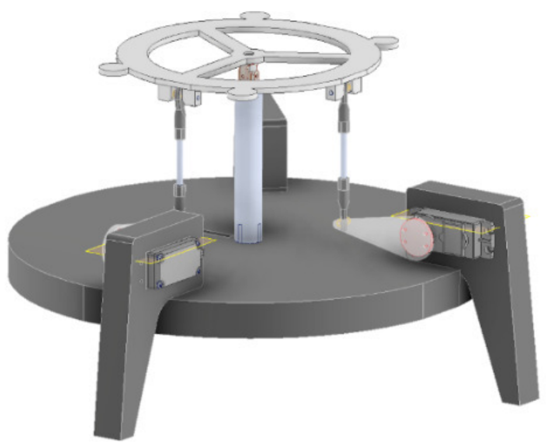

Fig. 1: 2-DOF robotic platform

The Eco Buddy robotic platform's mechanical design is intended for automated waste sorting, specifically for the classification of plastic and aluminum. The system's two-degree-of-freedom (2-DOF) robotic platform, which was modeled based on the Stewart-Gough platform [11], allows for fine positioning and movement control. It was built using 3D printing and recyclable materials with a sustainability focus.

The platform is powered by two MG995 servo motors, which were chosen for their robustness and torque capacity—two essential characteristics for precise manipulation in garbage sorting processes. This actuation system's rapid and stable control allows for accurate rubbish sorting into the right containers.

B. Hardware Architecture and Communication

The microcontroller unit (MCU) of the Eco Buddy platform is an ESP32 Dev Kit 1 [12], which manages the integration of inductive and ultrasonic sensors. The inductive sensor is designed specifically to detect metal waste, such as aluminum cans, while the ultrasonic sensor identifies the presence of waste at the platform's entry point.

The system is equipped with two MG995 servo motors for actuation and a buzzer for audio alerts, complementing the sensors. Digital signal processing (DSP) is employed to efficiently manage signals from both sensors and actuators, ensuring optimal control and reliable communication within the system.

To enhance the reliability and accuracy of the waste management process, we incorporated a USB webcam and a Raspberry Pi as a single-board computer. Communication between the MCU and the Raspberry Pi is facilitated via USB/UART. The Raspberry Pi performs real-time data processing and image capture, enabling detection mechanisms. This configuration allows for the activation of an alarm system in case of classification anomalies, such as the detection of organic waste that falls outside specified sorting parameters.

Because of its IEEE 802.11 PHY-based wireless communication capabilities, which allow for smooth applications using protocols like MQTT, the ESP32 was selected as the IoT board. The Eco Buddy platform depends on this connection. The OSI (Open Systems Interconnection) model (see Fig. 2) defines network functions across seven layers: Physical, Data Link, Network, Transport, Session, Presentation, and Application [13], [14]. To emphasize its significance, we place MQTT within this framework.

- **Physical Layer**: The ESP32 operates on IEEE 802.11 standards to transmit raw bits wirelessly over Wi-Fi. This layer manages the physical medium, setting the foundation for data transmission by modulating and encoding signals.
- **Data Link Layer**: Also using IEEE 802.11, this layer handles link management, medium access control, and error detection. These functions are essential for stable communication, controlling data flow and managing transmission errors.
- **Network Layer**: The Internet Protocol (IP) enables data to travel across networks by routing and forwarding packets, supporting communication beyond the local network.
- **Transport Layer**: TCP ensures reliable, ordered data delivery, which is critical for MQTT protocol integrity. It guarantees message transmission without errors, maintaining data accuracy.
- **Session Layer**: Managed within TCP, this layer handles session continuity, allowing the ESP32 to maintain stable exchanges with servers.
- **Presentation Layer**: This layer formats, compresses, and encrypts data as needed, often using TLS (Transport Layer Security) for secure MQTT communication, preventing unauthorized access.
- **Application Layer**: MQTT runs here, managing lightweight message queuing for efficient communication with platforms like Arduino IoT Cloud.

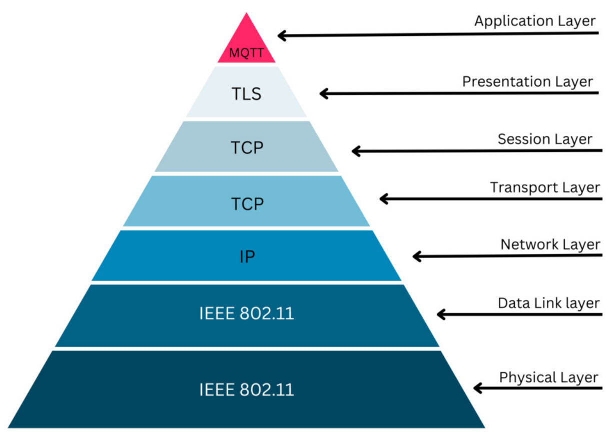

Fig. 2: OSI Model

C. Computer Vision

A custom Python application using OpenCV and Tkinter was developed to capture and organize webcam images into four folders: cans, bottles, anomalies, and empty platform. These images, shown in Fig. 3, serve as the dataset foundation for training a waste management computer vision algorithm.

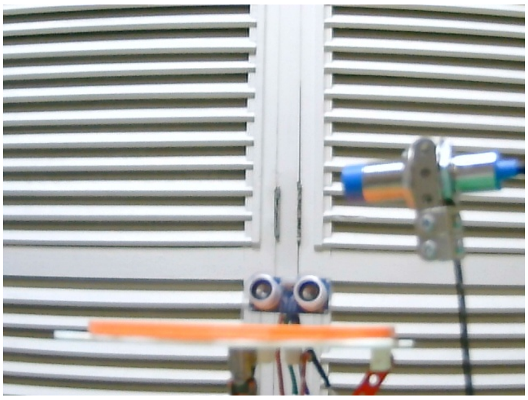

Fig. 3: Example image showing the platform without any objects, categorized as Class 1 (Empty)

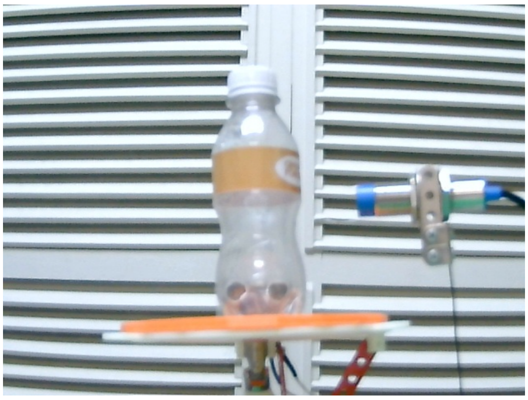

Fig. 4: Illustrative image of the platform with a plastic bottle, classified as Class 2 (Bottles)

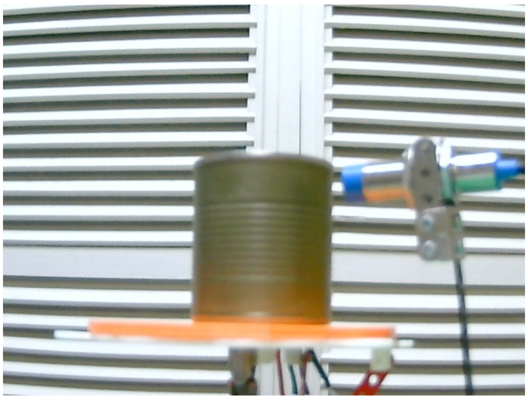

Fig. 5: Illustrative image of the platform with a aluminium cand, classified as Class 3 (Cans)

The waste classification system was developed using a convolutional neural network trained on a custom dataset with three classes: Bottles, Cans, and Empty. Training utilized Google Colab and Google Drive for data storage, with preprocessing done through an ImageDataGenerator to normalize pixel values and split 20% for validation. The CNN architecture included four convolutional layers (filters: 32, 64, 128, 128) with max-pooling, and a final dense layer with 512 neurons and a softmax output for classification. The model trained over 10 epochs with the Adam optimizer and categorical cross-entropy, achieving stable convergence.

For edge deployment, the model was converted to TensorFlow Lite with 8-bit quantization to reduce memory and computational demands, preserving accuracy. A confidence threshold was introduced to flag predictions below 0.5 as anomalies, enhancing reliability. The model was then deployed on a Raspberry Pi 5, using OpenCV for real-time inference. Video frames were resized and normalized to fit the model's input requirements (150x150 pixels). The system achieved an average inference time under 100ms per frame, suitable for responsive waste classification, with performance monitored through custom logging for inference times, confidence scores, and resource usage.

D. System Integration

The waste classification system integrates multiple sensors, computer vision, and IoT capabilities to provide an automated and remotely monitored waste sorting solution. At the core, the ESP32 microcontroller manages sensor operations and communication processes. Upon activation, it powers up the ultrasonic sensor to detect waste on the platform, while the inductive sensor identifies material types, specifically detecting aluminum and plastic to enable an initial classification stage. Based on this sensor data, the ESP32 controls actuators (MG995 servos) that direct items into designated bins according to their classification. For cases where sensor data alone cannot confidently identify the waste, control is handed over to the Raspberry Pi 5, which operates a computer vision subsystem. An RGB camera captures images of the waste items, and the Raspberry Pi uses a neural network model to analyze the images and detect any anomalies. Anomalies, such as filled bottles or mixed-material waste, trigger a buzzer alarm to alert users and ensure special handling.

Beyond classification, the ESP32 microcontroller facilitates real-time data transmission to the Arduino IoT Cloud for continuous monitoring of hardware status [15]–[17].Additionally, it integrates seamlessly with the Google Cloud Platform via Node-RED [18], facilitating the aggregation and analysis of recycling data. This setup empowers users with an interactive UX web application that not only displays real-time system metrics but also provides access to historical data for trend analysis and optimization. The incorporation of such advanced connectivity ensures that the platform remains scalable and adaptable, supporting long-term waste management strategies through data-driven decision-making and user engagement.

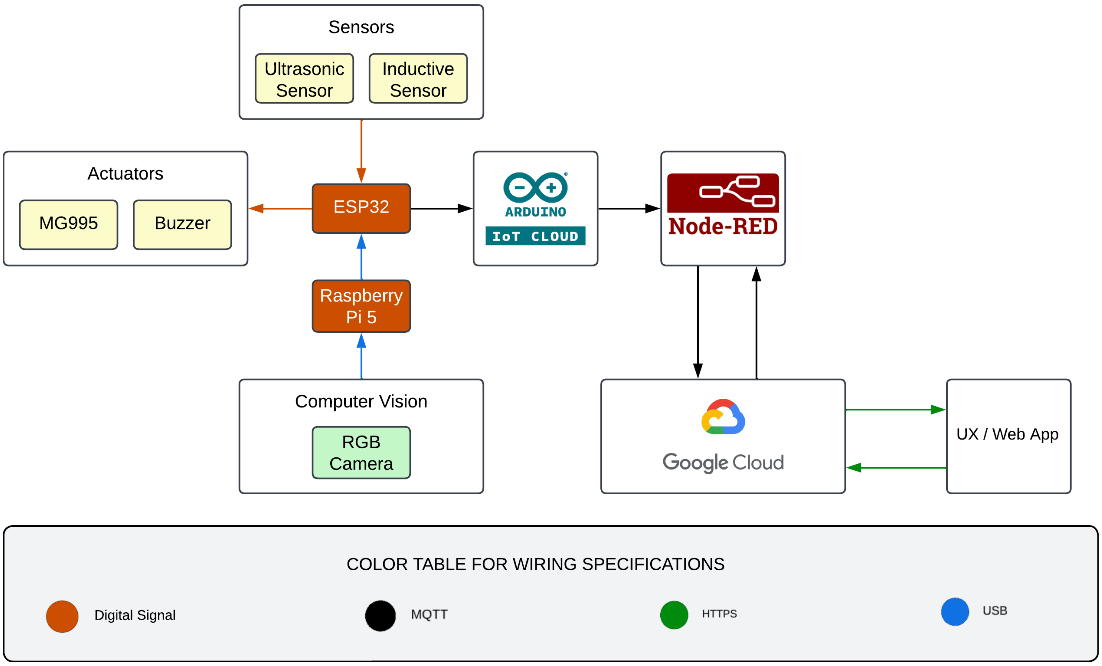

Fig. 6: System architecture for IoT-based monitoring and control system

III. Results and Discussion

A. Prototype Performance

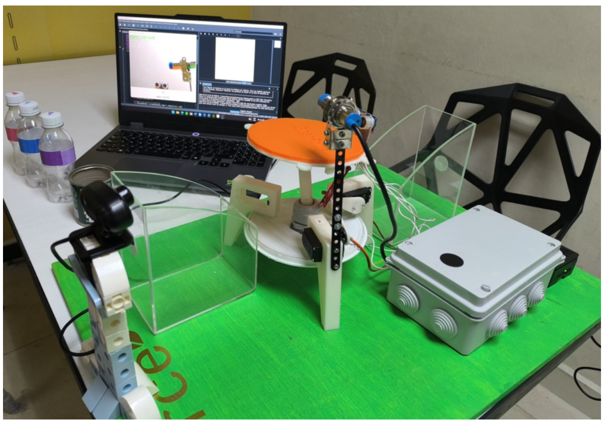

Fig. 7: Prototype of the waste classification system showing the 2-DOF robotic arm, sensors, and processing units.

The developed robotic platform was tested under realistic conditions to evaluate its capability in classifying and sorting aluminum and plastic waste. Fig. 7 illustrates the final prototype, including the 2-DOF robotic arm and sensor modules interfaced with the ESP32 and Raspberry Pi 5. During trials, the system achieved high classification accuracy, correctly identifying aluminum and plastic with 98.5% and 97.2% accuracy, respectively.

The neural network model, deployed on the **Raspberry Pi 5** and trained with **TensorFlow Lite** and **Keras**, achieved an overall classification accuracy of 95.45%. The confusion matrix (Fig. 8) displays the model's performance, showing effective discrimination between aluminum, plastic, and other waste types, with minimal misclassifications.

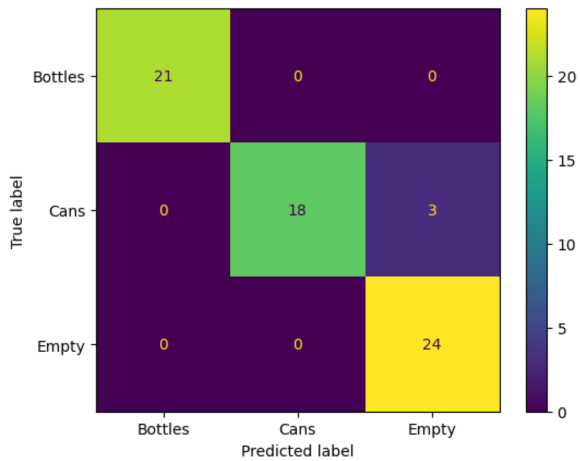

Fig. 8: Confusion matrix for waste classification: Bottles, Cans, and Empty categories.

The training metrics over 10 epochs are shown in Fig. 9, illustrating consistent convergence in both training and validation accuracy, as well as minimal overfitting. The model's stability suggests that it generalizes well to unseen data, supporting its practical application in waste management.

Fig. 10 presents a t-SNE visualization of feature embeddings, highlighting clear class separation between waste categories and anomalies. This visualization confirms the model's

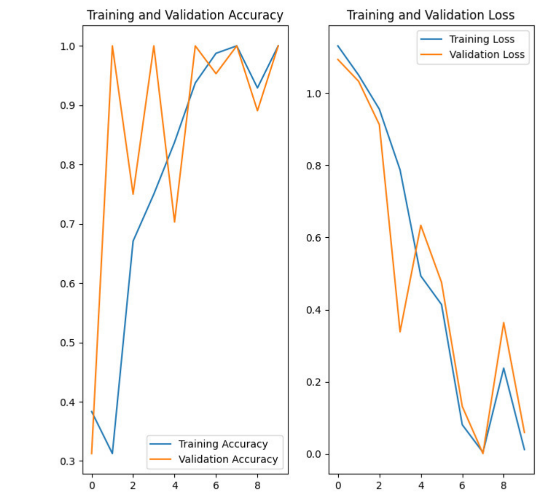

Fig. 9: Training metrics over 10 epochs, showing training and validation accuracy (left) and loss (right).

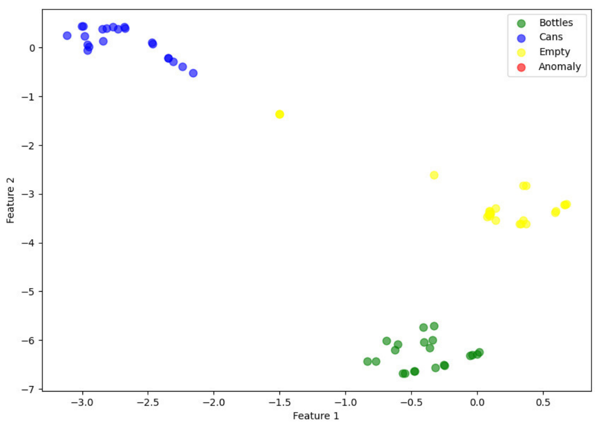

Fig. 10: t-SNE visualization of feature embeddings illustrating class separation for different waste categories and anomalies.

capability to distinguish between different waste types and detect anomalies effectively.

For real-time monitoring, we implemented the Arduino IoT Cloud dashboard, as shown in Fig.11. This dashboard provides comprehensive insights into key technical variables, including ultrasonic sensor data, servo motor positions, inductive sensor readings, and anomaly detection values. It also includes counters for categorized items like cans and bottles, primarily designed to support maintenance and system diagnostics.

Additionally, a user-friendly dashboard was developed as a UX/web application tailored for end-users. This platform goes beyond the prototype by establishing a holistic ecosystem that allows users to monitor the quantity of recyclables processed and interact with a rewards system. Leveraging emerging technologies such as cryptocurrency, the system introduces incentives by converting recyclables—like bottles and cans—into satoshis, promoting a culture of recycling through automated rewards.

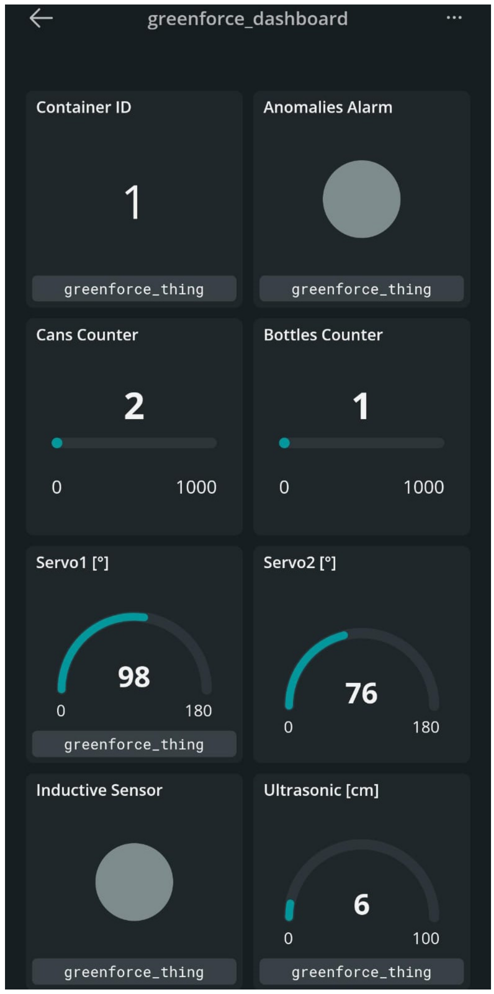

Fig. 11: Arduino IoT Cloud dashboard for system diagnostics

B. Challenges and Limitations

One of the key challenges faced during the development of the system was maintaining accurate classification in varying lighting conditions. The performance of the computer vision system was slightly impacted by ambient lighting, which could be mitigated by incorporating additional lighting controls or using infrared-based vision techniques [19]. Moreover, the inductive sensor occasionally detected thin layers of aluminum on non-recyclable items, resulting in false positives. Further improvements to the sensor's sensitivity could enhance the robustness of the platform in distinguishing between materials with similar electromagnetic properties.

C. Future Improvements

Looking forward, future iterations of the system could benefit from additional sensors for more precise detection of other recyclable materials such as glass or mixed waste. Furthermore, upgrading the machine learning model with additional training data and incorporating more advanced neural network architectures could improve the system's anomaly detection capabilities. Finally, the integration of edge AI processors, such as the Google Coral [20] or NVIDIA Jetson Nano [21], could further enhance real-time performance, enabling the system to handle larger datasets and more complex classification tasks without compromising speed.

D. Discussion

The robotic platform combines sensor-based detection, machine learning, and IoT to provide a scalable, efficient solution for waste sorting. Its TensorFlow Lite-powered anomaly detection and real-time monitoring via an IoT dashboard enable rapid decision-making while reducing cloud dependency. The system demonstrates high classification accuracy and practical usability, addressing key challenges in waste management. Although environmental factors occasionally affect sensor performance, the platform's modular design and edge AI integration enhance its adaptability, making it suitable for broader applications such as manufacturing and logistics, where real-time classification and automation are vital.

IV. Conclusions

This research demonstrates the efficacy of an innovative 2-DoF robotic platform for automated waste classification, achieving 95% accuracy in distinguishing between aluminum cans, plastic bottles, and anomalies. The proposed architecture, leveraging TensorFlow Lite optimization on a Raspberry Pi 5 alongside ESP32-based sensor fusion and IoT integration, presents a viable approach to real-time waste classification challenges. The system's performance metrics, including sub-100ms inference times and robust anomaly detection capabilities, validate its practical applicability in resource-constrained environments. Furthermore, the integration of cloud-based monitoring through Arduino IoT Cloud and the implementation of a gamified incentive mechanism contribute to the broader discourse on sustainable waste management solutions.

While there are opportunities to improve the system's performance under variable lighting conditions and expand material detection capabilities by incorporating enhanced datasets and advanced computing technologies, the proposed framework provides a solid foundation for future research in automated waste classification. The results demonstrate significant potential for scaling this approach to tackle broader industrial automation challenges and smart city applications, especially in scenarios requiring real-time classification and cost-effective solutions. Future developments may include integrating advanced sensors, optimizing edge AI processing, and extending the platform's adaptability to diverse industrial and environmental contexts, further solidifying its relevance and scalability.

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