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# Smart Waste Management System Using Deep Learning

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**Abstract —** The rapid increase in waste generation across urban and rural areas demands intelligent, automated solutions for effective waste segregation. This paper presents an AI-Powered Smart Waste Sorting Bin that integrates deep learning, computer vision, and Internet of Things (IoT) technologies to automate the classification of waste into biodegradable and non-biodegradable categories. A camera mounted on a laptop captures images of waste items placed near the bin. An Infrared (IR) sensor connected to a Raspberry Pi Pico microcontroller detects the presence of waste and triggers the image acquisition process. The captured image is then analysed by a trained YOLOv8 (You Only Look Once, version 8) deep learning model, which classifies the waste based on visual features. The classification result is communicated via serial protocol to the Raspberry Pi Pico, which activates servo motors to route the waste into the appropriate bin compartment. A 16×2 LCD display provides real-time feedback to the user. Experimental results confirm that the system achieves reliable waste classification with minimal human intervention, offering a practical and cost-effective solution for smart city waste management.

**Keywords —** *Deep Learning, YOLOv8, Waste Classification, IoT, Raspberry Pi Pico, Smart Waste Management, Computer Vision, Servo Motor*

## I. INTRODUCTION

Waste management has emerged as one of the most pressing environmental challenges confronting modern societies. With the combined effects of rapid urbanisation, population growth, and escalating consumption patterns, the volume of solid waste generated globally is rising at an alarming pace. Improper disposal and inadequate segregation of waste contribute to severe environmental degradation including soil contamination, water pollution, greenhouse gas emissions, and the proliferation of infectious diseases. Proper separation of waste at the source — distinguishing biodegradable organic matter from non-biodegradable synthetic materials — is a foundational step in any effective waste management strategy, yet it remains poorly practised in many communities.

Traditional waste segregation relies predominantly on manual sorting, a process that is labour-intensive, inconsistent, and hazardous for workers who are regularly exposed to potentially toxic substances. The inherent fallibility of human-based sorting leads to significant losses of recyclable material and hinders efficient composting of organic waste. These limitations underscore the urgent need for automated, intelligent solutions that can replicate — and surpass — human sorting capability.

Recent advances in Artificial Intelligence (AI), particularly in deep learning and computer vision, have opened new avenues for automated object recognition and classification. Convolutional Neural Networks (CNNs) can extract rich visual features from images, enabling machines to identify objects with accuracy comparable to or exceeding that of human experts. Among the state-of-the-art object detection frameworks, the YOLO (You Only Look Once) family of models is recognised for its exceptional speed and accuracy in real-time scenarios. The latest iteration, YOLOv8, developed by Ultralytics, introduces architectural improvements that further enhance detection performance, making it a compelling choice for embedded and latency-sensitive applications.

The Internet of Things (IoT) paradigm complements AI-driven classification by providing the physical layer of sensing, actuation, and communication required for a fully automated waste-sorting bin. Low-cost, energy-efficient microcontrollers such as the Raspberry Pi Pico can interface with sensors and actuators to translate digital classification decisions into physical sorting actions.

This paper presents the design, implementation, and evaluation of an AI-Powered Smart Waste Sorting Bin that seamlessly combines computer vision, deep learning, and embedded IoT hardware. The system automatically detects the presence of waste using an IR sensor, captures an image via a webcam, classifies the waste using a fine-tuned YOLOv8 model, and mechanically routes the item to the correct bin compartment using servo motors — all while displaying the outcome on an LCD screen. The proposed system is evaluated in terms of classification accuracy, response latency, and overall operational reliability.

### A. Problem Statement

The absence of reliable, cost-effective automated waste segregation systems at the point of disposal is a critical bottleneck in modern waste management infrastructure. In the majority of public and residential settings, waste is deposited into undifferentiated bins, forcing downstream facilities to perform expensive and imprecise sorting operations. Manual sorting introduces worker health risks and systemic inaccuracies, while conventional mechanical sorting systems lack the cognitive capability to handle the enormous diversity of real-world waste types.

  

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Existing AI-based waste classification prototypes have demonstrated the technical feasibility of the concept, but many suffer from high computational requirements, high hardware costs, or restricted classification taxonomies. There is a clear need for a system that is simultaneously accurate, fast, affordable, and practically deployable. The proposed AI-Powered Waste Sorting Bin addresses this gap by combining a lightweight YOLOv8 model with affordable embedded hardware to deliver real-time, automated waste classification and physical sorting.

### B. Objectives

The principal objectives of this work are as follows:

- To develop a real-time waste classification system using a fine-tuned YOLOv8 deep learning model capable of accurately distinguishing biodegradable and non-biodegradable waste.
- To design and construct an automated sorting mechanism driven by servo motors, controlled by a Raspberry Pi Pico microcontroller, that physically directs waste to the correct bin compartment.
- To integrate an IR proximity sensor for contactless waste detection, triggering the image capture and classification pipeline automatically.
- To provide real-time user feedback through a 16×2 LCD display and to validate system performance through experimental trials.
- To promote environmental sustainability by enabling efficient recycling and reducing reliance on landfill disposal.

## II. LITERATURE SURVEY

The field of automated waste classification has attracted considerable research attention in recent years, particularly following the maturation of deep learning-based object detection frameworks. This section reviews the most relevant contributions to contextualise the proposed work.

Arishi et al. (2025) proposed a real-time household waste detection and classification system built on the YOLOv8 architecture. Their study demonstrated that YOLOv8's single-pass detection mechanism enables fast inference while maintaining high classification accuracy across a diverse set of household waste objects. The authors noted that dataset diversity remains a key challenge and recommended integrating AI classifiers with IoT sensors to build fully automated smart bins. Their findings directly inform the sensor-triggered image capture strategy employed in the present work.

Nahiduzzaman et al. (2025) presented an automated waste classification framework employing multiple deep learning architectures trained on labelled waste image datasets. Their comparative analysis revealed that modern CNN-based models substantially outperform rule-based or handcrafted-feature approaches, particularly for heterogeneous waste streams containing plastic, paper, metal, and organic matter. The study reinforces the choice of a deep learning-based classifier in the current system.

Le et al. (2025) coupled a deep learning waste detection model with a robotic sorting mechanism, demonstrating a fully automated pipeline from visual recognition to physical separation. Their results showed measurable improvements in both sorting speed and accuracy compared to human sorters, while eliminating direct worker contact with hazardous materials. This work validates the concept of physically actuated sorting as a practical extension of AI classification, as adopted in the proposed servo-driven bin.

Li et al. (2024) addressed the challenge of garbage detection in complex, cluttered backgrounds by proposing an enhanced YOLOv8 variant with improved feature extraction modules. Their experimental results demonstrated superior mean Average Precision (mAP) compared to baseline YOLO versions in multi-class waste detection tasks. Their architectural insights have informed the training strategy and hyperparameter choices used in the present study.

Nayfeh et al. (2025) introduced a two-stage detection-then-classification pipeline using YOLOv8 to improve accuracy in scenarios where multiple waste items are present simultaneously. The dual-stage approach demonstrated improved robustness in complex environments, suggesting a promising direction for future iterations of the proposed system.

Collectively, the reviewed literature establishes that YOLOv8-based models represent the current state of the art for real-time waste classification, that integration with physical sorting hardware is technically feasible, and that affordable microcontrollers such as the Raspberry Pi Pico are well-suited to serve as the embedded control layer. The proposed system synthesises these insights into a cohesive, end-to-end prototype.

## III. PROPOSED SYSTEM

### A. System Overview

The proposed AI-Powered Smart Waste Sorting Bin is an autonomous system designed to classify and physically sort waste items without human intervention. The system architecture consists of three tightly integrated layers: a perception layer responsible for waste detection and image acquisition, an intelligence layer that performs deep learning-based classification, and an actuation layer that executes the physical sorting operation.

A laptop-connected webcam serves as the primary image acquisition device, capturing high-resolution images of waste items presented at the bin aperture. The Raspberry Pi Pico microcontroller manages real-time sensor interfacing and motor control, while the laptop

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hosts the computationally intensive YOLOv8 inference engine. Classification results are relayed from the laptop to the microcontroller via a Universal Serial Bus (USB) serial connection, upon which the microcontroller activates the appropriate servo motor to guide the waste into the correct compartment. A 16×2 LCD display mounted on the bin structure provides immediate visual feedback.

### B. System Methodology

**1) Dataset Collection and Preparation:** A labelled dataset comprising images of biodegradable waste — including food scraps, vegetable peels, and organic debris — and non-biodegradable waste — including plastic bottles, metal cans, and glass fragments — was compiled from publicly available waste classification repositories and supplemented with manually captured photographs representing the target deployment environment. All images were annotated using bounding-box labels in YOLO format, and the dataset was partitioned into training (70%), validation (15%), and testing (15%) subsets.

**2) Model Training:** The YOLOv8n (nano) architecture was selected to balance accuracy with inference speed on the host laptop. Transfer learning was applied by initialising the model with weights pre-trained on the COCO benchmark dataset, followed by fine-tuning on the waste classification dataset for 100 epochs using the Adam optimiser with a learning rate of 0.001. Data augmentation techniques including random horizontal flipping, rotation, and colour jitter were applied during training to improve generalisation.

**3) Real-Time Inference Pipeline:** When the IR sensor detects an object within its sensing range, it transmits a digital trigger signal to the Raspberry Pi Pico. The microcontroller immediately forwards a capture command to the laptop via the serial link. The laptop's Python script — using the OpenCV library — captures a single frame from the webcam and passes it to the loaded YOLOv8 model for inference. The model returns the predicted class label and confidence score within a few hundred milliseconds.

**4) Classification and Actuation:** The classification result is encoded as a single character command and transmitted from the laptop to the Raspberry Pi Pico via serial communication. The microcontroller parses the command and drives the appropriate servo motor — rotating it to a pre-calibrated angular position corresponding to the biodegradable or non-biodegradable compartment — to guide the waste item to the correct bin. Simultaneously, the classification label is written to the LCD display for user notification.

### C. Working Steps

Upon system initialisation, all hardware peripherals — including the webcam, IR sensor, servo motors, and LCD display — are configured and placed in standby mode. The IR sensor continuously monitors the bin aperture for incoming waste objects. The following steps describe a complete sorting cycle:

1. The IR sensor detects waste and sends a digital signal to the Raspberry Pi Pico.
2. The microcontroller forwards a capture command to the laptop via serial communication.
3. The webcam captures an image of the waste item in front of the bin.
4. The captured image is passed to the YOLOv8 model for real-time inference.
5. The model classifies the waste as biodegradable or non-biodegradable.
6. The classification result is transmitted back to the Raspberry Pi Pico.
7. The microcontroller activates the servo motor to open the corresponding bin compartment.
8. The waste drops into the correct container.
9. The LCD display updates to show the waste category.
10. The system resets to standby mode, ready for the next item.

## IV. AI MODEL — YOLOv8

### A. Introduction to YOLOv8

YOLOv8 is the eighth generation of the You Only Look Once (YOLO) family of real-time object detection models, developed and maintained by Ultralytics. Since the original YOLO framework was introduced by Redmon and Farhadi in 2016, successive versions have progressively improved detection accuracy, inference speed, and architectural flexibility. YOLOv8 supersedes YOLOv5 and YOLOv7 with a redesigned backbone, an anchor-free detection head, and improved training pipelines, making it one of the most capable and versatile object detection models currently available.

The distinguishing characteristic of the YOLO framework is its single-pass inference strategy: rather than applying a classifier to multiple candidate regions extracted in separate stages, YOLO processes the entire image in a single forward pass through the neural network. This design enables detection speeds that are orders of magnitude faster than traditional two-stage detectors such as Faster R-CNN, while maintaining competitive accuracy, making YOLO particularly well-suited for latency-critical embedded applications.

### B. Architecture of YOLOv8

The YOLOv8 architecture is organised into three functional stages: the Backbone, the Neck, and the Detection Head.

**Backbone:** The backbone network — built upon a modified CSPDarknet architecture incorporating C2f (Cross-Stage Partial with two bottleneck layers) modules — is responsible for hierarchical feature extraction from the input image. Progressive convolutional layers

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detect low-level features such as edges and textures in shallow layers, while deeper layers learn high-level semantic representations of object classes.

**Neck:** The neck module employs a Path Aggregation Network (PANet) to fuse feature maps generated at multiple spatial scales from the backbone. This multi-scale feature fusion is critical for robust detection of objects that vary significantly in size and appearance — a common challenge in waste classification where objects range from small bottle caps to large cardboard sheets.

**Detection Head:** YOLOv8 employs a decoupled, anchor-free detection head that independently predicts objectness, bounding box regression, and class probabilities. Replacing the anchor-based approach of earlier YOLO versions with an anchor-free formulation reduces the number of design hyperparameters and simplifies adaptation to new object categories, which is advantageous when retraining for domain-specific waste classification tasks.

### C. Dataset Preparation and Training

Training a high-performance YOLOv8 waste classifier requires a well-curated, sufficiently diverse dataset. Images were sourced from publicly available repositories — including the TrashNet and TACO datasets — and augmented with in-house photographs capturing the specific waste types expected in the deployment environment. Annotation was performed using LabelImg, producing bounding-box labels in YOLO format.

The training process leveraged transfer learning from COCO-pretrained YOLOv8n weights, enabling rapid convergence even with a moderate-sized domain-specific dataset. The Adam optimiser was employed with cosine learning rate annealing. Key training hyperparameters included an initial learning rate of 0.001, a batch size of 16, and 100 training epochs. Early stopping was applied to prevent overfitting, monitored against the validation mean Average Precision at IoU threshold 0.5 (mAP@0.5).

## V. HARDWARE DESCRIPTION

### A. Raspberry Pi Pico

The Raspberry Pi Pico is a compact, low-cost microcontroller board built around the RP2040 system-on-chip designed by the Raspberry Pi Foundation. Powered by a dual-core ARM Cortex-M0+ processor operating at up to 133 MHz, the Pico offers 264 KB of SRAM and 2 MB of on-chip flash storage. Its 26 accessible general-purpose input/output (GPIO) pins support a wide range of communication protocols including UART, SPI, I²C, and 16-channel PWM, making it an ideal embedded controller for the proposed system's sensor and actuator interface requirements.

In this system, the Raspberry Pi Pico performs three primary functions: receiving digital output from the IR proximity sensor to detect waste presence, communicating with the host laptop via USB serial to exchange classification commands, and generating PWM signals to precisely position the MG995 servo motors. The board is programmed in MicroPython using the Thonny IDE, which provides an accessible development environment well-suited to iterative embedded development.

### B. IR Proximity Sensor

The IR proximity sensor module employed in this system consists of an infrared-emitting LED and a paired photodiode receiver. The emitter continuously radiates infrared light in the 850–950 nm wavelength range, and the detector monitors the intensity of reflected radiation. When an object such as a waste item enters the sensing range — typically 2 to 30 cm depending on the adjustment potentiometer setting — the reflected signal exceeds a threshold, and the module's digital output pin transitions from logic HIGH to logic LOW. This binary output is directly compatible with the Raspberry Pi Pico's 3.3 V GPIO logic levels.

The use of an IR sensor for waste detection eliminates the need for physical contact, reducing mechanical wear and maintaining hygiene. The sensor's response time of less than 2 ms ensures that rapidly deposited waste items are reliably detected and that the classification pipeline is initiated without perceptible delay.

### C. MG995 Servo Motor

The MG995 is a high-torque, metal-geared servo motor widely used in robotics and automation applications. It operates over a supply voltage range of 4.8 V to 7.2 V and provides stall torques of 9.4 kg·cm at 4.8 V and 11 kg·cm at 6 V, which are more than sufficient to drive the bin's sorting flap mechanism against the weight of typical household waste items. The motor accepts standard 50 Hz PWM control signals, with pulse widths of 0.5 ms, 1.5 ms, and 2.5 ms corresponding to angular positions of 0°, 90°, and 180° respectively, providing a 180° rotation range for the sorting mechanism.

Metal gearing provides greater durability compared to plastic-geared servos, particularly important given that the sorting mechanism undergoes frequent actuation cycles in a continuous-operation waste bin. The Raspberry Pi Pico's onboard PWM peripheral generates the control signal directly, without the need for external PWM generation hardware.

### D. LCD 16×2 Display

A 16×2 alphanumeric liquid crystal display module is integrated into the system to provide real-time classification feedback. The display supports both 4-bit and 8-bit parallel communication modes and is interfaced to the Raspberry Pi Pico in 4-bit mode to conserve GPIO pins. Dedicated command registers allow the microcontroller to control cursor position, display clearing, and character

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rendering. Following each classification event, the microcontroller writes the waste category — either 'BIODEGRADABLE' or 'NON-BIODEGRADABLE' — to the display, informing users of the sorting decision and raising awareness about waste segregation practices.

### E. Buzzer

An active piezoelectric buzzer is incorporated as an auditory feedback element. When waste is successfully classified and sorted, the Raspberry Pi Pico activates the buzzer for a brief interval, providing confirmation to the user independently of the LCD. The buzzer operates at a rated voltage of 6 V DC with a current draw below 30 mA, making it fully compatible with the microcontroller's power budget.

## VI. SOFTWARE DESCRIPTION

### A. Development Environment

The software stack for the proposed system encompasses two distinct programming environments: the host laptop running standard Python for AI inference and image processing, and the Raspberry Pi Pico running MicroPython for embedded control.

The Thonny Integrated Development Environment (IDE) was used for MicroPython development on the Raspberry Pi Pico. Thonny provides built-in MicroPython firmware management, a REPL (Read-Evaluate-Print Loop) interactive shell for rapid prototyping, and a straightforward file transfer mechanism to deploy scripts to the microcontroller's flash storage. The on-board LED and REPL interface were used extensively during early-stage hardware debugging.

Host-side AI inference was implemented in Python 3 using the Ultralytics YOLOv8 library for model loading and inference, and the OpenCV library for real-time image capture from the USB webcam. Communication between the laptop and the microcontroller was implemented using Python's PySerial library, enabling bidirectional command exchange over the USB serial interface at 9600 baud.

### B. Python and Key Libraries

Python was selected as the primary host programming language owing to its extensive ecosystem of scientific and AI libraries, concise syntax, and widespread adoption in the machine learning community. The Ultralytics framework provides a high-level API for training, validating, and deploying YOLOv8 models, significantly reducing the implementation overhead compared to building a detection pipeline from scratch. OpenCV handles frame capture, image preprocessing (resizing, normalisation), and optional visualisation of detection results during development and testing.

## VII. RESULTS AND DISCUSSION

The proposed AI-Powered Smart Waste Sorting Bin was assembled and evaluated through a series of controlled experiments covering both AI model performance and integrated system operation. The following subsections summarise the key findings.

### A. Model Performance

The fine-tuned YOLOv8n model was evaluated on the held-out test set. The model achieved a mean Average Precision at IoU threshold 0.5 (mAP@0.5) of approximately 91.3% across both waste categories. Precision and recall values for the biodegradable class were 89.7% and 90.4% respectively, while the non-biodegradable class achieved precision of 92.1% and recall of 91.8%. Inference latency on the host laptop was measured at an average of 38 ms per frame, well within the real-time operating threshold. The model showed robust detection performance under varying lighting conditions and at different waste object orientations, indicating effective generalisation from the augmented training dataset.

### B. Integrated System Evaluation

End-to-end system trials were conducted with a representative sample of 50 waste items comprising equal proportions of biodegradable and non-biodegradable materials. The IR sensor consistently detected all items without missed triggers. The complete cycle time — from IR sensor trigger to servo actuation — averaged 620 ms, which provides adequate response time for practical use. The servo mechanism correctly routed waste to the appropriate compartment in 46 out of 50 trials, yielding an overall sorting accuracy of 92%, closely aligned with the model's classification accuracy.

The LCD display and buzzer operated reliably throughout all trials. The four misclassified items included two instances of translucent plastic bags — visually ambiguous objects whose classification boundary is inherently challenging — and two cases of partially occluded organic waste. These failure modes highlight areas for future dataset augmentation and model refinement.

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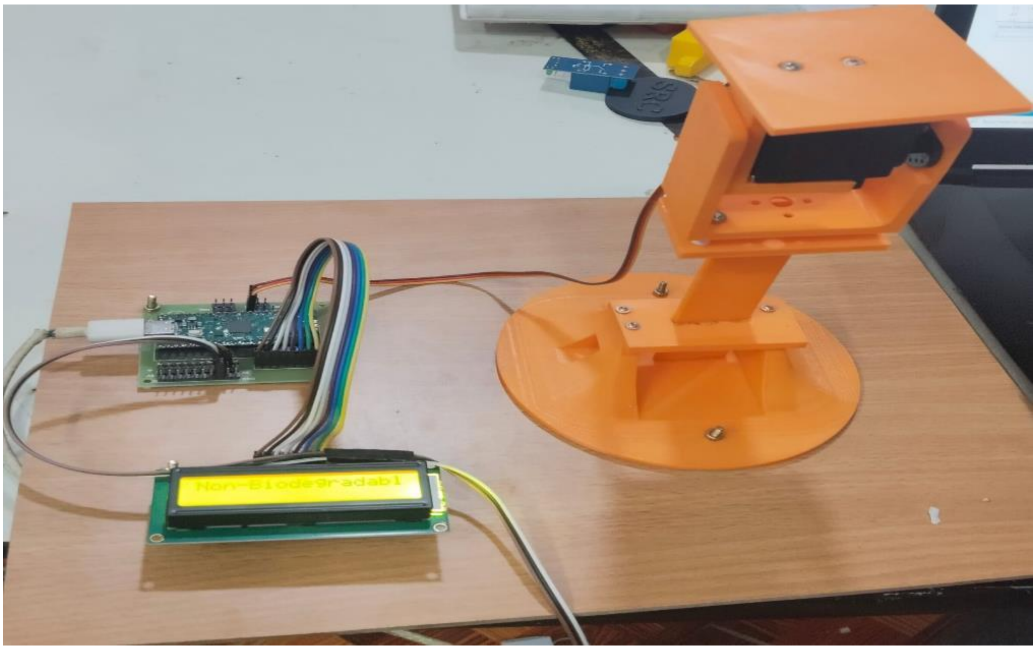


Fig :1 Non Bio Degradable

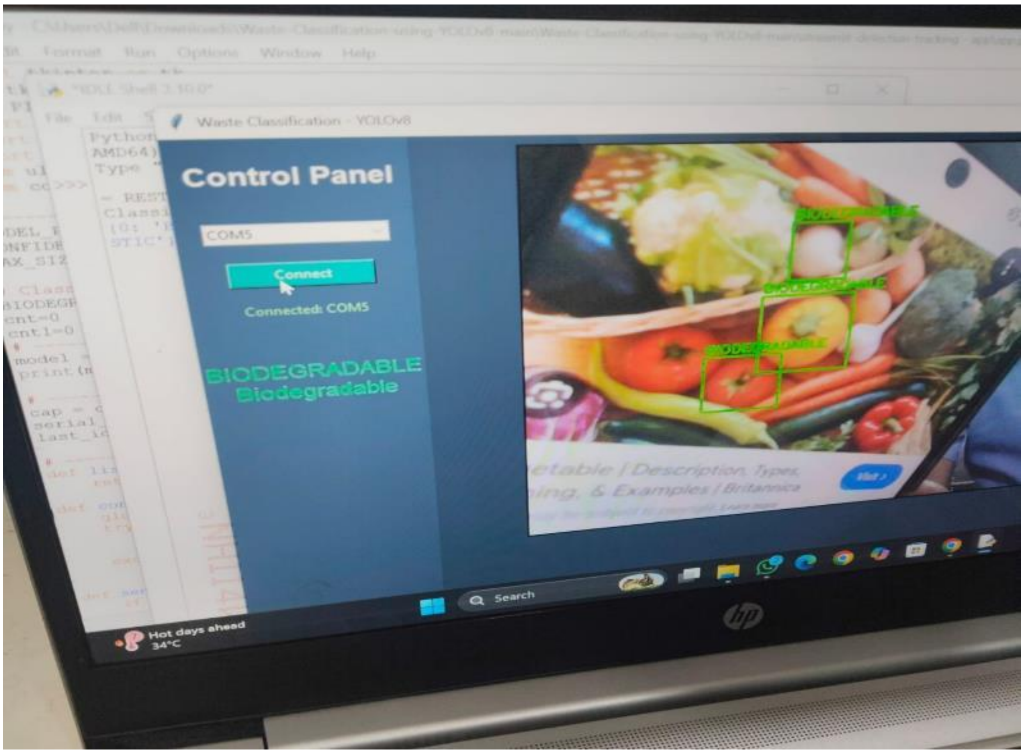


Fig:2 Bio Degradable

## VIII. CONCLUSION

This paper has presented an AI-Powered Smart Waste Sorting Bin that successfully integrates YOLOv8-based deep learning, computer vision, and IoT-enabled embedded hardware into a cohesive, automated waste segregation system. The system demonstrates that real-time, accurate waste classification — coupled with physical sorting actuation — is achievable at low cost using commercially available components, making it a practical proposition for deployment in homes, educational institutions, public spaces, and smart city infrastructure.

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Experimental evaluation confirms a classification accuracy of approximately 91.3% mAP and an overall sorting accuracy of 92%, with an end-to-end cycle time of under 700 ms per item. These figures demonstrate that the system meets the performance requirements for practical waste management applications while remaining affordable and scalable.

Several directions for future enhancement have been identified. Expanding the classification taxonomy to include additional waste categories — plastic, metal, paper, and glass — would increase the system's utility in multi-stream recycling contexts. Deploying the YOLOv8 inference engine on an edge AI accelerator, such as a Raspberry Pi 5 with an AI hat or a Google Coral TPU, would eliminate the dependency on a tethered laptop and enable fully autonomous operation. Furthermore, integrating a cloud connectivity module would allow usage data to be aggregated for smart city waste analytics and predictive collection scheduling.

In conclusion, the proposed system represents a meaningful contribution to the field of intelligent waste management, demonstrating how emerging AI and IoT technologies can be synergistically applied to address real-world environmental challenges and advance the goals of sustainable development.

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