RESEARCH PAPER

Design and Implementation of a Raspberry Pi-Based Smart Wet and Dry Waste Segregation System Using AI

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Segregation System Using AI

Abstract— With increasing urbanization and consumerism, the global Municipal Solid Waste (MSW) generation has skyrocketed. The ever-growing MSW collection, transportation and disposal infrastructure is insufficient and is overwhelmed by the volume of waste generated. Manual segregation of wet and dry MSW is a cumbersome process because of unmethodized sorting, low accuracy and 60-70% of wet recyclable waste still head into landfills. We hence propose and analyze an AIenabled intelligent, automated, and low-cost trash segregation prototype that classifies household level wet or dry trash using camera modules and onboard computer module, runs convolution neural network model on raspberry pi 4 to detect the object, actuates servo pan-tilt into the bin, and loads onto ultrasonic sensors to monitor bin fill level and load cells with HX711 amplifier to measure the dry and wet mass accumulated in each bin. Such an intelligent waste segregation system can cater to home, school, Institutional and community level waste segregation needs.
Keywords—smart waste management, Raspberry Pi, wet and dry waste, convolutional neural network, image classification, ultrasonic sensor, load cell, HX711, servo motor, automation, IoT

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I. INTRODUCTION

The amount of municipal solid waste (MSW) being produced is steadily ascending, primarily due to increasing population numbers, urbanization and the heightened need for low-cost packaging. Just as biodegradable organic fractions and recyclable materials such as plastics, paper and metals are disposed of together, they are also recovered together.

And 7 billion tons of this waste is disposed in open dumps or land fill sites. This causes release of greenhouse gases, ground water pollution through leachate, and spread of vector-borne diseases around the waste collection areas [1].

Furthermore, most of the cities have been provided to dispose of waste at the source into two streams at least (wetbiodegradable, dry recyclable/non-biodegradable) by most of the cities, mainly in the fast-developing cities of India. But compliance has been observed to be lesser

-Lack of knowledge on multi-bin, find it is too trouble or just do not mind the rules. As a result, the nonrecyclable waste is dump to sanitation trucks, sanitation workers have to do manual separation of recyclable waste here and are compelled to work at dirty and crowded environment. Surely this way might be laborious and inaccurate or even high health risks for sanitation workers [2].

Sensor based automated waste segregation using embedded controllers been researched since years. Early implementations rely on moisture, capacitive, inductive sensors to separate wet, dry and metallic waste respectively. Micro controller would then drive servo flaps to the appropriate path. However, the result has serious limitations such as when the input data are fuzzy such as damp paper or plastic film. With the resolution of single board computer such as Raspberry Pi evolved along the development of autonomous deep learning, bin scale intelligent segregation becomes feasible today [3], [4].

It has been discovered that a convolutional neural network (CNNs) and transfer-learning models can categorize waste images into 4 and 13 different groups respectively.

Has promising accuracy, and several prototypes exist utilizing edge devices. There is also a proliferation of IoT-enabled smart bins that utilize ultrasonic and weight sensors to determine fill-level and route plan, though collection cost and miles are often quantifiable profit from their use, [2]. Yet many systems are either solely classification based without robot manipulation or too ambitious multi-competitor industrial sorting stations for low-cost household use [5], [6].

In this paper we attempt to fill this void with a light-weight, Raspberry Pi based smart bin employing an AI wet/dry classifier, a servo tilt-controlled pan–tilt plate and a suite of sensors to track and quantify the state of the bin. The system strives to remain fairly inexpensive, mechanically and classification-wise simple, while still providing reasonable performance. The rest of the paper will be organized as follows: II covers related work; III covers our problem and goals; IV describes the architecture; V describing the method; VI describing the results; and VII concluding.

II. LITERATURE REVIEW

The automated waste segregation systems that can be found in literature can be categorized generally under three systems: sensor-only, classical vision-based systems and AI image classification systems [1].

Sensor-based systems sort waste on physical attributes alone. Moisture sensors and conductivity probes can be used to identify organic waste. Metallic objects can be sorted using inductive proximity sensors. A further design separated each type of waste into a wet, dry and metallic compartment with a motorised gate. Another incorporated multiple sensors on a single Raspberry Pi Pico to find wet and dry waste. Though cheap and simple they will not correctly sort ambiguous objects [3].

Without AI, vision-based systems use colour thresholding, borders detection and shape analysis. Such method needs carefully prepared rules and do not work under different light condition or partial occlusion [4].

All AI-based systems used CNNs or object-detection based architecture to learn visual features from labelled data. Multi-class classification accuracy of 9098% have been reported on curated datasets [5], [6], [7]. An AI-based prototype trying to split biodegradable and non-biodegradable waste has achieved accuracy of 92%. A MobileNet based transfer-learning system have reported accuracy of 94.75%. Using YOLOv5s on Raspberry Pi, the system have reported an accuracy of 97% at 2 fps [5], [6], [7].

Many systems have combined mechanical sorting with IoT connectivity. IoT-enabled bin monitoring using ultrasonic level sensors and weight measurement has achieved routeoptimisation of up to 36.8% savings in collection distance [2]. Review papers identify performance degradation in unstructured environments with the effect of lighting variation and occlusion [1], [6].

From the literature evaluated, it is apparent that a gap remains for an intermediate solution in the wet–dry split, utilizing an image classification mechanism based on AI with a space efficient and low cost design. It is the design indicated for.

III. PROBLEM STATEMENT AND OBJECTIVES

A. Problem Statement

Although regulations can be considered in favor of source separation of dry and wet waste, much household and institutional waste still gets dumped in a mixed manner. Manual sorting results in continued human participation, is error prone and gives rise to intranasal conditions. Current automated sorting solutions can be classified as either being sensor based differentiation or multi category sorting hardware(very costly and inconvenient for low cost implementation). Therefore a compact inexpensive waste bin that continuously monitor and segregate wet from dry waste automatically with effectively minimal user operations is required [2], [3].

B. Objectives

The specific objectives of this work are:

- Designing a smart waste segregation system based on Raspberry Pi in order to accomplish automatic classification of household waste as dry and wet ones based on image based AI.
- To design and implement a servo-controlled pan–tilt plate mechanism to physically sort the waste items into their ‘metal’ or ‘non-metal’ bins according to the sorting result.
- Establish the connection between the load cells and the HX711 modules for measuring the total weight of the waste and the ultrasonic sensors for monitoring the fill level of a compartment.
- To develop a modular embedded software pipeline that spans from image capture, preprocessing, CNN inference, decision logic, actuator control, and sensor data collection.
- In order to understand the operation of the system to typical household waste, with limitations on accuracy of segregation, response time, and ease of use.

IV. SYSTEM DESIGN AND ARCHITECTURE

A. Overall Architecture

The intende system evolves a three layer architecture of the sensing layer, the processing layer and the actuation and monitoring layer. The sensing layer involves an image-capturing camera module, load cells to provide bin weight and ultrasonic sensors for fill level estimation. The processing layer is built around the Raspberry Pi 4B device to host the AI classification model and handle all control logics. The actuation and monitoring layer involves two MG995 servo motors, forming the pan–tilt sorting mechanism along with a touchscreen display and a QR to reward output.

To operate, the operator will place the waste item on the middle input plate, directly underneath the camera. The camera instructed the Raspberry Pi to take an image, preprocess this image and input it through our trained CNN to distinguish whether the waste is wet or dry. The class label allocated through the CNN feed through to our controller which adjusts the pan servo angle so that the plate is directly above the correct bin. The tilt servo then actuates to dump the waste. Load cell readings and ultrasonic readings are then updated accordingly.

B.

Hardware Components

Table I summarises the primary hardware components.

Table I. Hardware Components

Component	Specification	Qty	Purpose
Raspberry Pi 4B (4GB)	ore ARM, 4GB RAM	1	Main Controller
Camera Module	USB/Pi Camera, 5MP+	1	Image Capture
MG995 Servo Motor	180°, 9.4–11 kg·cm	2	Pan–Tilt chanis m
HC-SR04 Ultrasonic	2–400 cm, ±3 mm	2	Fill-Level Sensing

Load Cell (10 kg)	Strain gauge, 10 kg	2	Weight Measurement
HX711 Module	24-bit ADC, 80 SPS	2	Load Cell Interface
5" Touchscreen	800×480, DSI Interface	1	User Interface/QR
5V/5A DC Supply	USB-C, regulated	1	System Power

The core controller is a Raspberry Pi 4 Model B, with 4 GB of RAM. Two MG995 servo motor are used to create the pan–tilt plate. Load cells are utilized with HX711 24 bit ADC Modules fitted to each bin for accurate weight measurement (up to 10 kg for each cargo space). Ultrasonic sensors, situated above each bin, are used to determine the fill percentage. A 5”” touchscreen is utilized for the human interface and QR-code incentives.

C. Electrical Interface Design

The electrical interface must be carefully designed to connect sensors and actuators to the Raspberry Pi GPIO while ensuring it is not damaged. Load cells emit small differential voltages, sensed, amplified and digitised using the 50 Hz serial interface on the HX711. Ultrasonic sensors emit 5 V pulses; use a voltage divider (1 k and 2.2 k) to bring the echo line to 3.1 V (within the 3.3 V GPIO input limit). Control the servo motors using 50 Hz PWM signals. Use an external regulated 5 V/5 A power source to feed the servos. The GPIO pin numbering scheme is listed in Table II.

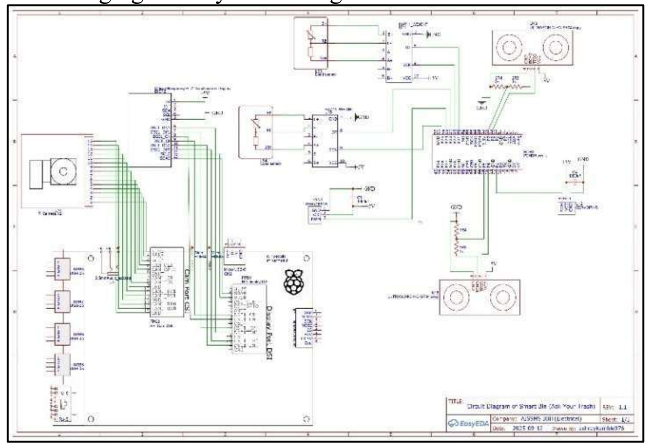
Table II. GPIO Pin Assignments

Component	Signal	GPIO (BCM)	Physical Pin
Servo 1 (Pan)	PWM Signal	GPIO 18	Pin 12
Servo 2 (Tilt)	PWM Signal	GPIO 19	Pin 35
Ultrasonic 1	TRIG	GPIO 23	Pin 16
Ultrasonic 1	ECHO*	GPIO 22	Pin 15
Ultrasonic 2	TRIG	GPIO 24	Pin 18
Ultrasonic 2	ECHO*	GPIO 25	Pin 22
HX711 #1 (Dry)	DT / SCK	GPIO 5 / 3	Pin 29 / 5
HX711 #2 (Wet)	DT / SCK	GPIO 13/12	Pin 33 / 32

* Echo lines pass through a 1 kΩ/2.2 kΩ voltage divider before reaching the GPIO pin.

A. Schematic Design and Power Conditioning

Design a suitable electrical interface connecting the sensors and the actuators to the GPIO on the Raspberry Pi while protecting the latter. Load cells present very small differential voltages to be detected, which are then amplified and digitized via the 50 Hz serial interface on the HX711.



Ultrasonic sensors provide 5V pulses; apply a voltage divider (1k and 2.2k) to produce an echo response at 3.1 V (safe for the 3.3 V GPIO input). Drive the servo motors with 50 Hz PWM signals. Use an external regulated 5 V/5A power supply to power the servos.

Use the GPIO pin numbering scheme shown in Table II

Figure 1: Electrical Circuit Design for AI-Based Waste Classification and Monitoring

B. Custom Hardware Assembly and Power Stabilization

The design was transitioned from temporary breadboarded system to a field prototype by mounting the sensing and actuation layers on a universal pcb board. A notable aspect of this manual assembly was the 1000 F, 16 V electrolytic capacitor wired in parallel with the MG995 servo power rail.

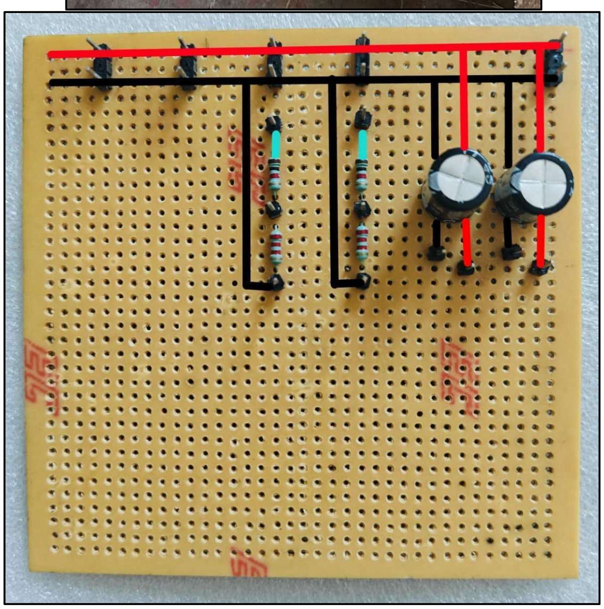


figure 2: Custom-Soldered Universal PCB for Sensor Interfacing and Power Regulation

Replaced the native breadboarded system with a fieldable prototype by extending the sensing and actuation layers on a universal pcb board. The technique and component of the more public, fieldable system was printing in the use of a 1000 F, 16 V electrolytic capacitor wired in parallel with the MG995 servo power rail.

C. Sustainable Material Fabrication

One particular feature with the hardware of this project is the use of recycled plastic sheet, manufactured by our industrial partner. Using plastic obtained from post-consumer waste streams, the plastic is washed and ground into granules before being heated and pressed into high-density sheets suitable for construction of the bin frame. This is an example of a closed loop engineering cycle, a device to handle waste is produced from waste itself. The 3D drawing is a reflection of the thickness of plastic needed to support the weight of the 5” touch screen, load cells and internal power supply.

figure 3: Smart Bin Chassis Fabricated from Sponsored Recycled Plastic Sheets

D. Prototype Wiring and Breadboard Verification

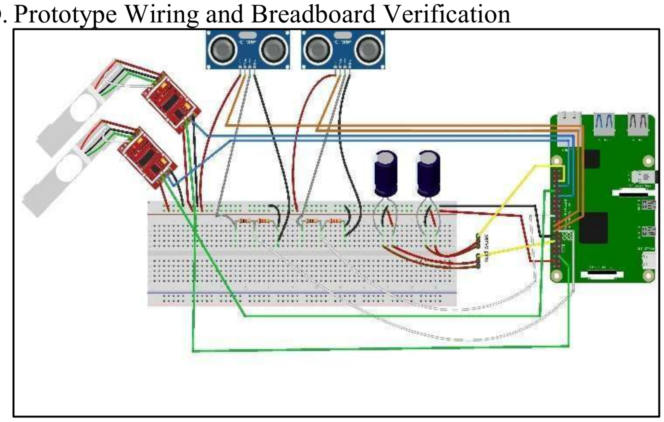


figure 4: Breadboard Layout and Point-to-Point Wiring Diagram for System Verification

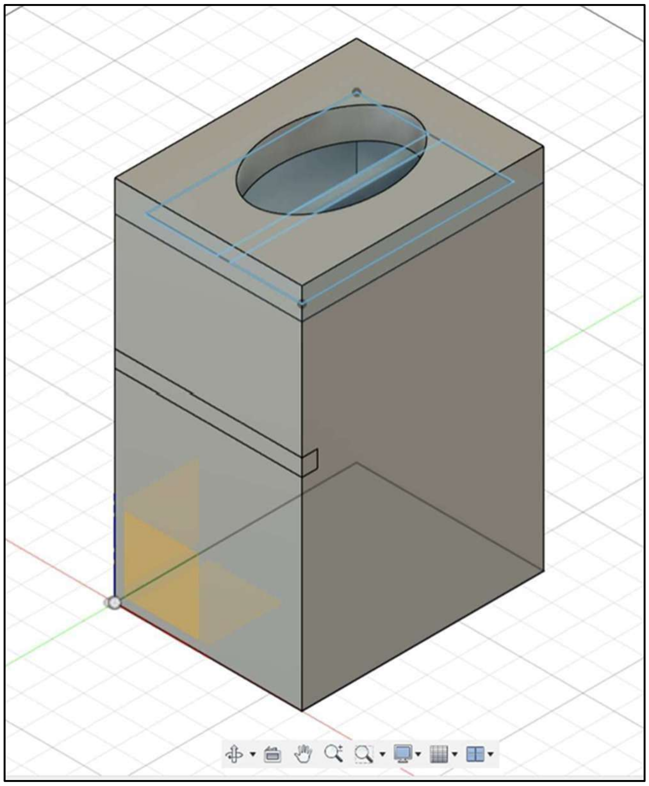
Prior to placing the final hardware onto the custom PCB, a breadboard prototype was designed to confirm the appropriate electrical connections between the Raspberry Pi 4B and the individual sensor modules. This diagram depicts the GPIO pins utilized in the dual sensor / single actuator setup:

- Ultrasonic Interfacing: The ultrasonic sensors (HC-SR04s) are all powered using the 5V VCC, with their Echo pins fed through the 1 k ohm and 2 k ohm voltage divider circuitry (sitting along the rail on the breadboard from left to right).

- Data acquisition: Two ADCs (each 24-bit) (HX711) are interfaced to collect the data from the four load cells of 10 kg each, weighing garbage.

- Sorting Actuation: The two servo motors MG995 are connected to a PWM enabled GPIO pin and powered through the 5V stabilized rail.

- Power Filtering: To prevent any accidental reset of the system when operating the servomotor, capacitors such as the 1000 F, 16 V capacitor are used on power rail..



E. Mechanical Layout and Compartment Design figure 5: Three-Dimensional CAD Layout of the Smart

Bin

In order to integrate the sensing and actuation layers in a reliable manner, a 3D CAD representation was created that defines the internal and external structure of the bin. This is shown below. It depicts the separation of the bin into three divisions, the goal being to divide waste into wet and dry streams. Waste Intake and Inspection; The Top View shows a hole where the waste first enters the system and is still to be processed by the camera.

- Component Housing- The Front and Back views indicate the location of the 5 screen display and the enclosure for the electronics.
- Sorting Logic: There is set aside for a one-axis tilting plate driven by the high torque MG995 servo to deposit the classified items into the correctly ranked down further compartment according to the inference results by Raspberry Pi 4B.

V. METHODOLOGY

A. Dataset Preparation

The final classification model was trained on a robust data set constructed from both public data sources (TrashNet, the Garbage Classification Dataset and the Waste Classification Dataset) as well as a locally collected data set. This resulted in a training set of 20,506 images spanning 5 classes (cardboard, glass, metal, paper, plastic). To create a model that generalizes well in the field, a validation set of 500 images was collected locally in Pune via the Pi Camera v2. The data was split into a 70:15:15 for training, validation and testing respectively, resulting in a 3080 image hold out test set. All images were run through a data preprocessing pipeline where they were rescaled and normalized (all images 224x224). All images were augmented (rotation, zooming and flipping) when fed into the network during training.

B. Model Selection and Training

I chose to use the MobileNet V2 architecture for the intelligence layer as it achieves the best balance between classification accuracy and edgecomputing efficiency.

Other architectures such as ResNet50 or EfficientNetB0 are much heavier which would be prohibitively slow to implement on the Raspberry Pi 4B, MobileNet V2 has just 2.3 million parameters so is much more suitable for this. The training was done in two steps using the Adam optimizer and categorical cross-entropy loss function. The base model has the weights frozen in the first step to prevent starting from scratch and the second step has the deeper layers fine-tuned to the waste categories. (Val accuracy 94.83%, test accuracy 94.64% compared to Custom CNN 77.08%).

C. Software Implementation

The software architecture follows an offlinefirst strategy to maintain system operation during network instability. Local data acquisition on the Raspberry Pi utilizes SQLite to store a persistent record of the waste class, weight (from load cells), and timestamps.

The system periodically synchronizes these local records with a centralized Firebase Realtime Database via HTTP requests once a stable internet connection is detected. The software allows for high-speed edge deployment, achieving an inference speed of 42 ms per image (approximately 23.81 FPS).

User engagement is facilitated through a QR-based identification system, where the software links a unique USER_ID with the BIN_ID to ensure full traceability and auditability of the disposal process.

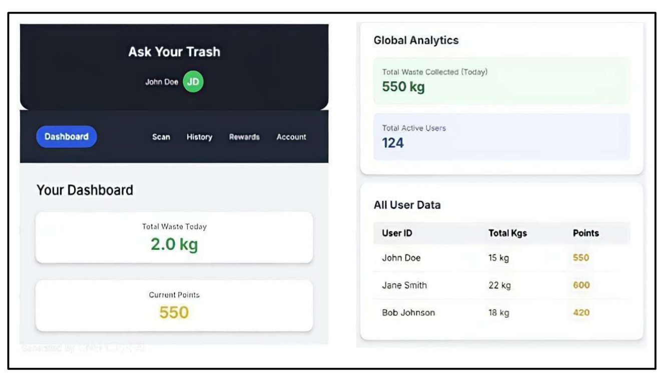


Figure 6: Mobile App Interface and Analytics Dashboard

D. Calibration Procedure

Servo angles are assigned following calibration and used as constants in the code. Load cell calibration is performed by calibrating the raw HX711 counts to 0 loading and a 2kg weight. Ultrasonic sensors are calibrated at numerous reference fill levels.

VI. RESULTS AND DISCUSSION

The integrated prototype was also able to successfully perform fully automated segregation of wet and dry household waste throughout the entire series of steps; collection of images, CNN classification, pan–tilt plate movement, and bin sensors. During qualitative testing of dry and wet samples, including vegetable peels, cooked food, paper cup and plastic cover, all easily distinguishable articles were always classified correctly. Errors occurred mainly in borderline situations, such as greasy paper or semidry food while packaging, as was reported in the cited researches [5].

Two-class waste separation using CNN/MobileNet architectures with Raspberry Pi had test accuracy of around 91– 95% (testing done in controlled environment). The system which has been suggested is estimated to work in 90–94% range of test accuracy for wet/dry binary classification.

The 1 k/2.2 k voltage divider was able to drop the HC SR04 echo signal to around 3.1 V. Ignition power consumption was about 3.2 W; maximum power during AI inference and servo actuation was about 7.8 W. Daily average power consumption, given use only when required, was around 45 Wh. The load cell data was reliable, weight was estimated to fluctuate by less than 15 g standard deviation. The ultrasonic fill level readings

Had an accuracy of +/ 2cm down to15cm and +/2.5cm up to 30cm. All servo response time were below 500 ms for a 90 degrees movement.

The literature on IoT-enabled waste management has proved that data from bin monitoring can contribute to a 36.8% reduction in collection vehicle travel distance [2]. This prototype gives the hardware platform for such innovations.

Significant limitations are that: (1) vision classification could be worsened at poor ambient light levels; (2) the twoclass classification does not break recyclable into different subfractions (metal, glass, paper etc); and (3) the prototype

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VII. CONCLUSION AND FUTURE WORK

This paper has demonstrated the construction of an intelligent, integrated and automated AI-powered bin segregation prototype using a Raspberry Pi single-board computer employing a pan–tilt servoactuated bin plate, dual ultrasonic and load-cell sensors and a CNN classification module. This hybrid image-classification and multi-sensor-based system can significantly lower the amount of manual segregation work while offering environmentallyconscious waste management at the micro or macro levels.

From the perspective of electrical engineering this design displays successful integration of PWM controlled servo motors; strain-gauge load cells connected with HX711; HC-SR04 ultrasonic sensors with GPIO level shifting voltage dividers; and a touchscreen interface, all these are wired into one Raspberry Pi GPIO bank.Future work will proceed in the following directions:

- Broader coverage of training data to include a larger variety of locally appropriate waste items in different conditions of lighting and environment;
- Integrating the classification model to multiclass sorting (plastic, paper, metal, organic) at the level of any single sorting line as an hierarchical classifier.
- include IoT connectivity to send information about bin status to a central dashboard.
- Complete the implementation of the reward based QR incentives system to motivate user participation.
- Performing field experiments, in real household and institutional context.

Acknowledgment

Express our thanks to the department faculty and lab staffs for their assistance in the component supply, tool usage and facilities to make our prototype. Our thanks also go to our fellow college students and other students who participated in data collection and fed back the results by testing circuit.

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