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Development of a Solid Waste Collector Robot for Cleaning in Public Areas

Desarrollo de un robot recolector de residuos sólidos para limpieza en áreas públicas

Dick Díaz-Delgado[1] and Alexander Inga-Alva[2]

ABSTRACT

Solid waste management reduces pollution, protects public health, conserves ecosystems, and promotes recycling and circular economies in a sustainable manner. This study analyzes the pollution issues caused by inefficient solid waste management in urban areas, highlighting its negative impact on the environment. In this vein, the T5R-bot collection robot was developed, designed through 3D printing and implemented with an artificial vision model for object detection based on the single shot multibox detector (SSD) and the MobileNetV2 neural network architecture. This system allows for the autonomous identification and collection of up to 12 types of debris, achieving an accuracy of 98% and a mAP of 97.81%. The methodology included the mechanical design of the robot with a rocker-bogie mechanism, ultrasonic sensors for navigation, and a robotic arm with four degrees of freedom. The model was trained with a dataset collected from 2890 images, demonstrating high efficiency in detecting and collecting waste in contaminated environments in public areas. The results confirm the viability of the robot as a tool for improving solid waste management. In addition, the future integration of segregation and adaptive learning capabilities is proposed.

Keywords: IoT, robotics, waste management, deep learning, MobileNet

ABSTRACT

La gestión de desechos sólidos reduce la contaminación, protege la salud pública, conserva los ecosistemas y fomenta el reciclaje y las economías circulares de manera sostenible. Este estudio analiza la problemática de la contaminación causada por la gestión ineficiente de desechos sólidos en áreas urbanas, destacando su impacto negativo en el medio ambiente. En este orden de ideas, se desarrolló el robot recolector T5R-bot, diseñado mediante impresión 3D e implementado con un modelo de visión artificial para la detección de objetos basado en el *single shot multibox detector* (SSD) y la arquitectura de red neuronal MobileNetV2. Este sistema permite la identificación y recolección autónoma de hasta 12 tipos de residuos, alcanzando una precisión del 98 % y un mAP de 97.81 %. La metodología incluyó el diseño mecánico del robot con un mecanismo *rocker-bogie*, sensores ultrasónicos para navegación y un brazo robótico con cuatro grados de libertad. El modelo fue entrenado con un conjunto de datos recolectado a partir de 2890 imágenes, demostrando gran eficiencia en la detección y recolección de residuos en ambientes contaminados de áreas públicas. Los resultados confirman la viabilidad del robot como una herramienta para mejorar la gestión de residuos sólidos. Además, se propone la integración futura de capacidades de segregación y aprendizaje adaptativo.

Palabras clave: IoT, robótica, gestión de residuos, aprendizaje profundo, MobileNet

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Introduction

Living sustainably, reducing the carbon footprint, and building a better planet for all are steps that humankind must take immediately. Today, carbon emissions into the environment are primarily generated by 1% of the world's population (wealthy individuals), wo are the main contributors, in contrast to the world's poorest 50% [1]. Therefore, measures must be taken to reduce the overall consumption, such as using cleaner vehicles and adopting healthier diets, which could the lower environmental impact by 40-70% as of 2050, especially among the upper class. This is particularly important since, out of the 300 million tons of plastic produced worldwide, less than 70% is recycled [2]. Specifically, 79% ends up in the environment, 9% is recycled, and 12% is incinerated. Much of the solid waste is carried by rainwater through drains and sewers, which usually flow into larger rivers that end up in the seas [3]. This waste clogs sewers and ditches, causing floods that damage both homes and crops, contaminating them while endangering living beings and people's health.

German research confirms that 90% of the world's terrestrial plastic ends up in the sea, originating in the basins of ten large rivers, eight in Asia and two in Africa [4]. In the subtropical vortex of the North Pacific, American oceanographer Captain Charles Moore discovered an artificial island, which he described as a floating waste dump. There, he observed bottles, wrappers, containers, bags, and diapers, among other items, estimating that, by 2050, there could be more plastic than fish in the sea [5, 6]. The Caribbean is the world's second most polluted sea in terms of plastics and microplastics, as half of the urban

[1]Computer engineer, Universidad César Vallejo, Tarapoto, Peru. MSc in Computer Engineering with a mention in Strategic Management, Universidad Internacional Iberoamericana de México, Campeche, México. Affiliation: Professor, Universidad César Vallejo, Tarapoto, Peru. E-mail: ddiazde@ucv.edu.pe

[2]Geographic engineer, Universidad Nacional Mayor de San Marcos, Lima, Peru. MSc in Software Engineering with a mention in Strategic Management, Communications, and Technology, Universidad Nacional Mayor de San Marcos, Lima, Peru. Affiliation: Professor, Universidad Nacional Mayor de San Marcos, Lima, Peru. E-mail: alexander.inga@unmsm.edu.pe

waste in this region ends up in open landfills, and 85% of its wastewater is discharged without treatment into the sea [7], causing harmful effects and health risks [8].

Urban solid waste management is an urgent global problem that is exacerbated by unregulated population growth. In Peru, despite the General Law on Solid Waste, enacted more than 15 years ago, the situation remains critical. 75% of the population lives in cities, generating 1-1.5 kg of waste per person on a daily basis, which has increased total waste production from 13 000 to 18 000 tons per day over the last decade. This has resulted in littering and pollution in urban areas and bodies of water. Addressing this issue requires a long-term public policy that integrates standards, incentives, innovative projects, technological solutions, decentralized technical assistance, and educational programs [9]. Municipalities are responsible for providing solid waste collection services to approximately 91.21% of the urban population across Peru's 1867 districts. However, most lack an integrated management system with clear and effective implementation processes [10].

The expansion of deep learning algorithms in computer vision applications has led to state-of-the-art results in object detection systems through the automatic extraction of complex features from input images by means of self-learning. This allows computational models to process and interpret data at multiple levels of abstraction, mimicking the human brain's ability to distinguish multi-modal information [11].

Machine learning (ML) and deep learning (DL) algorithms have also been widely adopted in mobile cleaning robots for tasks such as stain and waste detection and route planning. Additionally, 3D printing technology has facilitated the design and production of innovative components, contributing to the development of higher-quality products. In this context, our work focuses on developing an advanced object detection model by introducing improvements to the conventional MobileNetV2 architecture.

The main contributions of this study include an innovative algorithm capable of automatically identifying debris using advanced computer vision techniques, a model that achieves rapid convergence to reduce training times while enhancing detection accuracy through improved nonlinear feature extraction, the validation of a solid waste collection framework tested with an internally developed cleaning robot, and the proposal for a suspension system based on the rocker-bogie mechanism to enable safe traversal over obstacles exceeding twice the diameter of the wheels.

This document is structured as follows. First, the state of the art on object detection and solid waste collection methods is analyzed. The next section describes the methodology of the proposed approach. Then, the experimental results obtained are presented and discussed. Finally, the conclusions section summarizes the findings of this article.

Related works

Solid waste collection using mobile robots is an emerging field that addresses challenges stemming from rapid economic growth and population increase [12, 13]. While this research area has primarily focused on developing countries, our analysis included studies from developed nations for a more comprehensive perspective. Table I lists the countries that have conducted research specifically on mobile robots optimized for solid waste detection and collection using ML and DL techniques.

Table I. Studies on mobile robots for waste collection by country

Item	Country	Studies
1	India	4
2	United States	3
3	Indonesia	2
4	Pakistan	1
5	Italy	1
6	Australia	1
7	Singapore	1
8	Malaysia	1
9	China	1
10	Germany	1
11	Bangladesh	1
12	United Kingdom	1
13	Romania	1
14	Cuba	1
15	Mexico	1
16	Brazil	1

Source: Authors

In Australia, research on waste management found that Internet of Things (IoT) and sensor network-based approaches are unsustainable for smart cities, proposing the use of swarm intelligence and the Internet of Vehicles (IoV) to enhance energy efficiency in data collection and waste traffic management [12]. In Italy, Industry 4.0 and IoT devices have been proposed to reduce operating costs and environmental impact by monitoring real-time waste levels in containers. Additionally, CO_2 emissions have been tracked from collection to waste separation using metaheuristic algorithms [13].

In Pakistan, a smart system was designed to manage waste in streams and sewers using a sensor kit that sends data to the cloud when thresholds are exceeded, notifying collectors in real time to enhance operational efficiency, quality of life, and investment opportunities [14]. In Singapore, an innovative framework addressed the challenges of cleaning complex public spaces like hospitals and shopping malls by employing RGB-D sensors, CCTV, DL algorithms, and route planning to target only dirty areas. The results demonstrated a 90% accuracy, with a 15% reduction in navigation times and 10% lower battery consumption compared to conventional methods [15].

In Malaysia, an autonomous river-cleaning robot was developed using an improved Yolo model, achieving 89% accuracy in identifying five types of trash under various conditions [11]. In Germany, a waste collection robot focused on human-robot interaction (HRI) was designed with a modified double-diamond frame, successfully implementing and testing hardware functions to meet ease-of-use requirements [16]. In China, a trash rescue system was constructed with autonomous navigation and debris detection powered by DL. The system, equipped with ROS, LiDAR, a robotic arm, and YoloV4, operates in real time at 45 FPS with 88% detection accuracy [17].

In India, an autonomous robotic arm was developed for solid waste segmentation using a customized LeNet model. This AI technique classified cardboard and plastic, achieving high accuracy in object capture and categorization. System performance was evaluated using the metrics presented in [18]. In Bangladesh, a sensor-controlled prototype was designed to detect metallic and non-metallic waste, monitor water levels in containers, and send real-time notifications displaying the current container status via a mobile app (or SMS when offline) [19]. In the UK, an automated recycling system integrated ML and IoT to sort and separate recyclable materials. In this approach, the devices installed in waste bins monitor real-time waste generation, process images to calculate waste rates, and provide suggestions to enhance recycling productivity [20].

The SIRAMAND project in Romania developed an autonomous mobile robot to collect solid urban waste (*e.g.*, bottles and cans) in parks and streets, which follows a programmable trajectory and detects, collects, and deposits waste in containers, with remote control available in case of failure. The robot achieved 100% efficiency in both laboratory and outdoor tests [21]. In India, researchers introduced a mobile robot based on transfer learning to identify and segregate electronic waste. With a 96% sorting accuracy, this robot reduces risks to unskilled labor, cuts costs by 20% over five years, and minimizes human intervention [22]. Another Indian project developed a rocker-bogie robot using YoloV4-tiny, a camera, an ultrasonic sensor, GPS, Raspberry Pi, and Arduino. YoloV4-tiny demonstrated similar accuracy to YoloV4, albeit with faster detection times and reliable performance on various terrains [23].

Researchers in Indonesia developed a robotic boat controlled via an Arduino micro-controller and a PS2 joystick connected to an Android smartphone. This system includes a relay to regulate electric current for the DC motor and a camera to display results. Communication between the joystick and Arduino was efficient at distances of up to 25 m without barriers and 15 m with barriers. The prototype is capable of removing small trash items such as bottle caps, gallon containers, and 200 g drinking glasses [24].

Researchers in Cuba developed an efficient, low-cost embedded system for controlling and managing an autonomous naval vessel. The system demonstrated proper planning and route compliance, with a margin of error of 2 mm at each checkpoint and smooth operations during starts, stops, and alarms [25]. In the US, efforts have focused on promoting ecological and environmental literacy. One initiative, the Smart Trash Junior Robot, is a mechatronic trash can equipped with vision to identify recyclable objects, which is designed to teach elementary school children about recycling [26]. Additionally, a water-cleaning robot was developed in the US, achieving a 90.6% sorting accuracy. The robot successfully performed aquatic navigation, gripper handling, color recognition, and waste sorting tasks [27].

In Indonesia, researchers integrated mobile and stationary robotic systems for waste collection, demonstrating efficiency in collecting egg and bottle waste with ultrasonic sensors and a navigation system [28]. In Mexico, a waste collection robot with a volume capacity of 100 to 180 cm^3 was developed for beaches. Using Bluetooth, an ATMEGA microcontroller, and ultrasound sensors, this robot collects three solid objects in seven minutes and operates autonomously for 60 minutes [29]. In the US, soft robotics was applied to recycling through an electric robotic gripper that detects paper, metal, and plastic while being puncture-resistant. The gripper achieves 85% accuracy in stationary setups and 63% in simulated recycling pipelines [30].

In India, researchers proposed using IoT within containers to improve waste management by enabling comprehensive communication with collection carts [31]. In Brazil, a study analyzed the participation of waste collectors in Caxias do Sul's waste management system through observations, interviews, and waste characterization using two types of trucks. 12 samples were categorized as organic, plastic, paper, cardboard, metal, glass, Tetra Pak, and other types of waste, providing a diagnostic for municipal management [32]. In the United Kingdom, researchers classified various types of waste, including urban, construction, industrial, agricultural, commercial, market, hotel, and restaurant waste [33].

Methodology

IoT-based applications integrate various technologies to develop cohesive systems. This section outlines the steps taken to create the mobile cleaning robot, as well as the criteria used for evaluation.

Block diagram

Fig. 1 shows the block diagram of the T5R-bot prototype designed for solid waste collection. The robot is powered by a lithium battery (a *power bank*) managed by a BMS and connected to an Arduino Nano and a Raspberry Pi 4, which runs the object recognition and waste detection model. Motion is controlled by signals sent to the H-bridge, driving the DC motors to move forward or backward or rotate. An ultrasonic sensor calculates the distance, guiding the gripper to pick up and deposit objects into the container.

Mechanical design

The following activities were considered for the mechanical design.

3D printing

3D printing is an additive manufacturing technology that has significantly advanced in recent years across various disciplines [34]. The versatility of 3D printing materials stems from the wide variety of printer models and types, as well as from innovations in material processes, making it an essential component of multi-process systems to support the development of new materials and product requirements [35]. Figs. 2 and 3 show the design created in FreeCAD, which allowed for a rapid and efficient creation of parts. The design was then exported to UltiMaker Cura to configure its properties before 3D printing (Fig. 4).

Rocker-bogie mechanism

The rocker-bogie mechanism was developed by NASA in 1988 to easily adapt to unknown and rugged terrain during Mars expeditions, allowing for relatively smooth movements on rough surfaces [23]. An interesting feature of this mechanism is the differential constraint, which was used in the Mars Science Laboratory (MSL) rover to maintain the symmetry of the mobility system during the launch, cruise,

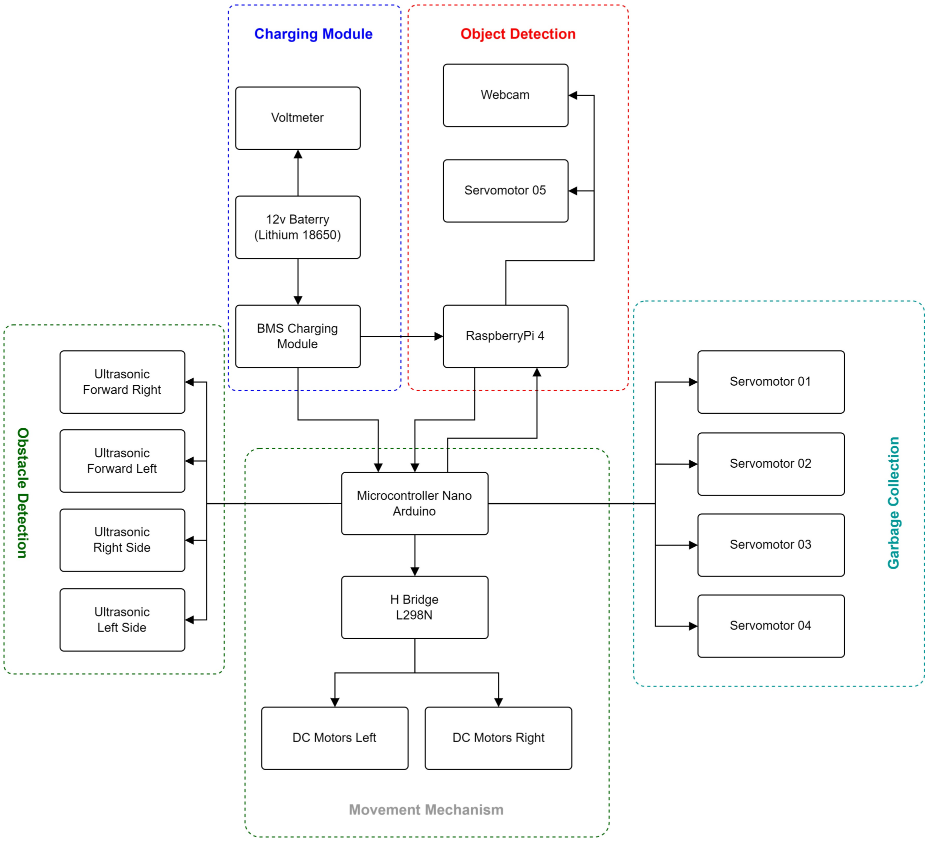

Figure 1. Block diagram
Source: Authors

entry, descent, and landing phases of the mission. This mechanism underwent almost three design cycles before being successfully completed [36]. To power our robot, six JGA25-370 DC gear motors were implemented, one for each leg of the mechanism. These motors are connected to an L298N driver, also known as an H-bridge, powered by 3000 mAh lithium batteries. A Raspberry Pi Model B computer supplies control signals to the H-bridge, allowing the wheels to move forward, backward, right, or left as needed.

Gripper

Handling objects can be dangerous for operators [37]. Gripping forceps, widely used in various research fields, provide reliability, precision, and safety. A study on automation in seedling transplantation achieved a 99% success rate [38]. Other research works highlight the development of ultra-compact and soft grippers capable of performing rapid, high-amplitude multidimensional maneuvers on microscale objects [39]. Various types of tweezers have been developed; among them, recent research introduced a compressible tweezer that adapts to the shape of objects, thereby improving grip efficiency [40].

The developed gripper features four degrees of freedom (DoF), as shown in Fig. 5. The model was 3D-printed, and its movement is powered by four servomotors installed at the joints. To ensure smooth operation, the maximum force required from these servomotors was calculated while considering several factors. The S3003 servomotor can lift 4.1 kg at a distance of 1 cm from its axis. Given that the effective distance from the first motor axis to the tip of the first link is 150 mm, and it operates at inclination angles between 0° and 180°, the calculations using Eqs. (**??**) and (**??**) yield a required force of 0.615 kg.

$$\tau = F \cdot b \tag{1}$$

$$\tau = F \cdot r \cdot \sin\phi \tag{2}$$

Where:

τ : Torque or force of movement

b : Distance

F : Force

r : Radius

ϕ : Angle

Ultrasonic

Four ultrasonic sensors were installed: two at the front and one on each side of the robot. The front sensors can detect trash and stop the robot to allow the gripper to pick it up, while the side sensors are used to avoid obstacles.

Bucket

The design was created and 3D-printed, as shown in Fig. 6, with dimensions 380 x 320 x 75 mm. When the SSD MobileNetV2 algorithm running on the Raspberry Pi 4 Model B detects an object, the vehicle approaches it, picks it up with the gripper, and places it in the bucket. The recognition threshold was set to 90%.

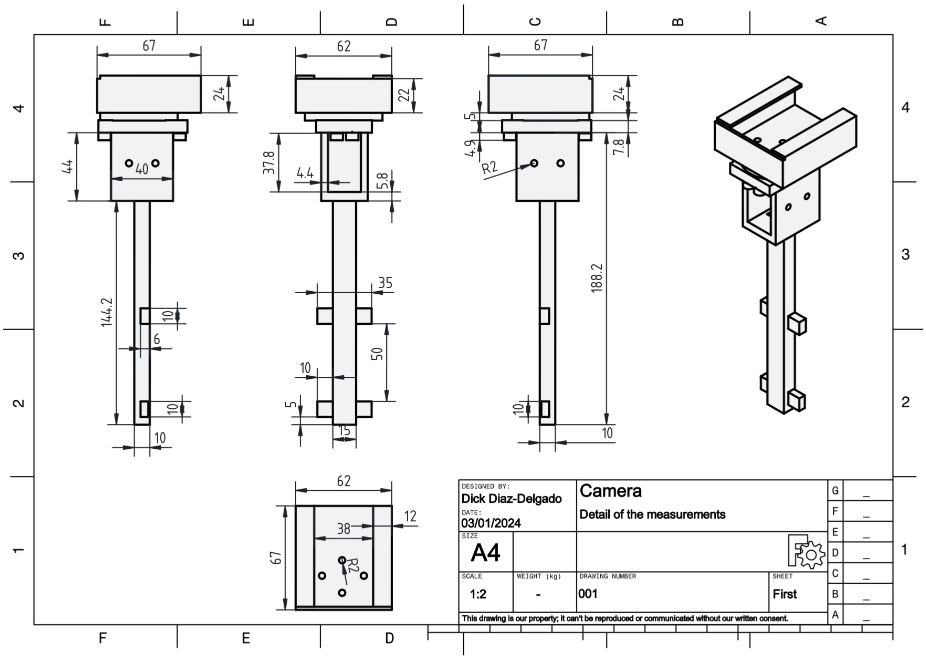

Figure 2. Tower measurements for the car camera
Source: Authors

Camera setup

The camera was mounted at the front of the robot using a 100 mm 3D-printed bracket, thereby enhancing the viewing angle and preventing obstructions to the pick-up gripper. Connected to an S3003 servo motor, the camera moves horizontally to detect and track solid waste. When debris is detected, it switches from search mode to tracking mode, maintaining the target in view.

Components list

The following components were used.

Raspberry Pi 4 Model B

This is one of the most basic and best-selling computers, featuring a Broadcom BCM2711 Quad-core Cortex-A72 1.8 GHz chip and SDRAM memory options of 1, 2, 4, or 8 GB depending on the model. It includes dual-band Wi-Fi (2.4 GHz and 5 GHz), Bluetooth 5.0, Gigabit Ethernet, two USB 3.0 ports, one USB 2.0 port, 40 GPIO pins, two micro-HDMI ports, and a Micro-SD slot for storage. It operates within a temperature range of 0 to 50 °C, with dimensions 94 x 70 x 26 mm and a weight of 66 g. Power over Ethernet (PoE) is supported but requires a separate HAT [41, 42, 43]. The SSD MobileNetV2 algorithm runs continuously via the webcam to recognize solid waste objects.

Arduino Nano

This compact and versatile micro-controller measures 18 x 45 mm, weighs 7 g, and is compatible with IoT components. It features 14 digital pins, eight analog pins, two reset pins, six power pins, and a mini-USB connection. Operating at 16 MHz with a power consumption of 19 mA, it is based on the ATmega328P. The power supply is 5 V, with an input range of 7 to 12 V, and it includes 1 or 2 KB of SRAM and 512 bytes or 1 KB of EEPROM depending on the model [19, 44, 45].

HC-SR04 ultrasonic sensor

This sensor measures distances using ultrasonic sound pulses and features four pins (Vcc, Trig, Echo, GND). It operates with a 5 V power supply, has a quiescent current of less than 2 mA, and measures 45 x 20 mm [46].

Servomotor S3003 (REES52)

This servomotor has a motion range of 0 to 360° and requires a pulse width of 0.3 to 2.3 ms to achieve its maximum angle. It has a load capacity of 4.1 kg [47, 48].

Dahua UZ3

This device has the following characteristics: a capacity of 2 megapixels, video resolution of 1920 x 1080 pixels (Full HD 1080p), and dimensions 97 x 57 x 33 mm. It captures the images to be analyzed by the Raspberry Pi.

Power bank

The power bank consists of nine 18650 lithium-ion batteries, each with a nominal voltage of 3.7 V, a maximum voltage of 4.2 V, and a minimum voltage of 2.9 V. Each battery transfers 3 A per hour and was connected in series and parallel to achieve a required voltage of 12 V and a current of 9 A. The system can operate at 3 Ah (ampere-hours, representing the battery capacity supplied to the system) for one hour. The batteries measure 18 x 65 mm and are cylindrical in shape [49].

BMS-3S charging module

This intelligent component enables the advanced control and management of a lithium battery storage system with a maximum output and charging power of 252 W, following the wiring diagram 0 V/4.2 V/8.4 V/12.6 V. Its main function is charge and discharge control, in addition to the collection,

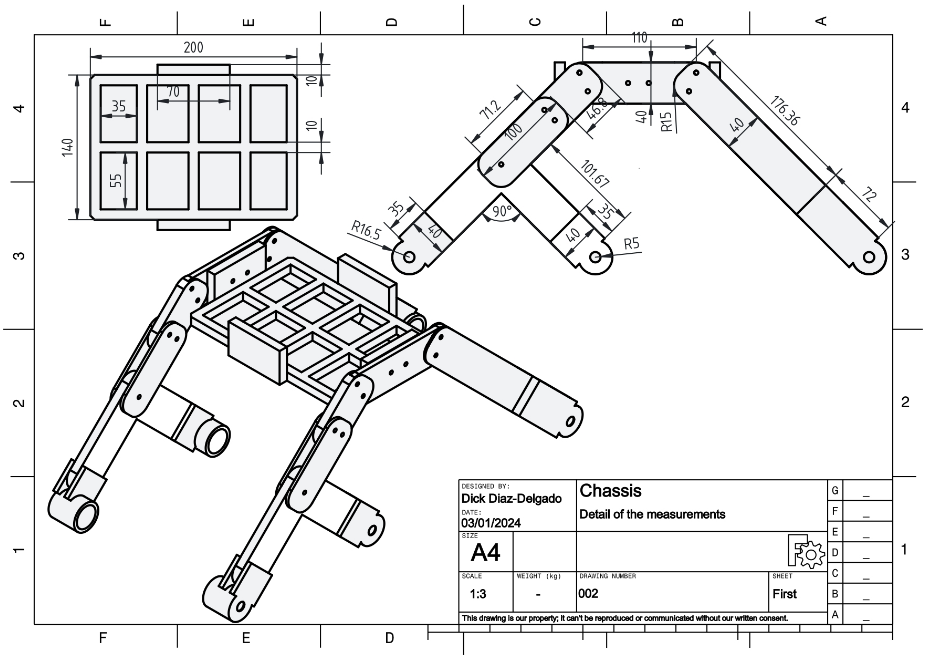

Figure 3. Car chassis measurements
Source: Authors

processing, and storage of real-time information on battery operation [50].

Mini digital voltmeter

This is a high-quality, durable component with a long service life. It features a 0.025% resolution core, ensuring a sufficient margin and high precision. It offers a direct power supply for testing, a low starting voltage, and a reverse connection protection function to prevent damage. The measurement range is between 2.4 and 32 V, and its dimensions are 30 x 11.7 x 9.2 mm [51].

L298N H-bridge

This module controls the direction and speed of two motors, operating at voltages from 3 to 35 V with a current capacity of 2 A. It includes a regulator that provides a 5 V output when powered within a range of 5 to 12 V. The module measures 43 x 43 x 27 mm, weighs 30 g, and delivers a power output of 25 W [52].

JGA25-370 motors, DC 12 V

These devices convert electrical energy into mechanical energy, or *vice versa*. They are widely used in nearly all human activities [53] and can function as generators or motors depending on the application [54, 55]. In the robot, the motors allow moving forward, backward, left, and right.

Electronic design

Fritzing was used to create the basic electronic design diagram by incorporating library components (Fig. 7).

Object detection model

Below are the implementation steps followed for the computer vision system using the MobileNet architecture and the SSD model.

Preparation and pre-processing data

To collect the dataset, photographs were taken in public places, such as parks, squares, sports fields, markets, roads, towns, and river slopes, among others. Additionally, free images were sourced from the Internet and the TACO (trash annotations in context) image collection [56], resulting in a total of 2890 images representing the four types of solid waste considered in this research. Common objects included bottles, cans, boxes, and cups captured against various backgrounds such as grass, sidewalks, and debris at different times of the day, with resolutions ranging from 3000 to 4500 pixels. These images were used to train the waste collection robot, with resized 300 x 300 pixel images to accelerate training and reduce processor load.

The images were manually annotated using LabelImg and MakeSense.AI, creating bounding boxes to classify waste into four categories: box, bottle, glass, or can. The annotations, including XY coordinates, were saved in the YOLO (.txt) and PASCAL VOC (.xml) formats. The dataset was divided into 80% for training (2312 images) and 20% for testing (578 images), totaling 2890 images.

Fig. 8 illustrates the working principle of the object detection system for solid waste using SSD MobileNetV2 and its processes. First, the dataset is collected for training and testing. Next, image pre-processing is performed, which includes tagging the images, converting the XML (eXtensible Markup Language) dataset to the CSV (comma-separated values) format, and then converting the CSV file to the TFRecord format. The final pre-processing step involves creating a tag map. In the image processing phase, the pre-trained MobileNetV2 SSD model is selected, and the *pipeline.config* file is configured. The model is then trained using a convolutional neural network (CNN) architecture, resulting in a classification, detection, and prediction model. The non-maximum suppression (NMS) process is applied to generate a model with a minimum intersection over union

Figure 4. Printing parts with 3D technology
Source: Authors

(IoU) of 0.5. Once the model has been trained, it produces outputs that are converted into estimates of solid waste.

The main method calculates bounding boxes and object classes from images using the SSD model with MobileNet. Designed for fast detection and optimized for mobile devices like the Raspberry Pi, it efficiently detects objects and provides information about their position and class.

Structure model

Object detection is a highly competitive field dominated by models such as SSD (MobileNet), RCNN (Mask and Faster), and YOLO in various versions. While these models are accurate, they can be computationally expensive and require significant inference time. SSD, as its name suggests, performs multiple object detections in a single shot, unlike other two-stage models. This makes it much faster without compromising accuracy. SSD operates in two main steps: feature map extraction and object detection using convolutional filters [57]. The primary SSD models are SSD512, designed for high-resolution images (500×500), and SSD300, optimized for faster processing and used with low-resolution images (300×300). The SSD rendering architecture is illustrated in Fig. 9, where each feature layer generates a fixed set of detection predictions using convolutional filters.

MultiBox detector

The specific location information corresponds to the various outputs of the detector, which vary depending on the position, proportion, and size of objects. In SSD, the MultiBox loss function is employed, which consists of the weighted sum of the localization loss (L_{loc}) and the confidence loss (L_{conf}), as described in Eq. (3). In this context, N represents the number of matching predefined boxes. The localization loss refers to $smooth_{L1}$, calculated between the predicted (l) and actual box parameters (g), as shown in Eq. (4). Additionally, SSD adjusts the center coordinates (cx, cy), height (h), and width (w) of the detection boxes. The confidence loss, detailed in Eq. (7), corresponds to the softmax loss applied to the confidence scores (c) of various categories.

$$L(x,c,l,g) = \frac{1}{N}(L_{conf}(x,c) + \alpha L_{loc}(x,l,g)) \tag{3}$$

$$L_{loc}(x,l,g) = \sum_{i \in Pos}^{N} \sum_{m \in \{cx,cy,w,h\}} x_{ij}^{k} smooth_{L1}(l_i^m - \hat{g}_i^m) \tag{4}$$

$$\hat{g}_j^{cx} = (g_j^{cx} - d_i^{cx})/d_i^w \quad \hat{g}_j^{cy} = (g_j^{cy} - d_i^{cy})/d_i^h \tag{5}$$

$$\hat{g}_j^{w} = log(g_j^w/d_i^w) \quad \hat{g}_j^{h} = log(g_j^w/d_i^w) \tag{6}$$

$$L_{conf}(x,c) = -\sum_{i \in Pos}^{N} x_{ij}^{p} log(\hat{c}_i^p) - \sum_{i \in Neg}^{N} log(\hat{c}_i^0) \tag{7}$$

MobileNet

A key function of the backbone is to extract detailed features from the input image and pass them to the subsequent SSD layers. The MobileNet network configuration employs depthwise separable convolutions, as illustrated in Fig. 10, significantly reducing the network's size and yielding a lightweight model with lower computational complexity. Additionally, two hyperparameters (width and resolution) control the input/output of the convolutional layer and the resolution, providing better control over the trade-off between computational cost and network accuracy based on end-user requirements [57].

The integration of this framework with SSD enhances the performance of real-time applications using low-capacity or low-end devices such as mobile phones. After each layer in the main network structure, batch normalization and a rectified linear unit (ReLU) function are applied, except for the last fully connected layer. The final layer bypasses a nonlinear function, passing the data directly to a softmax layer for classification [58].

Implementation and operation

The implementation and operational procedures of the autonomous robot for solid waste collection are described below, along with the challenges encountered and potential solutions to enhance our proposal's functionality.

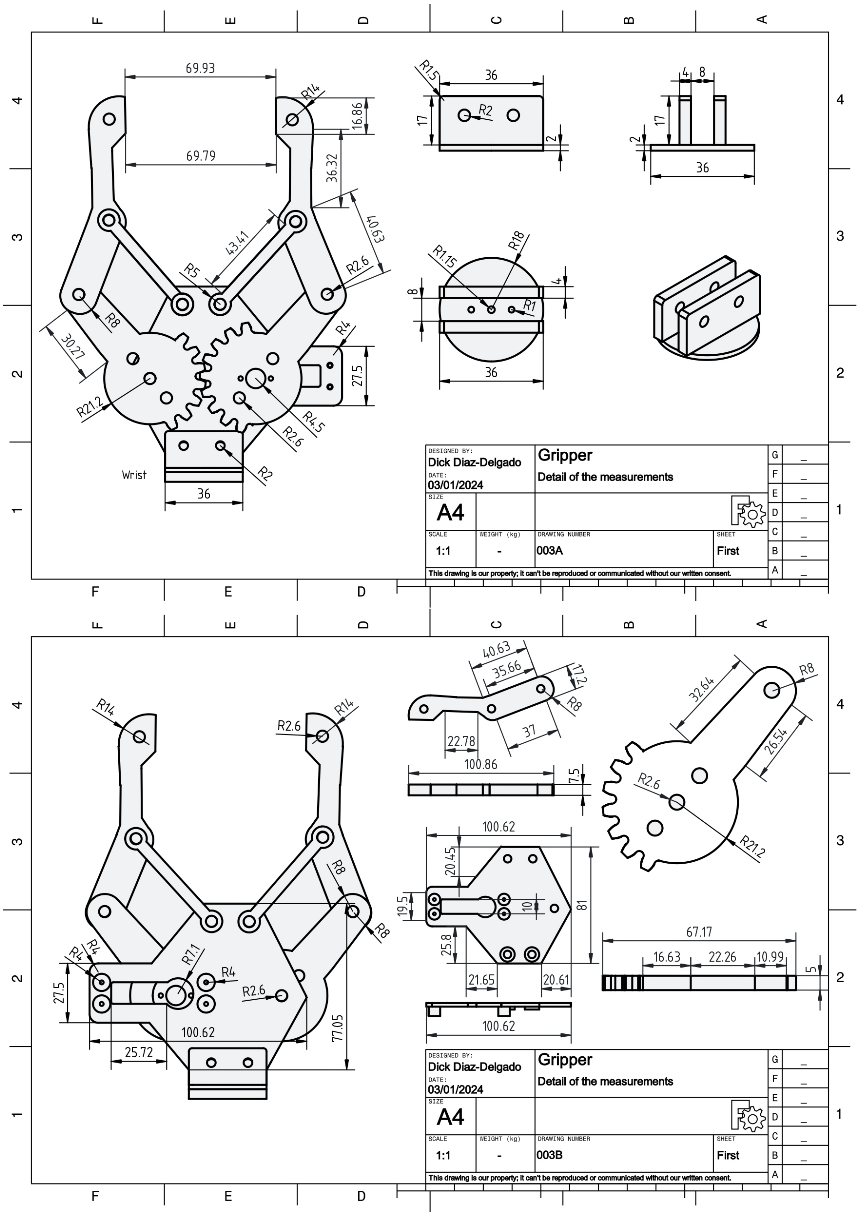

Figure 5. Gripper with four degrees of freedom
Source: Authors

Preparing the object-detection model

The Raspberry Pi 4 Model B was chosen to run the DL model. The weights of the MobileNet FPNLite SSD model were exported as a .ZIP file due to their compact size. Subsequently, the model was converted to TensorFlow Lite for deployment on the Raspberry Pi.

Challenges and possible solutions

Training requires a large number of suitable, manually annotated images, which is labor-intensive and increases the training time as the dataset grows. For robot production, greater computational power is needed, which can be obtained through cloud services such as AWS, Azure, or IBM, leveraging multiple GPUs. Companies must pay for access to these services on a pay-as-you-go basis. Another option is the Coral USB Accelerator, which enhances processing and reduces object detection time.

Robot path planning

The robot searches for solid waste using its camera while navigating obstacles with ultrasonic side and front sensors, pausing for 1-2 s to assess the surroundings. Its design allows it to overcome obstacles up to twice the diameter of its wheels. When debris is detected, the robot aligns itself and calculates the object's center along the X-axis of the camera (Fig. 11). It then aligns the object's center with the gripper and slowly approaches to pick up the debris. After selecting the object closest to the axis for collection, the robot continues scanning the area to complete its task.

Monitoring the collector bin

Given that the average volume of objects is 720 000 mm^3, it is estimated that the repository can store up to 12 objects. Consequently, this number was established as the maximum limit to ensure a proper distribution within the container and prevent exceeding the weight limit of 0.615 kg. To this effect, the robot keeps track of the number of objects it collects and

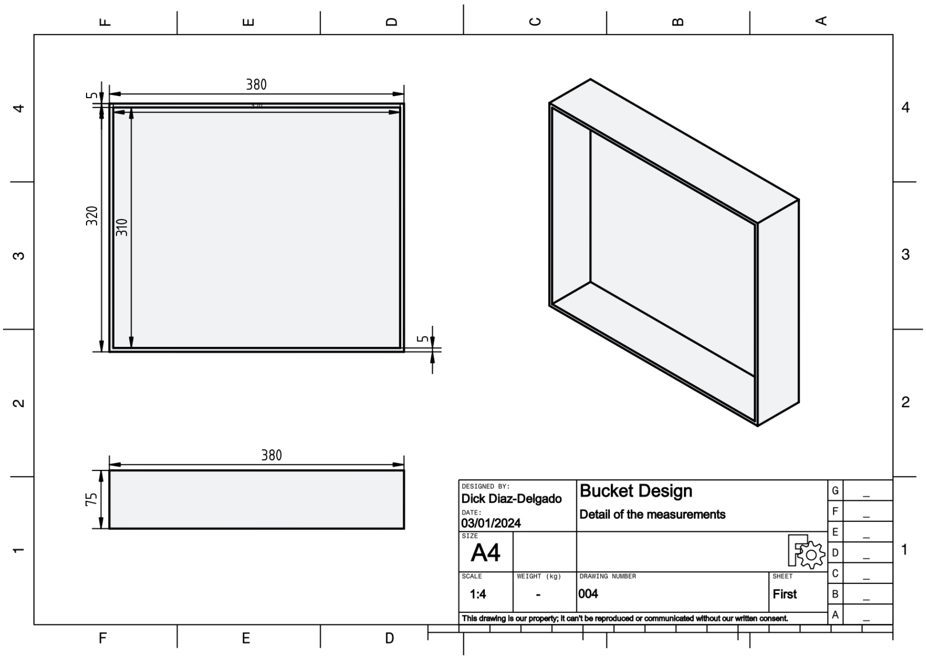

Figure 6. Perspective view of the design
Source: Authors

stores in the bucket, which allows it to determine when its task is complete.

Results

The decrease in losses (Figs. 12 and 13) suggests that, as the training period grows longer, the reliability of the model's predictions improves. The model exhibits a sharp decrease in losses during the initial training phase, followed by a gradual and continuous decline. The final loss achieved after 50 000 training steps was 0.1085.

Object detection model

While training was performed, the mAP (mean average precision) showed an increasing trend with occasional small decreases. The SSD MobileNetV2 model demonstrated a significant advantage, achieving a reduction in losses (*Lost*) during the initial training phase. A 80-20 split was chosen given its recognition as a standard in the field, ensuring a representative evaluation and allowing for direct comparisons against previous studies. This ratio provides an optimal balance between the size of the training set and the ability to effectively measure performance. The model's inference times are very fast and exhibit high accuracy, with mAP results from the test run reaching 94.84%. This is considered an ideal result, as the IoU threshold exceeds the expected 50% (IoU ≥ 0.5) [23] (Table II).

Table II. Performance metrics

Nº	Class	0.5 IoU	0.95 IoU	mAP @ 0.5:0.95
1	Box	100%	52%	95.2%
2	Bottle	100%	80%	98%
3	Can	100%	80.56%	98.06%
4	Glass	100%	100%	100%
Total		100%	78.14%	97.81%

Accuracy test

In evaluating the model, the IoU and mAP metrics were key. IoU is a measure used to compute the accuracy of an object detection model on a specific dataset. Also known as the *Jaccard index*, it is calculated using Eq. (8).

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|} \tag{8}$$

J, A, and B represent the Jaccard distance, the first set, and the second set, respectively. The IoU measures object detection performance by comparing the ground truth bounding box with the one generated by the model. Eq. (9) was used to calculate the IoU value.

$$IoU = \frac{(Area\ of\ Overlap)}{(Area\ of\ Union)} \tag{9}$$

The confusion matrix presented in Table III evaluates the performance of the object detection model in classifying solid waste into the following categories: box, bottle, can, and cup. Each column and row of the table represents the number of correctly identified cases (true positives, TP), misclassified cases (false positives, FPs), and undetected cases (false negatives, FNs). It also includes true negatives (TNs), although, in this case, there are always zero TNs because the problem does not include explicit negative examples.

For example, for the box category, the model correctly detected 48 boxes (TP), reported two errors by classifying other objects as boxes (FP), and left no boxes undetected (FN). The same analysis was applied to the other categories with similar results, reflecting an excellent model performance with accuracy and recall rates close to 100%. This analysis confirms the system's ability to reliably detect solid waste in different environments.

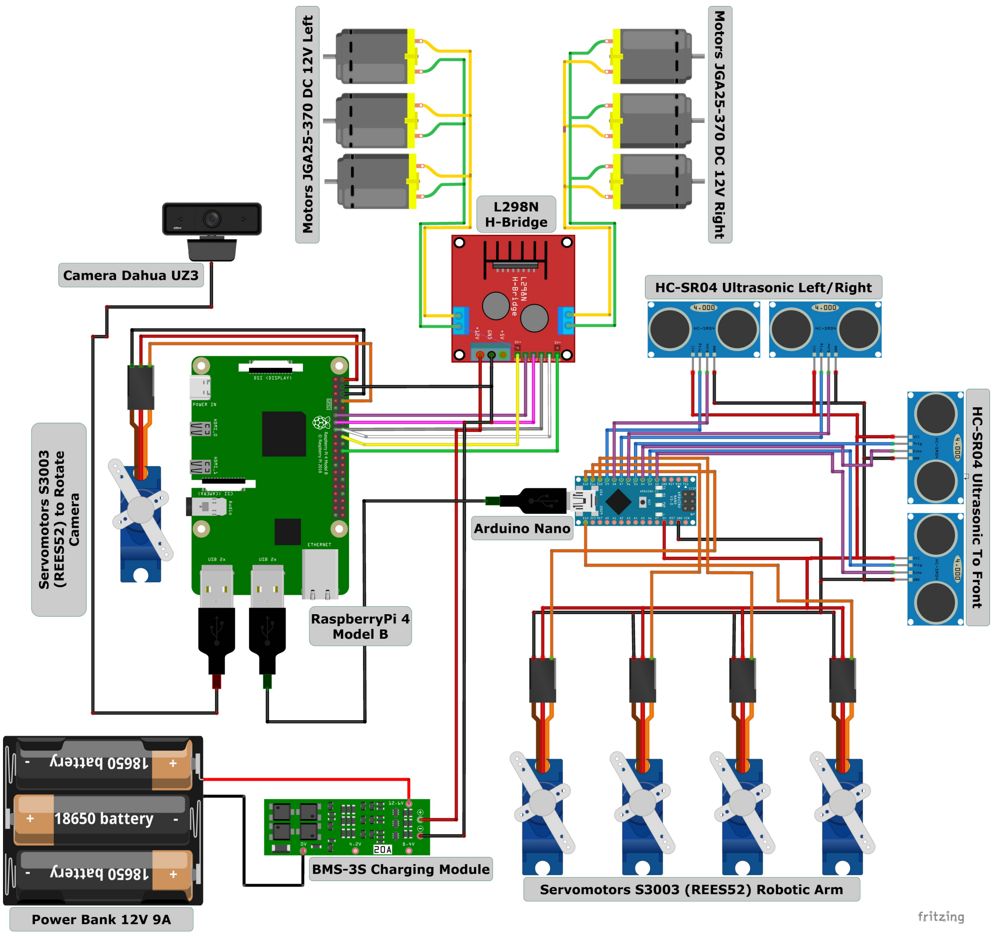

Figure 7. Circuit diagram
Source: Authors

The evaluation metrics used for the calculation of performance parameters were accuracy (10), precision (11), recall (12), and the F1-score (13).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (10)$$

$$Precision = \frac{TP}{TP + FP} \quad (11)$$

$$Recall = \frac{TP}{TP + FN} \quad (12)$$

$$F1 - score = 2\,X\,\frac{Precision\ X\ Recall}{Precision + Recall} \quad (13)$$

To calculate the average precision (AP) and the mAP, Eqs. (14) and (15) were used.

$$AP = \int_0^1 P(R)dR \quad (14)$$

$$mAP = \frac{\Sigma_{i=1}^{N} AP_i}{N} \quad (15)$$

Table IV shows the precision, recall, and F1-score values calculated to evaluate the model's effectiveness and quality.

Table III. Confusion matrix

Nº	Type	TP	FN	FP	TN
1	Box	661	0	28	0
2	Bottle	674	0	14	0
3	Can	812	0	14	0
4	Glass	688	0	0	0

Source: Authors

Table IV. Accuracy test results

Nº	Type	Precision	Recall	F1-Score
1	Box	98%	100%	99%
2	Bottle	96%	100%	98%
3	Can	98%	100%	99%
4	Glass	100%	100%	00%

Source: Authors

Table V presents the image detection results, including the overall values for accuracy, recall, and the F1-score. The MobilenetV2 SSD algorithm achieved a 94% accuracy in solid debris detection, enhancing detection applications by expanding the dataset.

Fig. 14 shows the object detection of the SSD MobileNetV2 model, which was integrated into the Raspberry Pi through the webcam. The movement and search algorithm allowed the robot to operate in an endless loop to locate and collect

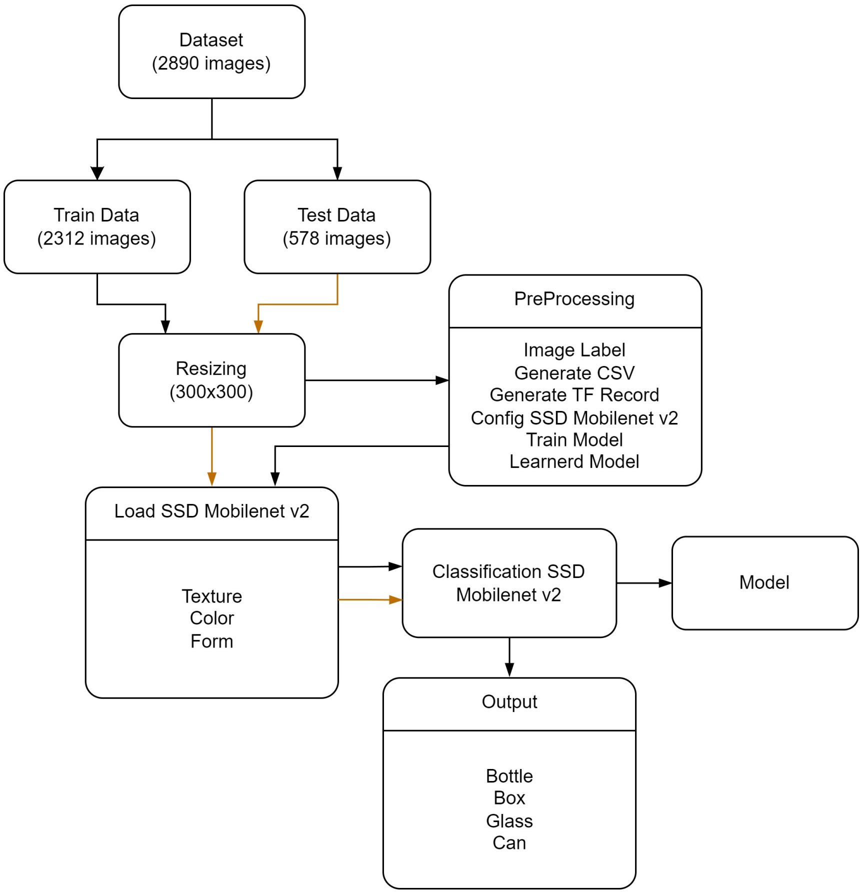

Figure 8. General architecture
Source: Authors

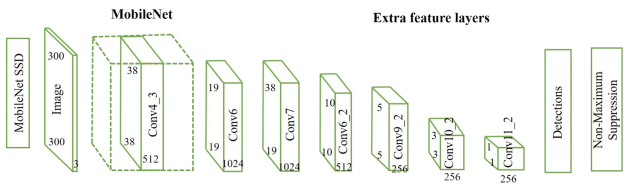

Figure 9. MobileNetV2 model [57].
Source: Authors

Table V. Percentage results

Precision	Re-call	F1-Score
98%	100%	99%

Source: Authors

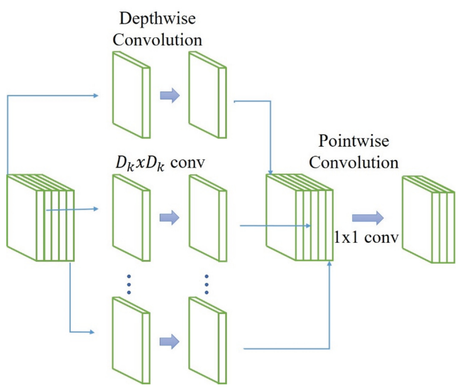

Figure 10. Depthwise convolutional layer architecture [57]
Source: Authors

waste, influencing detection by up to 20%. The robot also featured an emergency switch to stop its operation in case of unforeseen events.

Regarding the process of grabbing and placing objects on the tray, the robot takes 7 s per object once it focuses on the target (Fig. 15).

As reported in the specialized literature, [11] achieved a mAP of 89% by training the YoloV4 model. Additionally, [23] achieved a value of 97.1% in the same model, 83.3% in the Mask-RCNN model, and 95.2% in another instance of Mask-RCNN. For comparison, SSD MobileNetV2 achieved a 98% precision and a 97.81% mAP (Table VI).

Discussion

The implementation of the T5R robot using the MobileNetV2 SSD architecture for solid waste detection and collection yielded promising results, achieving an accuracy of 98% and a mAP of 97.81%. These outcomes surpass those reported in previous studies using models such as YOLOv4 and Mask-RCNN, which achieved accuracies of 89 and 83.3%, respectively, as cited by [11, 23]. This performance underscores the model's effectiveness in hardware-constrained environments (*e.g.*, deployment on a Raspberry Pi) while maintaining low computational costs without sacrificing accuracy.

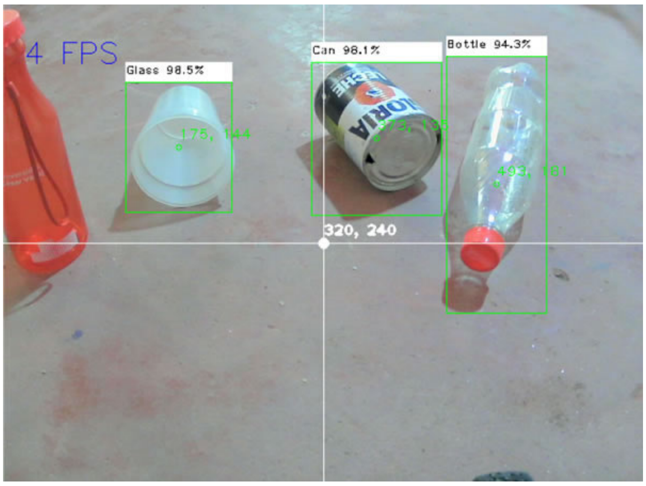

Figure 11. Object detection
Source: Authors

Table VI. Model comparison

Source: Authors

Research	Algorithm	mAP
[11]	YoloV4	89%
[23]	YoloV4	97.1%
	Mask-RCNN	83.3%
	YoloV4-tiny	95.2%
Ours	MobileNetV2	97.81%

The results obtained in controlled environments are promising. However, it is essential to evaluate the robot's effectiveness in real-world and diverse scenarios. Factors such as variations in waste type, climatic conditions, and the distinctive characteristics of urban environments can significantly affect system performance. These variables may pose challenges that are not evident in controlled settings, emphasizing the importance of additional testing. Conducting pilot tests in various locations would not only help identify areas for improvement; it would also allow adapting the system to specific contexts. This approach would ensure that the robot meets the standards necessary for large-scale deployment while maintaining efficiency and functionality under practical conditions. Such evaluations are critical to validating the system's feasibility and its effective contribution to waste management in complex urban environments.

Conclusions

In this work, a dataset of 2890 images collected under various scenarios and conditions was consolidated for the training and testing of solid waste detection. The T5R robot was built from scratch using 3D printing technology and ABS, featuring a suspension system inspired by the rocker-bogie astromobile mechanism, which allows for safe movement in work areas. The robot employed computer vision and a versatile clamp to autonomously collect waste on different terrains. Its MobileNetV2 SSD architecture operated in TFLite for efficient execution on the Raspberry Pi, identifying solid waste through an advanced approach. This facilitated fast convergence, reduced training times, improved accuracy to 98%, and allowed reaching a detection threshold of 90% and a mAP of 97.81%.

The T5R robot is capable of storing and detecting up to 12 objects, including bottles, boxes, cans, and glasses, in just 7 s, highlighting its effectiveness in contaminated environments. The innovation represented by the T5R underscores the feasibility of collection robots as an effective solution to the challenges of waste management in urban environments.

The development of the T5R robot represents a significant advancement in sustainable solid waste management. By automating waste collection, it reduces dependence on human labor for repetitive and potentially hazardous tasks, thereby minimizing the health risks associated with such activities. Moreover, the deployment of this technology in urban environments has the potential to make a positive impact by lowering contamination levels and increasing recycling rates. These advancements could play a pivotal role in facilitating the transition to a circular economy, fostering more sustainable and responsible waste management practices.

Recommendations and future developments

Currently, the robot only picks up objects, but, in the future, waste segregation and categorization capabilities will be added. We also plan to integrate LiDAR technology in order to improve navigation. Additionally, the DL model will be optimized to avoid overfitting and detect moving obstacles, such as people and vehicles. Future versions of the robot will use reinforcement learning to acquire knowledge of the environment and make more intuitive decisions. It would also be advisable to incorporate techniques such as cross-validation or other partitioning schemes to verify and strengthen the generalization of the results.

Additionally, the robot's automatic classification capabilities could be enhanced through the use of deep neural networks specialized in waste segmentation, enabling a more efficient and precise handling of various waste types.

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Conflicts of interest

The authors declare no conflict of interest.

Data Availability

All data related to this research study can be requested from the corresponding author.

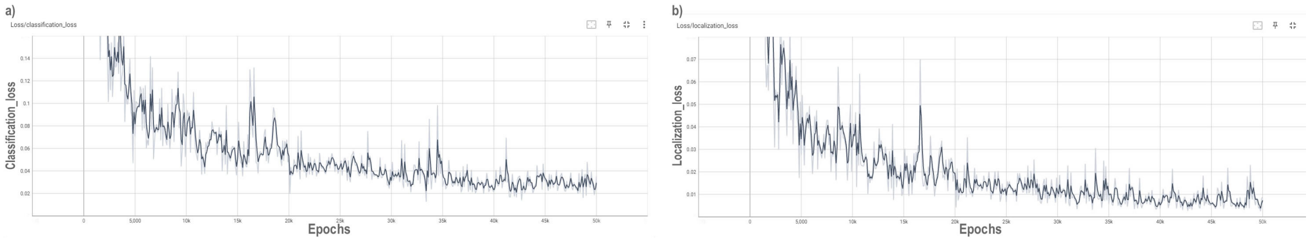

Figure 12. Model results regarding a) classification loss and b) localization loss
Source: Authors

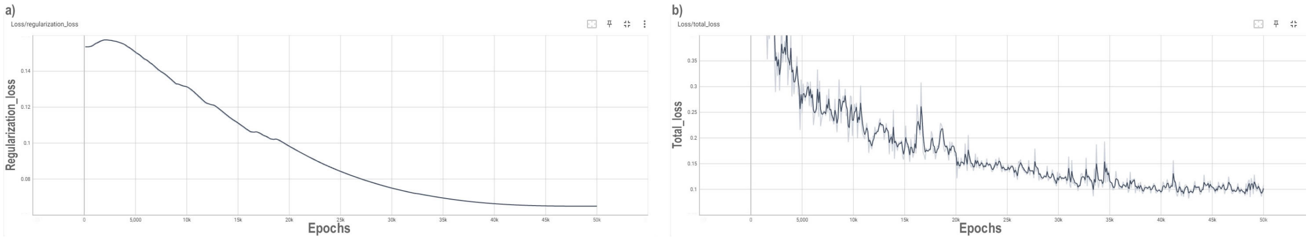

Figure 13. Model results regarding a) regularization loss and b) total loss
Source: Authors

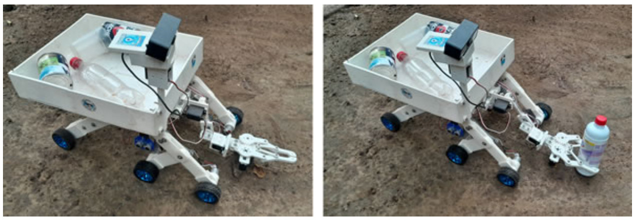

Figure 15. Solid waste collection
Source: Authors

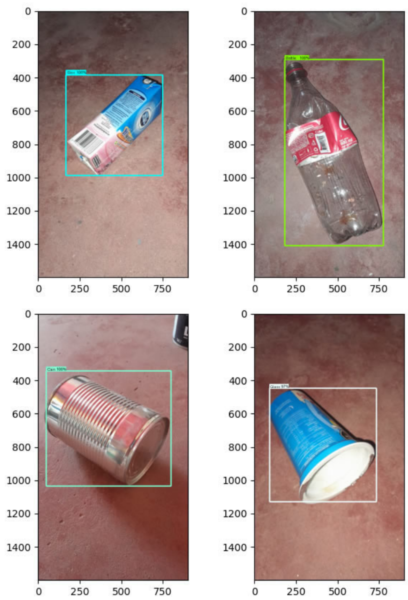

Figure 14. MobileNetV2 SSD results
Source: Authors

CRediT author statement

Dick Díaz-Delgado: conceptualization, methodology, software, formal analysis, investigation, data curation, writing (review and editing). *Alexander Inga-Alva*: conceptualization, methodology, investigation, validation, writing (original draft), writing (review and editing).

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