

Autonomous Litter Collecting Robot with Integrated Detection and Sorting Capabilities

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Abstract— This paper presents an autonomous robot that detects and collects litter in real time. The robot is designed for use in resource-limited urban environments in developing countries. Its main purpose is to automate the process of collecting waste and sorting it for recycling. It is made up of a combination of object detection using a raspberry pi camera module, autonomous navigation with ultrasonic sensors to measure the distance from obstacles, a YOLOv11 model to detect litter in real time and a custom robotic arm to collect the litter and sort it. Test results showed a detection accuracy of 87.87 %, with reliable navigation and collection performance. The system provides a practical and easy to scale solution for improving and supporting waste management in urban areas.

Keywords—YOLOv11, autonomous, litter, waste management; object detection, ultrasound sensors

I. Introduction

Litter includes waste like plastics, metal, paper, cans and glass that is not discarded properly.

Autonomous is the ability of an entity to act with minimal or no human supervision.

You Only Look Once (YOLO) is a series of real-time object detection systems based on convolutional neural networks that are used in computer vision for classification and detection.

As the population grows in the urban areas of developing countries, due to urbanisation, there is a rise of informal structures in the cities (Dube, et al., 2024) and the rate at which waste is generated also increases. This in turn introduces challenges in maintaining clean public environments. Litter usually accumulates in parks, high density residential areas streets, sports stadiums, market places, and high-traffic areas like taxi ranks. Traditional waste collection methods which mostly rely on manual labour are often inefficient, costly, and unable to keep up with the rate at which the waste is produced. This poses a threat to public health in the form of diseases e.g., cholera. It also affects environmental sustainability and urban aesthetics.

To solve this problem, there is a need for scalable, automated solutions that can keep up with the rate at which the litter is being produced without increasing the cost of waste management. Autonomous robots can detect, identify, and collect litter without human intervention or with minimum supervision.

This research presents the design, implementation, and evaluation of a low-cost, autonomous litter collection robot. The system integrates a YOLOv11-based object detection model, ultrasonic, and infrared sensors for obstacle navigation, and a 4-degree-of-freedom robotic arm for litter collection.

II. Literature review

Litter detection and collection have become key priorities in urban waste management, especially in fast growing towns and cities which are resource-constrained. Several research efforts have proposed robotic systems capable of automating the waste management process, using technologies such as computer vision, smart bins, autonomous navigating robots, and robotic arms for sorting litter for recycling. However, most existing systems are both too costly for deployment in low-income areas and are designed for areas with reliable power, good infrastructure, and roads, and they are not equipped for the challenge of navigating in the outdoor environments of cities in developing countries.

Existing Systems and their Limitations

Various autonomous systems have been developed to address waste management challenges, each with unique approaches to detection, navigation, and collection. The Outdoor Autonomous Trash-Collecting Robot (OATCR), aimed for a low-cost, efficient solution using a rocker-bogie mechanism for terrain adaptability and YOLOv4-tiny for real-time trash detection, but, faced challenges with extensive datasets and processing limitations (Kalshreshtha et al., 2021). Similarly, Koinig, (2023) designed a Garbage Collection Robot (GCR) integrating proximity sensors and a colour detection system; however, its limitation to classifying

only one type of litter at a time, limited its effectiveness. In contrast, the proposed system enhances classification by identifying multiple types of litter (paper, glass, plastic) for designated sorting, thus improving efficiency. An autonomous system with a 6-DOF robotic arm and Mask R-CNN for accurate litter classification and visual serving was introduced as LitterBot, demonstrating high success rates in static and dynamic environments but facing limitations related to gripper constraints and its stationary nature (Achmad et al., 2021). TRASH was a multi-robot system combining an aerial vehicle for scanning and a ground robot using a Convolutional Neural Network (CNN) for detection and mapping, its focus was on roadside litter collection (Mohan et al., 2021). The automated waste segregation system used conveyor belts and image processing to classify waste into two categories, biodegradable and non-biodegradable (Bansal et al., 2019). Internet of things devices have also been used for waste segregation (Raj et al., 2020). Another system focused on control of an autonomous mobile waste collection robot using SLAM and LiDAR for navigation and obstacle avoidance (Mărgăritescu, et al., 2020) while (Malik et al., 2023) developed a machine learning-based automatic litter detection and classification system using neural networks. Integrated solar-powered wireless autonomous trash collector robot, enhanced operational sustainability by using a renewable power source (Ajibola & Ogbolumani, 2024). The research focused on developing a cost-effective, physically implemented solution using an on board model (YOLOv11) for real time detection and sorting. YOLO was found to be the most efficient for object detection in comparisons by (Achmad et al., 2021) and (Liu et al., no date). This approach allowed for real-time classification of various litter types. Past local solutions that were developed were limited to collecting only one type of litter at a time (Koinig, 2023). This research offers a more adaptable and sustainable solution for urban waste management.

Comparative Insights and Positioning of This Study

Unlike prior systems, the solution presented in this research offers a low-cost, fully mobile litter collection robot suitable for unstructured outdoor settings. By using the YOLOv11 algorithm, which is the most recent version and the best performing according to Figure 1, it ensures that the detection accuracy is high while keeping computing requirements at a minimum. The use of affordable components like the raspberry Pi allows the robot to maintain high classification performance while remaining

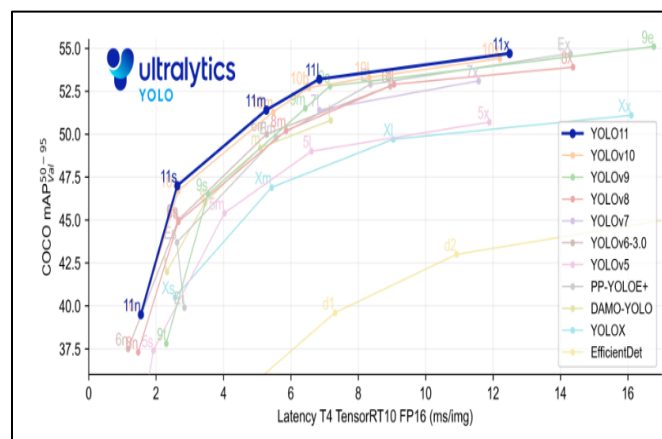


Figure 1 YOLO version comparison on COCO dataset

accessible for cities with limited resources. Additionally, the integration of a 4 degree of freedom laser-cut robotic arm for sorting the litter and the use of ultrasonic sensors for navigation, differentiates this design from others that lack either real-time manipulation or rely on pre-defined paths. Some of the systems are more focused on indoor environments and they depend on high-end sensors with restricted movement capabilities.

Identified Research Gaps

The primary challenge in densely populated urban areas is maintaining cleanliness across large spaces with limited manpower and resources. As a result, waste often accumulates faster than it can be collected, imparting both environmental and public health (Amato & Togo, 2021). Many previous studies assume advanced infrastructure, most of which does not exist in the target deployment area of this research. Moreover, there is a dominant reliance on object detection algorithms like Faster R-CNN and SSD, often overlooking YOLOv11's capabilities, especially when optimised for limited computing environments like the raspberry pi. This research fills that gap by demonstrating how YOLOv11 can be efficiently used on a raspberry pi for real-time detection and robotic actuation in open, outdoor settings.

III. Methodology

Research Approach

An experimental-based methodology was adapted, combining simulation (for design and testing) with physical implementation and field testing. This hybrid approach ensured that both the software (object detection and navigation) and hardware (collection

mechanism) were practically validated. The simulation based research involved creating virtual environments that replicated real-world conditions, allowing for testing of algorithms, sensor configurations and system interactions in a controlled and repeatable setting. This enabled the testing of various scenarios such as different lighting conditions, terrain types and clutter levels, without the risks associated with real world testing, like hardware failures or the robot getting stuck in complex environments. Webots and Gazebo platforms were used to simulate sensor inputs, such as cameras and ultrasonic, providing data on how the robot should react under specific circumstances. The Design Science Research (DSR) was used, as it involved designing and iteratively refining the robot's hardware and software components, such as litter detection algorithm, navigation system and the autonomous control mechanism.

Software Development Methodology

The methodology that was selected for software development was personal extreme programming. It was selected because of its emphasis on frequent releases and continuous feedback. This methodology was appropriate for this system because it required iterative design and continuous refinement to effectively integrate all the different modules.

System Architecture Overview

The robot is made up of three integrated modules that is detection, navigation, and collection. The detection module uses the YOLOv11 object detection model to identify three types of litter in real time from the camera feed. Figure 2 shows the system architecture and how the components are connected.

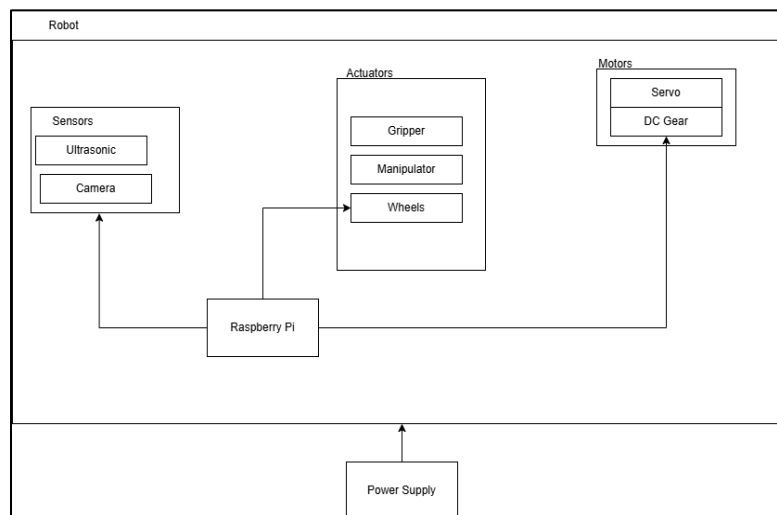


Figure 2 System architecture

The navigation module uses ultrasonic and infrared sensors to detect obstacles and plan safe paths, allowing the robot to move autonomously through its environment.

The collection module is a 4-degree-of-freedom (4DOF) custom made robotic arm that picks up the detected litter and sorts it into onboard bins based on litter type. Sorting the waste facilitates and encourages effective waste segregation and recycling practices. Figure 3 shows the components used in the construction of the robot and each core module.



Figure 3 Materials used for base construction

Model Training, Validation and Testing

A custom dataset that was used, Trash Annotations Dataset (TACO) had 1520 annotated images which were split into 70% for training, 20% for validation and 10% for testing. The dataset was expanded to include labels for litter material types (plastic, paper, glass). These additional labels were used to train the classification layers in the YOLOv11 model. YOLOv11 was chosen for its accuracy in feature detection. Data augmentation techniques including random flipping, rotation and brightness adjustment were applied to improve the model's generalisation and enhance data diversity.

The dataset had three output classes and it was initially trained for 100 epochs using Google Colab with a learning rate of 0.001. On validation, the results showed that the model successfully identified and classified different types of litter with high precision, confirming its effectiveness in real world scenarios. On the test set the following were achieved:

mAP@0.5: 0.8787

Precision: 0.8989

Recall: 0.8434

F1 Score: 0.8700

These test results demonstrate the model's ability to accurately detect and localise various types of litter, including glass, plastic and paper. The high mAP and precision indicate that the model makes confident and correct predictions in most cases, while the solid recall score confirms that the model is successfully identifying the majority of the relevant objects across diverse scenes.

IV. Results

During training the model detected different litter types by minimising the loss function, which measures the difference between predicted and actual bounding boxes. Fine tuning was performed by adjusting hyper parameters such as the learning rate and batch size. The model demonstrated a high performance of 87.87% in identifying and collecting the different kinds of waste, mostly recyclable materials. The classification accuracy at the point of collection enabled faster sorting thereby supporting recycling efforts. Furthermore, the navigation system proved reliable in enabling autonomous movement through various environments. Figure 4 shows the F1 confidence curve which provides a balanced view of precision and accuracy.

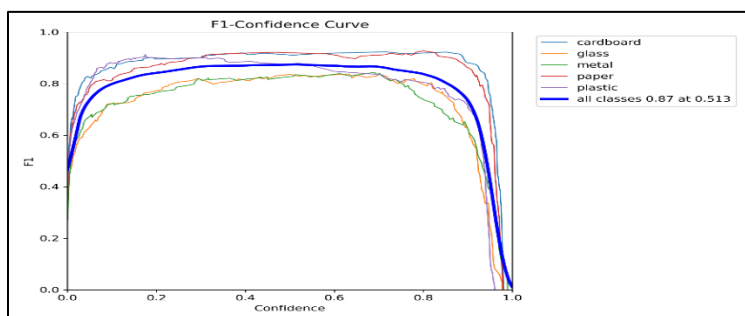


Figure 4 F1-confidence curve

The metrics used to evaluate the performance were precision, recall and the mean average precision which is the mAP50. The results are shown in Figure 5.

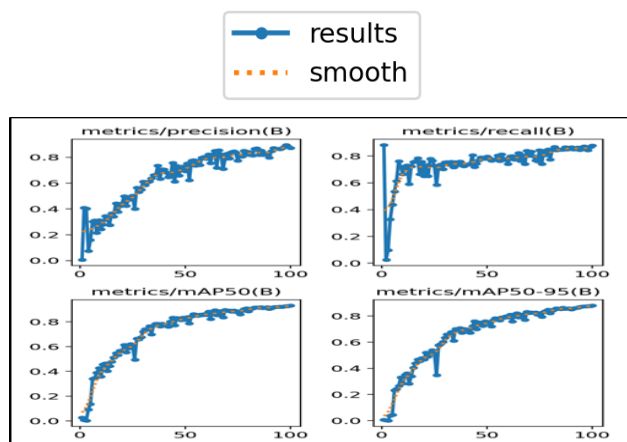


Figure 5 Performance metrics

Performance Comparison with Expectations

The robot's modular design makes the robot scalable, adaptable, and suitable for deployment in various environments, and allows for multiple robots in larger areas. The modular design also allows for easy adaptation to different terrains, litter types, and operational requirements.

Additional components were installed to allow the system to fulfil its objectives and these were the raspberry pi, motor driver and additional power supply. The servo motors were connected to the gpio pins as well as a fan to cool the microprocessor and motor driver pins IN1 to IN4 and ENA and ENB for speed control. Figure 6 shows the final system.



Figure 6 The Autonomous Robot

In order to deploy the model on the raspberry pi, it was necessary to convert it from YOLO format to ONNX. This conversion allowed for more efficient execution on the pi's hardware because it compressed the model, ensuring optimal performance for real-time inference.

V. Discussions

The autonomous litter sorting robot solves the problem of litter accumulation in urban areas through an automated process that combines detection, classification, and collection capabilities.

Traditional manual litter collection methods in growing urban areas are inefficient. The robot offers a sustainable solution by automating this process. The successful implementation of a low-cost, sustainable robot demonstrates a solution to waste management challenges even in resource-constrained environments. This approach not only solves the problem of litter but also promotes a circular economy through material reuse to cater for climate change as well where litter is recycled instead of being dumped all over.

The review showed the potential of advanced algorithms in improving detection and collection accuracy, and the efficiency of robots in urban environments through improved navigation.

While other systems used YOLOv4-tiny or Mask R-CNN for detection, and various robotic arm designs, many faced limitations in classification or adaptability to diverse terrains and cost constraints. The model's use of YOLOv11 for real-time detection and classification together with a custom 4-DOF robotic arm, offers a balanced approach to functionality and keeping costs low. Its focus is on classifying three main types of litter (paper, glass, plastic) at the point of collection. It improves upon existing systems with limited classification capabilities while also enhancing recycling efforts.

The development of the autonomous litter collection and sorting robot for resource-limited urban environments falls under the domain of adaptive urban service technologies that covers technologies that are designed to provide or improve urban services like waste management, in a flexible and open manner, frequently leveraging automation, artificial intelligence (AI), and sensor data to adapt to changing conditions and specific local contexts. The robot's autonomous navigation, real-time detection, and focus on resource-limited environments also aligns directly with the characteristics of adaptive urban service technologies.

This research was conducted with a pledge to ethical principles and responsible innovation. The design and future application of this robot acknowledges the social, economic, and environmental contexts of its proposed use in urban areas of developing countries. Approval should be obtained from the municipal council when the robot is deployed in public places. Proper international ethical guidelines should be followed.

Table 1 Comparison of Existing Systems

Author	Technologies	Future Recommendations
(Kulshreshtha et al., 2021)	Rocker-bogie mechanism for terrain, YOLOv4 tiny	Alternative energy source, expanding detection capabilities for segregation
(Mushiri and Gocheke, 2019)	Arduino based controlled navigation to detect and collect waste	Navigation and accuracy improvement. Sorting mechanism
(Almanzor, Anvo, Thuruthel, and Lida, 2022)	6DOF arm with main focus on roadside litter. Detectron 2 framework with Mask R-CNN using TACO dataset.	Enhancing gripper design and developing mobile deployment capabilities.
(Milburn, L., Chiaramonte, J., Fenton, J., and Padir, T., 2023)	CNN for detection and mapping. 2 devices, aerial vehicle to scan and gather data and ground robot for picking using greedy approach.	Real world deployment
(Mărgăritescu et al., 2020)	SLAM for mapping and navigation. LiDAR for obstacle detection and avoidance	Enhance adaptability and integrate more advanced control Algorithms.
The designed litter collection and sorting robot	Low cost material and YOLOv11, ultrasonic sensors for obstacle avoidance, raspberry pi and 4DOF robotic arm.	Improve accuracy in varying weather conditions, alternative power supply.

Table 1 shows a comparison of existing systems, technologies used in each and future work on each system.

Challenges Faced

The challenges faced were navigating diverse terrains, recognising different types of litter in various lighting and weather conditions, and ensuring effective operation in dynamic environments.

The iterative nature of the experimental and PXP methodologies ensured continuous improvement and adaptability to changing requirements, controlled environment testing for initial validation and reduced the risks associated with field testing as well as cost.

VI. Conclusion and Future Work

This project successfully developed an autonomous robot for detecting, classifying, and collecting urban litter using low-cost, sustainable components, including a robotic arm. The system integrated a YOLO-based deep learning model for real-time litter detection and classification, ultrasonic sensors for navigation, and a custom robotic arm for collection and sorting litter into different on-board compartments. The robot demonstrated strong performance in recognising and collecting various litter types, particularly recyclable waste like plastic and paper, thereby supporting recycling efforts and climate change. The navigation system also proved reliable in autonomous movement through diverse environments. The autonomous litter collection robot demonstrates how adaptive urban service technologies can leverage intelligent automation and data to provide practical, context-aware, and ethically comprehensive solutions for critical urban challenges, mainly in circumstances where traditional, high-cost approaches are not achievable.

This robot can also be adapted for usage in agriculture by small scale farmers, where it can be used to collect and sort/classify agricultural produce as the farmer prepares to go and make his sales at the market, especially in cases where the farm produce needs to be graded, e.g., tomatoes, potatoes etc.

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