Autonomous Litter Detection & Picking Drone

Athul Krishna N S, Nidhin Baby, Nizam P M, Sravan C Nipun*, Athira M, Julia T J

Department of Robotics and Automation, Adi Shankara Institute of Engineering and Technology, Kerala, India

* Corresponding author: sravancnipun@gmail.com
doi: https://doi.org/10.21467/proceedings.7.5.15

ABSTRACT

This paper suggests a drone system for automated trash discovery and collection that integrates robotic manipulation and computer vision to combat environmental declination in hard- to- reach places. The YOLOv8 object identification algorithm, which has an average perfection of 89.7 in a variety of outside circumstances, is used by the proposed system for real-time waste identification. Drone is incorporated with a specially designed 3- DOF robotic arm powered by MG996R servo motors to recoup waste. This arm is capable of precise and stable grasping and retrieval operations during flight or stationary hovering. The drone navigates autonomously using GPS and onboard sensors, while the YOLOv8 algorithm continuously processes camera input to detect and track waste. Experimental evaluations demonstrate the system's effectiveness in accurately detecting and retrieving litter across different terrains and conditions.

Keywords: YOLO V8, Fusion 360, Convolutional Neural Network, End effector

1 Introduction

People recklessly litter streets with bottles, tin cans, plastic covers, and banana peels. Most individuals also seem careless towards the environment as they spew and toss wrappers on both sides of the road. This littering is a major source of pollution, and the assigned staff are responsible for the time-consuming and difficult duty of cleaning it up. The effects go beyond people; garbage is frequently mistaken for food by animals and birds, which can cause harm or even death and disturb the environment. This effort, through automating litter identification and collection, solves the aforementioned issues and thus enables a cleaner environment, more powerful ecosystem for living beings, and a healthy environment [1]. Using onboard sensors and image processing tools, the autonomous drone litter detection method identifies and categorizes environmental debris. Its camera and machine learning models with object detection algorithms enable it to identify in real time different forms of trash such as plastic bottles, cans, and wrappers. These models, mostly CNNs-based, namely SSD (Single Shot Multibox Detector) and YOLO (You Only Look Once), assess the visual data and mark found litter with bounding boxes. They are properly classified appropriately. Therefore, this would enable the drone to look for and collect garbage on its own, giving it a scalable effective waste management system.

Recent advancements in drone technology combined with machine learning have significantly enhanced the capabilities of autonomous litter detection systems. Yandouzi, Mimoun, et al. developed the drone incorporated with deep learning techniques for real-time plastic litter detection, for enhancing environmental surveillance and waste management efficiency [2]. An instance segmentation-based approach for autonomous litter detection and collection using aerial vehicle is proposed in [3] but its performance is constrained by environmental variation and computational constraints on the aerial platform. A system that identifies and collects litter on Icelandic beaches, thereby developing a highly advanced method of addressing marine pollution without relying on labour-intensive clean-up is proposed in [4]. Varadaramanujan et al. presented the design of a drone equipped with a robotic end-effector having effective grasping capabilities, though its performance is limited by payload capacity and lack of full

Proceedings DOI: 10.21467/proceedings.7.5; Series: AIJR Proceedings; ISSN: 2582-3922; ISBN: 978-81-989164-7-1

autonomous control [5]. Merlino et al. developed a system that can effectively aid marine litter detection and classification [6]. A system based on deep learning approach is developed for detecting waste in natural as well as in urban settings, achieving high accuracy in various environments [7]. Escobar-Sánchez et al. developed a highly efficient aerial drone for monitoring macrolitter on Baltic Sea beaches [8]. A deep learning-based system using drones for intelligent and accurate garbage detection is developed in [9].These collective studies posit that robots and drones can change dramatically the face of industrial and environmental problems that we face. These technologies are able to fulfill needs safer, more intelligently, and more sustainably for the future, from maintaining infrastructure to cleaning the beaches.

In this work a drone system for automated trash discovery and collection that integrates robotic manipulation and computer vision to combat environmental declination in hard- to- reach places are suggested. The YOLOv8 object identification algorithm is used by the proposed system for real-time waste identification and drone is incorporated with a specially designed 3- DOF robotic arm powered by MG996R servo motors to recoup waste. The drone navigates autonomously using GPS and onboard sensors, while the YOLOv8 algorithm continuously processes camera input to detect and track waste. Even in inaccessible areas, the robotic arm of the drone with a gripper is activated when it detects litter, allowing it to collect the garbage precisely.. Real-time changes are possible since the movements of the drone are tracked by a ground control station. The detection algorithm of the drone is continuously improved as it gathers data, increasing its efficiency and accuracy.

2 Methodology

The block diagram of autonomous litter detection system is shown in Figure 1. The setup consists of an autonomous drone with a Raspberry Pi, Pixhawk flight controller, and 3-DOF manipulator for litter detection and collection. This model employs the latest and advanced, lightweight object-detection models YOLOv8 algorithm for identifying the litter. The core of the system is built around a Raspberry Pi that will process images coming from an onboard camera and control how the drone moves.

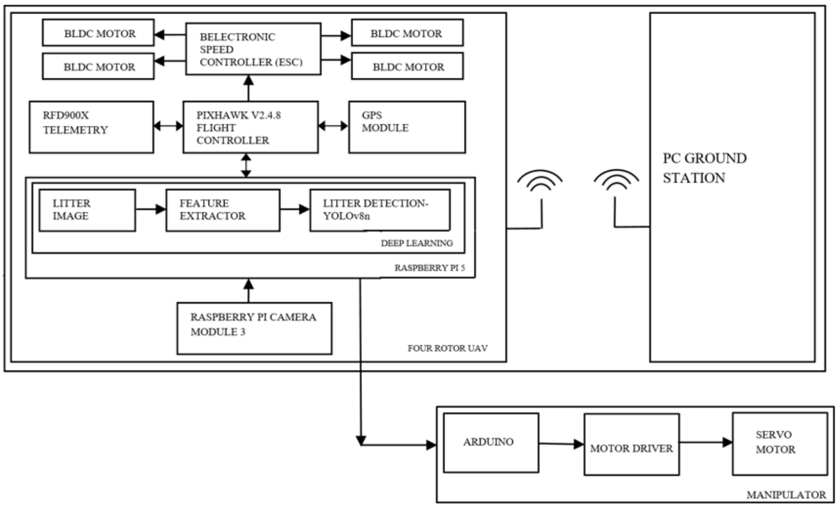

Figure 1: Block diagram of Autonomous Litter Detection System

YOLOv8 running on Raspberry Pi detects different litters like plastic bottles and bags by analyzing the live feed captured by the drone camera. It keeps recording live images that are later processed by the YOLOv8 model, which is trained to classify different types of litter, from metals and plastics to organic waste. Using a custom dataset, the model can accurately detect and label waste, drawing bounding boxes around it for precise localization. As soon as the litter is detected, it uses sensors and a flight controller to navigate and pick up litter with a gripper mechanism. The entire system, from recognition of litter to navigation and pickup, is operated by the Raspberry Pi, thus compact and self-sustained. Google Colab is used to train and optimize the object detection model, leveraging cloud-based computing to enhance performance without overloading the drone.

As the manipulator gathers the litter and feeds it into an onboard container, the Pixhawk maintains constant stability and identifies safer heuristics that enable the drone to avoid obstructions. Using optimization techniques, even the resource-hungry Raspberry Pi can do the work with remarkable efficiency. All of these make the drone an excellent tool for environmental monitoring and cleanup since they allow it to recognize, gather, and move litter on its own. The system here works very much for detection, navigation, and collection altogether. The Pixhawk ensures continuous stability and determining safer heuristics that allow the drone to avoid obstacles while the manipulator picks up the litter and feeds it into a compartment onboard using the 3-DOF manipulator. Together, these enable the ability of the drone to autonomously identify, collect, and transport litter, making it a fantastic agent of environmental cleanup and monitoring.

3 Object Detection Algorithm

The YOLOv8 architecture is built for both speed and accuracy in object detection. The block diagram of YOLOv8 architecture is shown in Figure 2. The architecture has three parts: the backbone, neck, and head. The backbone extracts key features from images, including edges and textures. It employs a C2F block to capture fine details and uses the Spatial Pyramid Pooling Fast module to merge features at different scales, helping it deals with objects of different sizes. The neck is a structure that connects the backbone and the head, thereby improving and combining features to increase the accuracy of the predictions. It fine-tunes the features with the C2F block, brings together information from different levels using the Concat layer, and aligns the features through Upsample layers to ensure smooth processing. Finally, the head puts together these refined features and makes final predictions—detects objects, classifies them and assigns confidence scores. This very inspired design allows YOLOv8 to make fast and reliable real-time object detection.

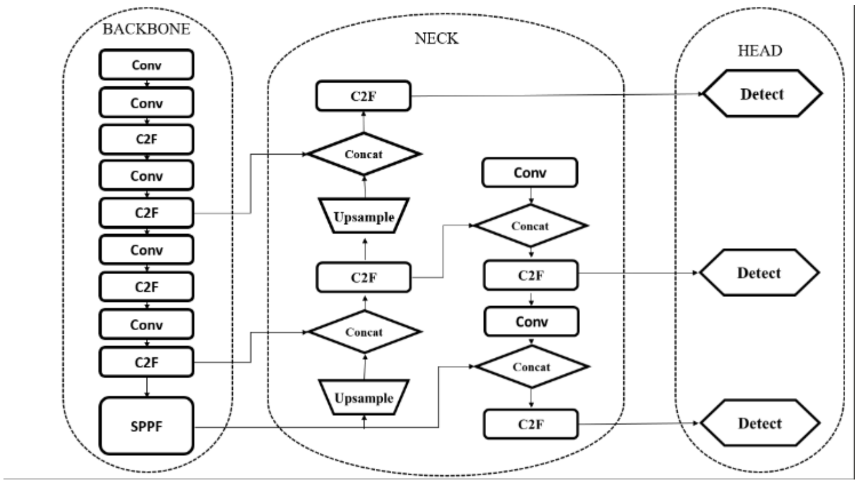

Figure 2: Architecture of YOLOv8

The flow chart for litter identification is shown in Figure 3. The litter detection process starts with system initialization, where the YOLOv8 model is loaded, and the onboard camera is activated. The system continuously captures video frames as the drone or robotic platform navigates through the environment. Each frame is processed in real time by the YOLOv8 model, which is trained to detect various types of litter such as plastic bottles, cans, and wrappers. YOLOv8 provides high-speed and accurate identification by drawing bounding boxes around detected litter and assigning confidence scores to each detection. If the confidence exceeds a defined threshold, the system logs the litter's position, potentially using additional sensors for GPS tagging or depth estimation.

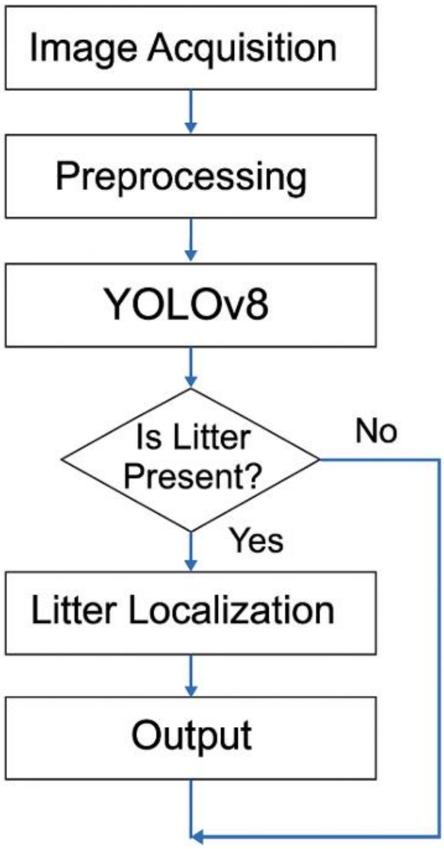

Figure 3: Flow chart for Litter Identification

4 End Effector for Litter Pick up

A servo motor-driven mechanical end effector with a 3-DOF (Degrees of Freedom) gripper is employed to pick and deposit litter efficiently. The design of end effector done in Fusion 360 is shown in Figure 4. Since the drone's flight controller or microprocessor will control the gripper's servo motor, this configuration will guarantee that the drone can effectively capture and manage the different kinds of litter when used. Basic control commands can be integrated into the mission planning of the drone for more complex activities to ensure optimal performance. The drone can also change its grip strength based on the weight and size of the litter by using machine learning algorithms to change the grip according to visual input. This versatility ensures that the drone can accurately handle a variety of objects.

Proceedings DOI: 10.21467/proceedings.7.5
ISBN: 978-81-989164-7-1

Series: AIJR Proceedings
ISSN: 2582-3922

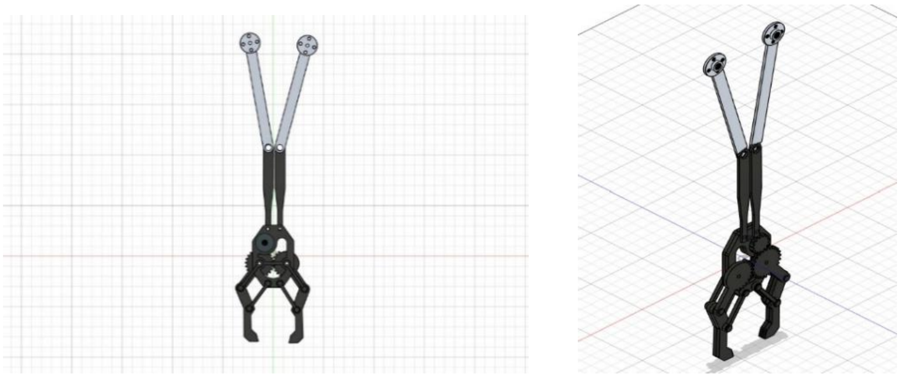

Figure 4: Design of End Effector

5. Hardware Used

The design of the developed system done in Fusion 360 is shown in Figure 5. The S500 Quadrotor Frame is a strong, lightweight chassis made of high-strength materials such as carbon fiber or plastic, designed for quadcopters. It has a PCB that controls the power distribution to the parts and supports four motors and ESCs. The integrated PCB not only ensures reliable power delivery, voltage control, and overcurrent safety for effective operation but also simplifies wiring.

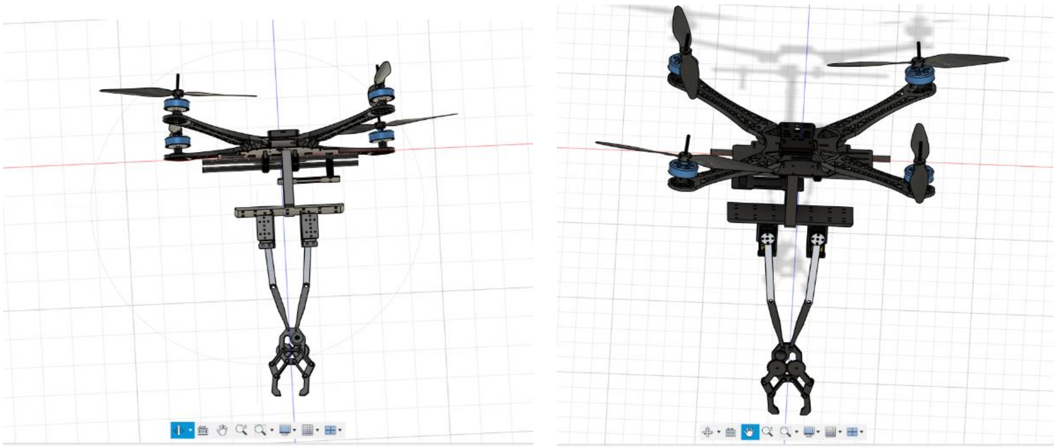

Figure 5: Design of Litter Picking Drone

The speed for each motor on the quadcopter is controlled. Therefore, there is exact control over the movement of the quadcopter. It can handle sudden acceleration or thrust changes due to its 40A rating in these ESCs. Therefore, reliable control is done over each of the four motors that make up the drone due to its steady and smooth throttle response in Simonk firmware. When combined with ESCs, brushless motors have a smooth-running performance, increased efficiency, and lower maintenance over brushed motors. The "750KV" rating of DT750 specifies that the motor spins at 750 RPMs per volt in order to increase thrust without contributing much to the total weight.

The RADIOLINK PIXHAWK 2.4.8 Flight Controller controls navigation and stabilizes the drone by analyzing data from sensors like accelerometers and gyros. The user can operate the drone manually or automatically due to communication between the FS-IA6B RF receiver and the FS-i6 2.4G 6CH AFHDS

RC transmitter. This method guarantees accurate control for steady flight and seamless drone-pilot communication. The litter-detection drone is built with a lightweight and robust frame, composed of aluminum or carbon fiber to hold all of its parts together. The machine is powered by high-capacity LiPo batteries, and flight controllers like Pixhawk or Betaflight, along with sensors including GPS, accelerometers, and gyroscopes, control and guide it smoothly. The vision system and onboard processing capability are the foundation of the litter detecting functionality. High-resolution cameras record live video and send it for real-time analysis; they are often mounted on gimbals for stabilization. The machine learning model YOLO is run in Google Colab on an onboard CPU, such as a Raspberry Pi or NVIDIA Jetson Nano.

6. Results and Discussions

An autonomous drone equipped with a vision-based litter identification system and a robotic gripper is developed to detect and collect waste objects in outdoor settings. The litters identified by YOLOv8 detection is shown in Figure 6 and the developed litter picking drone is shown in Figure 7.

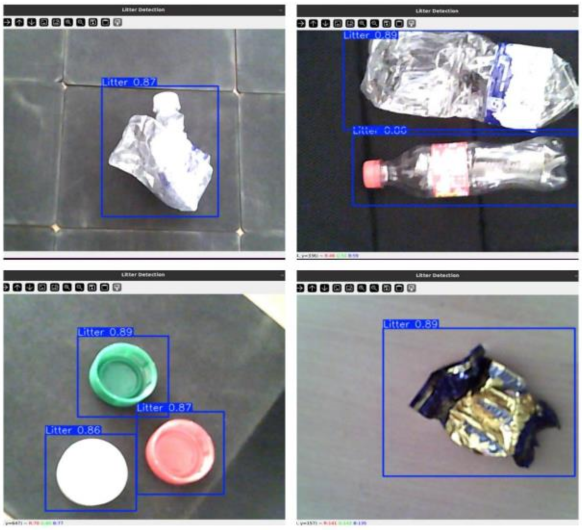

Figure 6: Litter Identification

Figure 7: Litter Picking Drone

While most of the existing works have focused mainly on litter detection, the work presented in this paper goes a step further by incorporating physical collection through a 3-DOF robotic arm. This enables not just identification but also removal of litter, making the system more practical and impactful. The autonomous litter detection and picking drone integrates advanced computer vision, robotic gripping, and autonomous navigation to function effectively in real-world scenarios. YOLOv8 is used for real-time object detection, while the 3-DOF robotic arm, driven by MG996R servo motors, ensures accurate grasping and retrieval. With GPS-based navigation and obstacle avoidance supported by the Pixhawk flight controller, the drone can operate across different terrains, including urban, rural, and natural environments. This comprehensive setup addresses the limitations of earlier systems by offering both detection and collection in a fully autonomous manner.

7. Conclusions

The developed autonomous litter-picking drone provides an effective solution for automated waste collection in outdoor environments. The system integrates an onboard camera, YOLOv8 detection algorithm, a flight controller, and a manipulator to autonomously identify, navigate and collect litter. This innovation contributes to cleaner communities but also demonstrates the application of artificial intelligence in the area of environmental conservation. The system possesses the potential for scaling, paving the way for broader applications, such as industrial waste management and urban clean-up effort.

8. Publisher's Note

AIJR remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

How to Cite

Krishna N S *et al.*, "Autonomous Litter Detection & Picking Drone", *AIJR Proc.*, vol. 7, no. 5, pp. 124-130, Sep. 2025. doi: https://doi.org/10.21467/proceedings.7.5.15

References

[1] S. B. Borrelle et al., "Predicted growth in plastic waste exceeds efforts to mitigate plastic pollution," Science, vol. 369, no. 6510, pp. 1515–1518, Sep. 2020

[2] M. Yandouzi, et al., "Elevating plastic litter surveillance: Drones and deep learning for efficient detection," *Journal of Theoretical and Applied Information Technology*, vol. 102, no. 11, Nov., 2024.

[3] F. Zoric, A. Franchi, M. Orsag, Z. Kovacic, and C. Gabellieri, "Towards Instance Segmentation-Based Litter Collection with Multi-Rotor Aerial Vehicle," *Proc. Int. Conf. Unmanned Aircraft Syst. (ICUAS)*, pp. 631–637, Jun. 2024.

[4] A. R. Frey, "Design of an autonomous litter detection and collection system for Icelandic beaches," *Diss.*, 2024

[5] Varadaramanujan, S., Sreenivasa, S., Pasupathy, P., Calastawad, S., Morris, M. and Tosunoglu, S., 2017, May. Design of a drone with a robotic end-effector. In Proceedings of the 30th Florida conference on recent advances in robotics, Boca Raton, FL, USA (pp. 11-12).

[6] S. Merlino, M. Paterni, M. Locritani, U. Andriolo, G. Gonçalves, and L. Massetti, "Citizen science for marine litter detection and classification on unmanned aerial vehicle images," *Water*, vol. 13, no. 23, p. 3349, Nov. 2021.

[7] S. Majchrowska et al., "Deep learning-based waste detection in natural and urban environments," *Waste Manag.*, vol. 138, pp. 274–284, Feb. 2022.

[8] M. Escobar-Sánchez, M. Haseler, N. Oppelt, and G. Schernewski, "Efficiency of aerial drones for macrolitter monitoring on Baltic Sea beaches," *Front. Environ. Sci.*, vol. 8, 2021.

[9] V. Verma, R. Kumar, R. Singh, P. K. Singh, A. K. Sangaiah, and R. Hong, "A deep learning-based intelligent garbage detection system using an unmanned aerial vehicle," *Symmetry*, vol. 14, no. 5, May 2022.