REAL TIME OBJECT DETECTION AND ROBOTIC RESPONSE FOR PLASTIC WASTE CLEANUP

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Abstract
This paper presents the development of a custom plastic bag detection and localization system using the YOLOv8 deep learning model. Aimed at addressing the growing issue of plastic waste, this project combines image annotation, real-time object detection, and robotic navigation to create an automated solution for identifying and retrieving plastic bags. Images were annotated using the Computer Vision Annotation Tool (CVAT) to create a robust training dataset for the YOLOv8 model, which was implemented with OpenCV for live frame capture and processing. Upon detecting a plastic bag, the system calculates the bounding box and centroid coordinates of the object, which are then transmitted to an Arduino Uno via PySerial. The Arduino controls a four-wheel robot to navigate to the plastic bag based on the received coordinates. This integrated system demonstrates the potential for enhancing waste management practices through automation, achieving high detection accuracy and reliable robotic navigation in real-time scenarios. Future improvements and applications of this technology are also discussed.

Keywords:
Machine Learning, Open CV, Sensors.

I. Introduction
Plastic pollution is one of the most pressing environmental challenges of the 21st century. Millions of tons of plastic waste are generated annually, with a significant portion ending up in natural habitats, where it poses severe threats to wildlife and ecosystems. Traditional methods of waste collection and management are often labor-intensive and inefficient, underscoring the need for innovative technological solutions to enhance these processes. Among the myriad types of plastic waste, plastic bags are particularly problematic due to their lightweight nature and tendency to be easily dispersed by wind and water. Detecting and collecting plastic bags manually in large areas, such as parks, beaches, and urban environments, is a daunting and resource-intensive task. Automation in waste detection and collection presents a promising avenue to tackle this issue more effectively.

I.I Objective
This research aims to develop a custom plastic bag detection and localization system utilizing the YOLOv8 (You Only Look Once, Version 8) object detection model. By integrating advanced image processing techniques and robotic navigation, the project seeks to automate the identification and retrieval of plastic bags.
The core objectives include Developing a robust dataset of annotated images for training the YOLOv8 model, Implementing real-time object detection using OpenCV to process live video feeds, Calculating the bounding box and centroid coordinates of detected plastic bags, Transmitting these coordinates to an Arduino-controlled four-wheel robot via PySerial, Enabling the robot to navigate accurately to the plastic bag for potential collection. By achieving these objectives, the project aims to contribute to

more efficient and autonomous waste management solutions, potentially reducing the environmental impact of plastic pollution.

II. Literature

The growing concern over plastic pollution has led to significant research in waste management technologies. According to the United Nations Environment Programme, approximately 300 million tons of plastic waste are produced each year, with at least 8 million tons ending up in the ocean, causing widespread environmental damage. The need for efficient and automated systems to manage and reduce plastic waste is more urgent than ever. Object detection has seen remarkable advancements with the advent of deep learning. The YOLO (You Only Look Once) series of models, in particular, have revolutionized the field with their ability to detect objects in real-time. The YOLOv8 model continues this trend, offering improved accuracy and speed over its predecessors. YOLOv8 employs a single neural network to predict bounding boxes and class probabilities directly from full images in one evaluation, making it highly efficient for real-time applications .

Accurate annotation of training data is crucial for the performance of object detection models. The Computer Vision Annotation Tool (CVAT) is widely used for this purpose, providing a user-friendly interface for annotating images and videos. CVAT supports various annotation formats and can handle complex annotation tasks efficiently, making it suitable for creating high-quality datasets required for training robust models.

2.1 Image Processing with OpenCV

OpenCV (Open Source Computer Vision Library) is an open-source computer vision and machine learning software library that provides tools for real-time image processing. It has been extensively used in various applications, including object detection, facial recognition, and motion tracking. OpenCV's integration with deep learning frameworks allows for seamless real-time processing, making it ideal for projects requiring live frame capture and analysis.

2.2 Robotic Systems and Arduino

The use of robotics in automated waste management has been explored in several studies. Robots equipped with sensors and cameras can navigate environments to identify and collect waste. The Arduino Uno, a popular microcontroller board, is often used in these systems for its simplicity and versatility. It can be programmed to control motors, read sensors, and communicate with other devices, making it a key component in robotic navigation and control.

2.3 Integration of Detection and Robotics

Integrating object detection with robotic systems involves several challenges, including real-time processing, accurate localization, and reliable communication between components. Studies have demonstrated the feasibility of using YOLO models in conjunction with robotic platforms to achieve tasks such as object picking, path planning, and navigation. The combination of deep learning for detection and Arduino for control provides a powerful framework for developing autonomous systems capable of performing complex tasks.

2.4 Proposed System

In this section, we introduce the proposed system architecture and operational framework of our posture detection and correction project. Through the utilization of a comprehensive flowchart, we aim to provide readers with a visual roadmap of the various components, functionalities, and interactions within our system. The flowchart serves as a blueprint, illustrating the step-by-step sequence of operations involved in plastic detection, data transmission, and user interaction.

Figure 1. Flow chart of how the overall system is going to work.

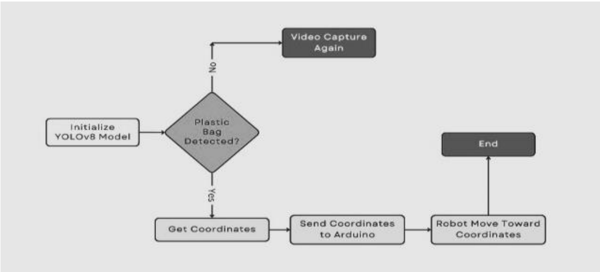


Figure 2. Flow chart of how the plastic detection code works step by step.

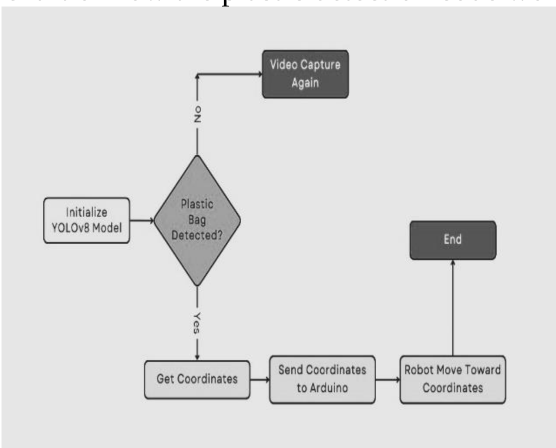
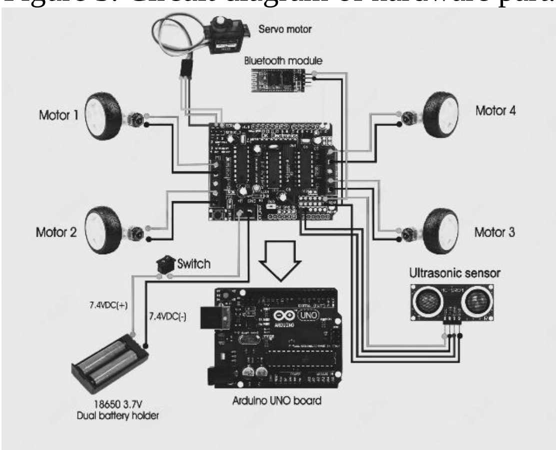


Figure 3. Circuit diagram of hardware part.



2.4 Data Collection and Annotation

A comprehensive dataset of images was collected from diverse environments, including urban areas, parks, and beaches. These images were captured using a high-resolution camera to ensure clarity and detail. The collected images were annotated using the Computer Vision Annotation Tool (CVAT), a web-based tool known for its efficiency and accuracy in annotating images. Annotators meticulously drew bounding boxes around each instance of a plastic bag in the images. Annotated images were reviewed by multiple annotators to ensure consistency and accuracy in labeling. Any discrepancies or errors were corrected through consensus. The YOLOv8 model was chosen for its state-of-the-art performance in real-time object detection tasks. Its architecture allows for rapid inference without sacrificing accuracy. The annotated dataset was pre-processed, including resizing images, normalizing pixel values, and splitting into training and validation sets. Data augmentation techniques such as rotation, scaling, and flipping were applied to augment the dataset's diversity. The YOLOv8 model was trained using the Darknet framework on a high-performance GPU cluster. Hyperparameters such as learning rate, batch size, and number of epochs were tuned using grid search and cross-validation techniques to optimize model performance. The trained model's performance was evaluated on the validation set using metrics such as mean Average Precision (mAP) and Intersection over Union (IoU) to assess detection accuracy and localization precision. need to have a proper camera alignment. We need to ensure that the camera looks at the side view from a proper distance.

2.5 Integration with OpenCV

OpenCV was integrated into the system to capture live video streams from the camera module. This provided a continuous feed of images for real-time processing Each frame from the live video feed was passed through the trained YOLOv8 model for object detection. The model outputted bounding boxes and confidence scores for detected objects. Detected objects with confidence scores below a certain threshold were filtered out to improve precision. Non-maximum suppression (NMS) was applied to eliminate redundant detections and refine bounding box predictions.

2.6 Coordination Calculation

For each detected plastic bag, the coordinates of the bounding box (x_min, y_min, x_max, y_max) were computed. The centroid coordinates (x_center, y_center) of the bounding box were then calculated using the formula:

x_center = (x_min+x_max)/2

y_center = (y_min+y_max)/2

The centroid coordinates of detected plastic bags were formatted into a serializable format and transmitted to the Arduino Uno microcontroller using the PySerial library. This facilitated communication between the detection system and the robotic platform.A four-wheel robotic chassis was chosen for its stability and mobility. High-torque DC motors were selected to ensure sufficient power for navigation.The chassis was assembled according to the manufacturer's instructions. Motors were securely attached to the wheels, and additional support structures were added to accommodate the motor driver and Arduino Uno.

2.7 Robot Car

The Arduino Uno microcontroller and motor driver were mounted on the chassis using mounting brackets and screws. Care was taken to ensure proper alignment and stability of the components. The Arduino Uno was connected to the motor driver and power supply. Digital pins on the Arduino were allocated for motor control, while PWM pins were used for speed modulation. The L293D motor driver was connected to the motors and Arduino Uno according to the datasheet specifications. Proper connections were made for motor direction control and PWM input. Separate power sources were used for the Arduino Uno and motors to prevent voltage fluctuations and ensure stable operation. Voltage regulators and capacitors were included in the circuit design for voltage regulation and noise suppression. The Arduino Uno was programmed with control logic to interpret received coordinates and translate them into motor control signals. Proportional control algorithms were implemented to adjust motor speeds based on the distance to the target. Ultrasonic sensors or infrared sensors were integrated into the robot to detect obstacles in the environment. Simple obstacle avoidance algorithms were implemented to steer the robot away from obstacles while navigating towards the target, The integrated system was tested in a controlled environment to verify individual components' functionality. This included testing the motor control, communication between the computer and Arduino, and the accuracy of object detection.

2.8 Calibration Process:

Parameters of the control logic, such as motor speed coefficients and PID gains, were calibrated to optimize navigation accuracy and responsiveness. The fully integrated system underwent extensive testing in real-world environments with varying conditions, including different lighting conditions, terrains, and obstacle densities. Performance metrics such as detection accuracy, navigation speed, and obstacle avoidance effectiveness were evaluated. In this section, we present a comprehensive demonstration of the functionality and effectiveness of our posture detection and correction system. Through a combination of captioned images, user interface descriptions, performance metrics, we provide a detailed exploration of how our project addresses the plastic waste issue.

Figure 4. F1 Confidence Curve

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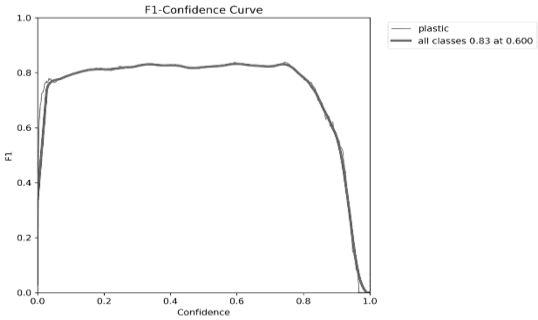


Figure 5. Plastic bag detected by model

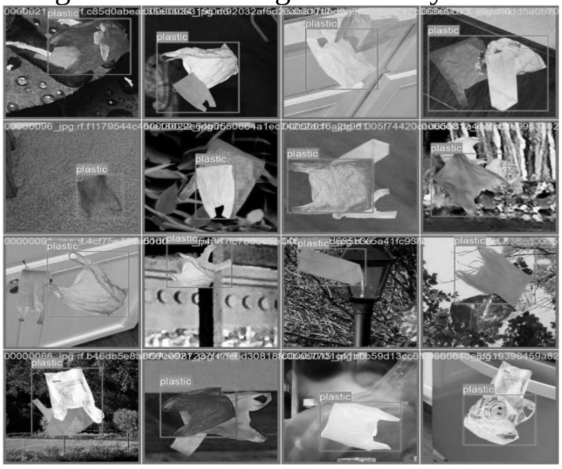
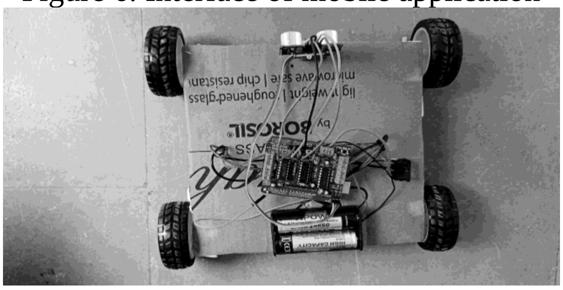


Figure 6. Interface of mobile application



III Conclusion

In this study, we developed a comprehensive system for custom plastic bag detection and localization using the YOLOv8 deep learning model integrated with a robotic platform controlled by an Arduino Uno microcontroller. The project aimed to address the pressing issue of plastic pollution by automating the detection and retrieval process of plastic bags in various environments. The results of our research demonstrate the feasibility and effectiveness of the proposed system. Through meticulous data collection and annotation, we curated a diverse dataset that facilitated the robust training of the YOLOv8 model. The model exhibited high accuracy in real-time plastic bag detection, thanks to its advanced architecture and rigorous training process. Integration with OpenCV enabled seamless processing of live video streams, allowing for continuous object detection in real-world environments. The calculated bounding box and centroid coordinates of detected plastic bags were transmitted to the Arduino Uno, which controlled the robotic platform's navigation towards the target objects.

The hardware component of the system, including the motor driver L293D and the assembled robot car, provided a reliable and versatile platform for executing navigation commands based on received coordinates. Through careful calibration and testing, we ensured the system's robustness and adaptability to different environmental conditions. Overall, our research represents a significant step towards the automation of waste management processes, particularly in addressing the pervasive issue of plastic pollution. By combining state-of-the-art deep learning techniques with robotic navigation, we have demonstrated a scalable and efficient solution for detecting and collecting plastic bags in real-time. Looking ahead, further enhancements and optimizations can be explored to improve the system's performance and applicability in practical scenarios. This includes refining the object detection model for increased accuracy and extending the robotic platform's capabilities for handling diverse terrain and obstacles. Additionally, integration with cloud-based services and remote monitoring capabilities can enhance the scalability and accessibility of the system for broader deployment in waste management initiatives.

In conclusion, our research underscores the potential of interdisciplinary approaches combining artificial intelligence, robotics, and environmental science to address complex societal challenges. By harnessing the power of technology, we can pave the way towards a more sustainable and environmentally conscious future.

References:

1. “Learning Open CV” by Gary Brad ski and Adrian Kaehler September 2008
2. “Open CV 4 Computer Vision with python Recipes” by Joseph Howse 2013
3. Machine learning for aquatic plastic litter detection, classification and quantification (APLASTIC-Q) by Mattis Wolf 11, 2020
4. CLOTH BAG OBJECT DETECTION USING THE YOLO ALGORITHM (YOU ONLY SEE ONCE) V5 by Rizki Hesananda, Desima Natasya and Ninuk Wiliani 2 July 2023
5. Somantri, Alun Sujjada, Yusuf Saeful Bayan, Viky Rodiatul Ulum, Fahmi Adrial Ilhami, “Enhanced Plastic Detection and Classification: Advancing Recognition of Plastic Varieties Using YOLOv8” · November 2023
6. Analysis of Object Following Robot Module Using Android, Arduino and Open CV, Raspberry Pi with OpenCV and Color Based Vision Recognition by A. Ambikapathy, Jyotiraditya Sandilya, Ankit Tiwari, Gajendra Singh 21 January 2021
7. Use of deep learning to automate the annotation of USG lung image data, by Martin Sarnovský, Michal Kolárik, 14 February 2024