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# Detection and Segregation of Plastic Waste using a Robotic Arm

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***Abstract*— Plastic waste pollution has become one of the most significant environmental concerns in recent years. The accumulation of plastic waste has been observed in various locations worldwide, leading to environmental damage and health hazards. In this paper, a system is proposed for the detection and segregation of plastic waste using a Robotic arm manipulator based on YOLOv5 and Raspberry Pi. YOLOv5 is an advanced object detection algorithm that can identify plastic waste in images. The Raspberry Pi is a low-cost, small-sized computer that can be used as the central processing unit for the proposed system. The system includes a camera module that captures images of the waste material in real time, and an ultrasonic sensor to measure distance of the object. It detects and identifies the plastic waste in the image. Then, using the 3-D coordinate values calculated from the data gathered from the camera and ultrasonic sensor, plastic waste is separated using a robotic arm by applying inverse kinematics, controlled by the Raspberry Pi. The proposed system's performance was evaluated using various custom datasets, and the results show that it can effectively detect and segregate plastic waste from other types of waste materials.**

***Index Terms*— Waste management, Plastic segregation, YOLOV5, Object detection, Robotics, Artificial Intelligence, Raspberry Pi 4.**

## I. INTRODUCTION

In Plastic waste is a growing environmental concern worldwide due to its harmful effects on the environment and human health. The accumulation of plastic waste can lead to the contamination of the soil, water, and air, which can be detrimental to both animals and humans. Therefore, it is crucial to find effective methods to reduce plastic waste and its impact on the environment. Manual plastic waste segregation can be subjective and prone to human error. Manual sorting of plastic waste requires significant human effort and time, limiting the amount of waste that can be processed within a given timeframe. It also exposes workers to potential health risks due to sharp objects, contaminated waste, and exposure to harmful chemicals. With the growing plastic waste problem globally, recycling facilities face the challenge of scaling up their operations to handle increasing waste volumes. Manual sorting methods require a significant increase in labor force, space, and resources, leading to financial constraints and operational limitations. In the proposed system for the detection and segregation of plastic waste, YOLOv5 is used as the object detection algorithm to detect plastic waste in images captured by the camera module in real time. The Raspberry Pi is used as the central processing unit to run the YOLOv5 algorithm and control the robotic arm that segregates the plastic waste. The camera module captures images of the waste material, which is then processed by the Raspberry Pi. The YOLOv5 algorithm detects and identifies the plastic waste in the image; once,

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a plastic object is detected, its 3D coordinate values collected from the ultrasonic and camera sensors are used to calculate inverse kinematics which returns the joint angles of the robotic arm. The Raspberry Pi then controls the robotic arm to segregate the plastic waste. The combination of YOLOv5 and Raspberry Pi provides a powerful and efficient system for the detection and segregation of plastic waste. YOLOv5 provides accurate and real-time object detection capabilities, while the Raspberry Pi provides a small and low-cost computing platform that can control the robotic arm and process the image data [2]. The proposed system has a potential to contribute to the reduction of plastic waste and its impact on the environment by effectively segregating plastic waste. It can also be expanded to detect and segregate other waste materials, making it a versatile system for waste management and recycling.

## II. RELATED WORKS

Christopher Igwe Idumah & Iheoma C. Nwuzor's [1] study shows that according to current statistics, the vast range of applications for plastics contribute to a constant rise in plastics consumption and waste. However, thevast amount of plastic garbage that has been released may be treated using processes that have been appropriately developed to permit the manufacture of fossil fuel substitutes. The method should be superior inevery way, but especially economically and environmentally. Monitoring and controlling the growing amountof MSW (Municipal Solid Waste) is extremely difficult in order to lessen its negative environmental effects. Traditional waste disposal practices like burning and landfilling have a negative impact on both the environment and people. Innovative waste management methods that may transform trash into useful goods and energy arebecoming more and more popular These strategies encompass biological and thermochemical conversions, and prior research has resulted in increased energy and product production, as well as a lower environmental effect.

Bhagyashri Patle et al. [2] showed the application of AI vision robotic arm using Raspberry Pi. Although not directly related to YOLOv5, it offers insights into the integration of deep learning algorithms in robotic systems. The review highlights the potential of combining computer vision techniques with robotic arms. It gives insightof how the signals from the 3-D visualization systems, which can identify the objects and gauge their separationfrom the end-effector, are sent to the drive system. The vision system would require specialized computer gearthat could handle complicated vision.

Olorunshola Oluwaseyi et al. [3] compares the widely used YOLOv5 and the relatively recent YOLOv7 in this paper. Comparing the experiment's results to other works already cited in the literature review, it makes a substantial contribution. It demonstrates how simple it is to set up and apply detection models, as well as how to use various evaluation criteria for experimentation and comparison. The experiment also shows that the YOLOv5model is more effective than the YOLOv7model. Precision, recall, and mAP were compared between these two YOLO iterations. According to the results of the experiment, YOLOv5 outperformed YOLOv7 in terms of performance.

Iza Sazanita Isa et al. [4] showed a study that enhanced YOLO model performance by fine-tuning the learning rate and momentum in the optimizer method. With a relative FPS of 106.4 and the highest mAP of all models, YOLOv5s stands out as an excellent model for underwater object recognition in blurry images.

Owen Tamin et al. [5] findings of this study suggest that the selection of the training dataset can have a considerable impact on how well object detection models function. The best-performing dataset differs according to the performance parameter of interest. Combining many datasets can enhance performance overall,demonstrating the potential advantages of employing various sources of training data in object detection applications. These results underline the significance of performing thorough evaluations and experiments to determine the best training datasets and methodologies for object detection models.

Ruslan Lys et al. [6] shows how using OpenCV and other cutting-edge technology improves the accuracy and dependability of the system by enabling more accurate object detection and identification and lowering the likelihood of false positives and false negatives.

Made Adi Paramartha Putra [7] We suggest a YOLOv5s with hyperparameter tuning optimization to lessen the waste product during the additive manufacturing procedure. A dataset from the FDM 3D printer was taken usinga web camera, and the hyperparameter was enhanced with 1000 iterations of the process. The outcome demonstrates that the performance following the tuning process is superior to the current YOLOv5s hyperparameter.

Sanskruti Patel & Atul Patel [8] shows that object detection systems that are quick and precise are essential giventhe increase in the use of face detection systems, video surveillance, vehicle tracking, and autonomous vehicle driving. Locating and identifying objects from a digital image is referred to as object detection. CNN-based object detectors are employed in a wide range of applications thanks to the progressive results from deep CNN structures.

Rafael Padilla et al. [9] presented research that explores and compares a wide number of criteria for evaluating the effectiveness of object-detection systems. Average precision (AP), which determines the area under the curve (AUC), is a standard metric for analyzing the accuracy of object detectors and the connection between precisionand recall. Bernd Heisele et al. [10] proposed a system for recognizing and identifying objects that is component-based. We retrieved a significant number of grey value and gradient components from a collection of training photos of a given object. These components were then divided into clusters using the K-means technique. An initial set of component templates was constructed by the cluster centres. By locating the maxima of the normalised cross-correlation within search zones, we were able to localize the image's constituent parts. Adaboost or Gentle-boost was used to pick components for the final classifier.

R. Padilla et al. [11] describes ways to measure the performance of object detection algorithms. The paper provides an overview of frequently used metrics of object detection and give insights for evaluating the performance of deep learning algorithms on object detection tasks. It covers various aspects of object detection,including feature extraction, classification, and identification. It also provides a more comprehensive understanding of the components involved in object recognition systems.

C. Kaymak et al. [14] introduced a component-based system for object detection and identification. Using a setof training images of a specific object, a number of grayscale and gradient components are extracted and split them into clusters using the k-means algorithm. The final classifier was created by choosing components with adaboost or gentle-boost. It has shown that the system is capable of competing with state-of-the-art detection and identification systems. The main advantages of our approach are its conceptual simplicity and broad applicability. The features calculation and matching algorithm are computationally simple, so real-time implementation is possible.

S. Majchrowska et al. [15] studies a set of training images of a given object, then extracted a number of grayscale and gradient components and split them into clusters using the k-means algorithm. Cluster Center created the first set of component templates. Tie components are identified in the images by finding the normalized cross-correlation maxima within the search region. The final classifier was created by choosing components with adaboost or gentle-boost. The main advantages of our approach are its conceptual simplicity and broad applicability.

W. Ge, S. Chen et al. [16] combining the YOLOv5 framework for object detection and localization with binocular computer vision, many methods such as image enhancement and K-means clustering are proposed toachieve object classification and localization. This changes effects such as illuminance and lighting. Reflectionson object surfaces are lowered. Which increases the resilience of machine vision-based classification systems.

M. Horvat et al. [17] shows there are two main advantages of YOLOv5. First, is to improve the object recognition performance of YOLOv5 by integrating advances in other research areas in computer vision theory. Second, they are offered to ML and data scientists as a collection of PyTorch frameworks that can be easily integrated and used in modern cloud-based application development environments and other software packages such as NumPy.

## III. METHODOLOGY

The whole system is comprised of three components: The YOLO model, the sensors, and the robotic arm.The YOLO model after being trained on the collected and annotated dataset, processes the first frame thatthe camera sensor captures once the system starts. If a plastic object is detected, it passes its bounding boxcoordinates, so that the inverse kinematics can be calculated. Using the IK1, it moves the base of the arm, then uses the ultrasonic detector to measure the distance which is used to calculate IK2. Then, it moves joint arm 1 and 2 simultaneously by controlling the joint angles, ultimately, picking the object and segregating it in a separate bin.

If the detected object is not a plastic it moves on to process the next frame, and runs till it detects a plasticobject in its frame.

### *A. Training YOLOv5*

Following the collection and labelling of data, the YOLOv5 model is trained on a custom plastic dataset. This involves fine-tuning the pre-trained YOLOv5 model on the annotated plastic waste images using a deep learning framework such as PyTorch or TensorFlow. The YOLOv5 model can be trained usingtransfer learning, where the pre-trained weights are used as a starting point, and the model is further trained on the custom dataset [7]. The project uses API calls for using the collected plastic waste dataset from Roboflow.

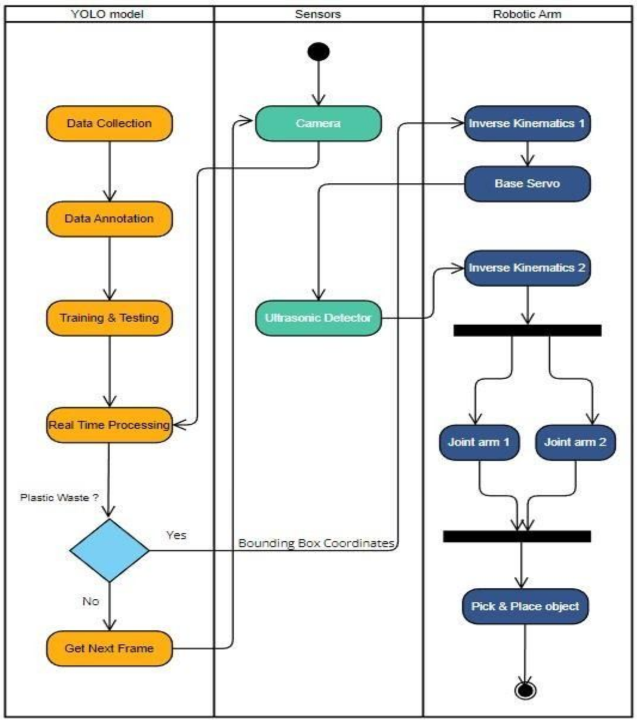



Fig 1: Activity Diagram

Fig 2: Labelled Dataset

### *A. Hyper parameter Tuning*

YOLOv5 features approximately 30 different hyperparameters that are utilized for various training settings. For achieving better results, they can be optimized. If there are better parameters optimization, therewill be better results. Hyperparameter evolution is a Hyperparameter Optimization method that employs a Genetic Algorithm (GA) for optimization purposes. The YOLO model's default optimizer is Stochastic Gradient Descent (SGD) with momentum. SGD computes the gradient of the cost function for the model's parameters θ for the entire training dataset, as given in Equation 1 [7]. It minimizes the objective function, J(θ), parameterized by a model's parameters θ∈Rd and updates parameters pointing in the opposite direction of the gradient of the objective function, ∇θJ(θ), for the parameters [7]. The amount of the steps needed to arrive at a local minimum is determined by the learning rate,. For each training example, xi, and label, yi, Equation 2 provides the updating of a parameter through SGD.

$$\theta=\theta-\eta.\nabla\theta J(\theta) \quad (1)$$

$$\theta=\theta-\eta.\nabla\theta J(\theta;xi;yi) \quad (2)$$

Equation 3 demonstrates that accelerating SGD in the appropriate directions while damping oscillations is accomplished by adding a fraction, $\gamma$ of the update vector, vt of the previous time step to the present updatevector. The modifications to Equation 4 are provided by this modification.

$$vt= \gamma vt-1+\eta\nabla\theta J(\theta) \quad (3)$$

$$\theta= \theta-vt \quad (4)$$

TABLE I: EVOLVED HYPERPARAMETERS

| Hyperparameters | Standard | Evolved |
|---|---|---|
| Lr0 | 0.01 | 0.01144 |
| Lrf | 0.01 | 0.01 |
| Momentum | 0.937 | 0.94315 |
| Weight Decay | 0.0005 | 0.00045 |
| Warmup Epochs | 3 | 3.6932 |
| Warmup Momentum | 0.8 | 0.46079 |
| Warmup Bias | 0.1 | 0.1446 |
| Box | 0.05 | 0.0359 |
| Cls | 0.5 | 0.5157 |
| Cls pw | 1 | 1.13115 |
| Obj | 0.05 | 1.13101 |
| Obj pw | 1 | 1 |
| Iou t | 0.2 | 0.2 |
| Anchor t | 4 | 3.508 |
| Anchors | 3 | 3.76161 |
| Hsv h | 0.015 | 0.018 |
| Hsv s | 0.7 | 0.50586 |
| Hsv v | 0.4 | 0.44928 |
| Translate | 0.1 | 0.10513 |
| Scale | 0.5 | 0.50586 |

### *C. Experimental Setup*

In order to separate plastic waste, a robotic arm with 6 DOF is utilized with a custom end-effector that is designed for grasping and releasing plastic waste items. A Logitech camera with video capture dimension up to 1280 x 720pixels is mounted on the side of the arm manipulator. An Ultrasonic sensor HC SR04 is attached to the arm manipulator enabling it to move along any angle the arm moves in. 6 servos are used to attach and control the joint angles. 3 TowerPro MG996R heavy servo with 360 degrees of rotation areattached at the base, then at the first and second joint. Another 3 TowerPro SG 90 Micro Servo motor is usedto attach the grappler as its end effector and to enable its grappling. All the sensors and motors are connectedto the Raspberry Pi 4 directly or indirectly via a breadboard enabling shared power usage and grounding.

### *D. Working of the robotic arm*

The robotic arm is controlled using Raspberry Pi, which send commands to the servo motors that control the movement of the arm. the robotic arm can move to the item's location and grasp it with the end- effector. After the item is placed in the bin, the robotic arm releases the item and return to its initial position todetect the next plastic waste item.

By integrating YOLOv5 with the robotic arm's control system, the arm can identify and track plastic waste items in real-time, allowing for quick and precise grasping and placement. After the YOLOv5 algorithmdetects an object, next step is to figure out where the object is in 3D space. This is achieved by normalizing thebounding box coordinates and extracting the x and z coordinates. However, the y coordinate is not directly provided by the bounding box. Therefore, It is placed at a fixed distance where the arm can operate. With all three coordinates determined, the robotic arm can use inverse kinematics to accurately compute the joint angles required to position the end effector at the object's location [2]. Once the joint angles are calculated, the roboticarm moves itself accordingly to the object's location and grasps it using the end effector.

It calculates the inverse kinematics of the robot arm. The first axis considered on the robot arm is the rotation of the base, it does not affect the height of the gripper. So, the angle between the x-axis and measured distance of the object is the base angle (b). Simple trigonometry is used to work out the angle (b), tan (b) equalsopposite (y) over to the adjacent (x). And the distance of the object (L) is worked out using an ultrasonic sensor. The HC SR04 ultrasonic sensor is utilized for measuring the distance between the robotic arm and the object, allowing for a more precise value to be considered. Then, the angle of the base can be worked out using (5).

$$b = \tan^{-1}(\frac{y}{x}) \qquad (5)$$

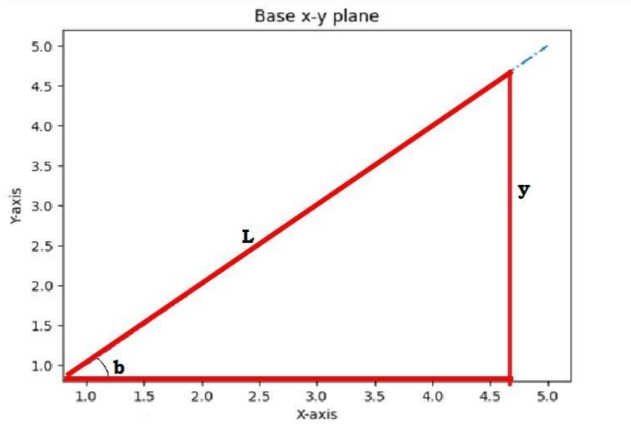
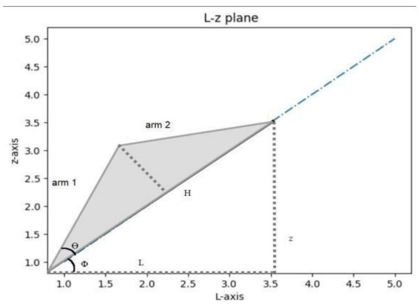
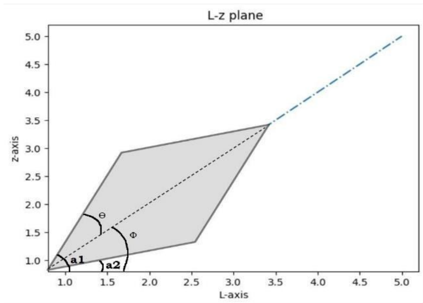



Fig 4. Base x-y plane

Similarly, for the other arms new plane is defined with z-axis and the side (L) as the other axis. Now inorder to move the arm to the right point, two things need to be known. First the angle (Φ) and length of the arm (H).




(a)




(b)

Fig 5. (a) L-z Plane (b) Finding a1 & a2 angles

Using the same method as before, as tan(Φ) will equal opposite (z) over the adjacent (L) and H2 = z2 + L2
As the robotic arm consists of two arms, in order to get to the object, it is defined by two angle and the length ofthe distance of the object. The length of the arm of the same length, the isosceles triangle can be split by the three lines (two lengths of the arm and the distance of the object) into two right angle triangles.Therefore, the angle cos(Θ) equals to adjacent over the hypothenuse which is (H/2)/ (length of one arm).

$$\Phi = \tan^{-1}(\frac{z}{L}) \qquad (6)$$

$$\theta = \cos^{-1}\frac{\frac{H}{2}}{arm} \qquad (7)$$

$$\text{Angle a1} = \Phi + \Theta \qquad (8)$$

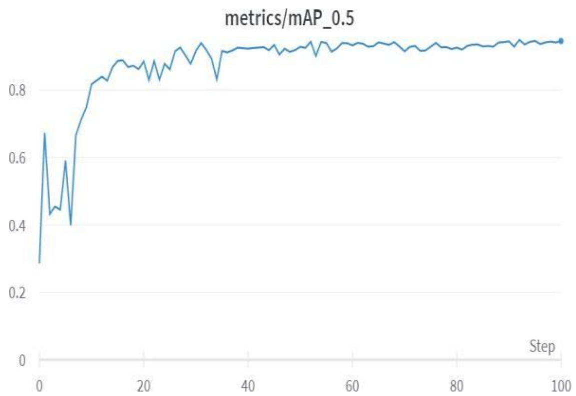
$$\text{Angle a2} = \Phi - \Theta \qquad (9)$$

Angle a1 and a2 is found by using (8) and (9) respectively.
Overall, this process of utilizing the coordinates provided by YOLOv5, in combination with the camera sensor, HC SR04 ultrasonic sensor and applying inverse kinematics, allows for accurate and efficient detection and manipulation of plastic waste items by the robotic arm.

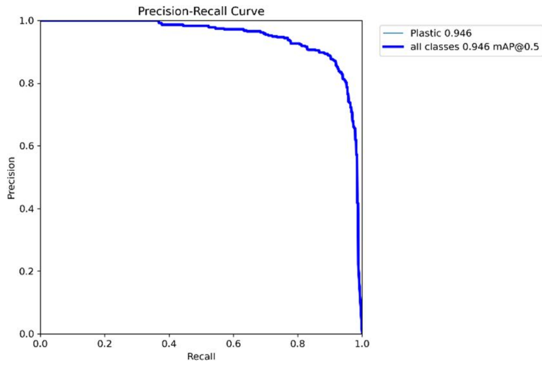
The algorithm can be trained to recognize different types of plastic waste items and their various orientations and sizes, enabling the robotic arm to make better decisions in grasping and releasing the items.
In summary, the use of YOLOv5 in the control system of a robotic arm for separating plastic waste can greatly enhance the system's accuracy, efficiency, and overall performance, contributing to a cleaner and more sustainable environment.

## IV. Results And Discussion

The effectiveness of the suggested system was evaluated using various datasets containing plastic waste. The findings indicate that the suggested system can detect and segregate plastic waste with an accuracy of over 94.5%. The system was also tested in a real-world environment, and it was found that it caneffectively detect and segregate plastic waste even in a noisy environment. The system's performance was evaluated based on its ability to accurately detect and locate plastic waste items in real-time, as well as manipulate them using the robotic arm.




(a)




(b)

Fig 6. (a) mAP score (b)PR curve

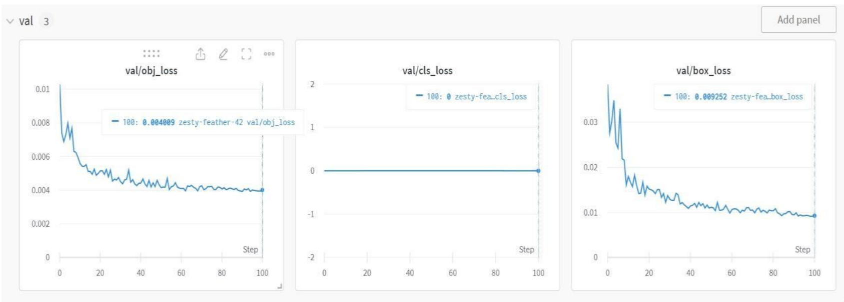
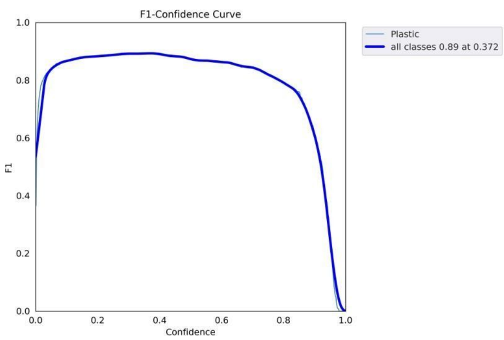
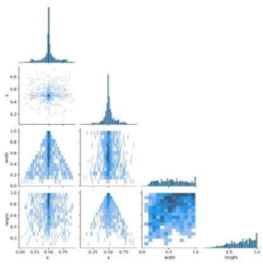



Fig 7. Training Loss

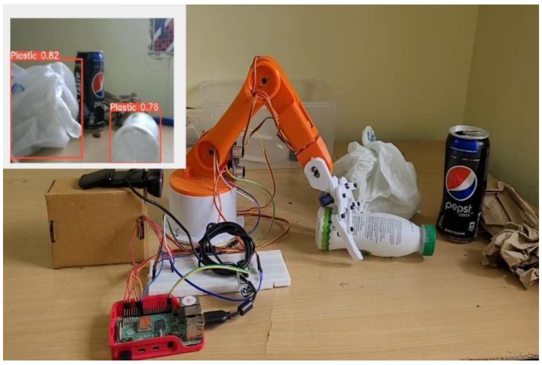



(a)

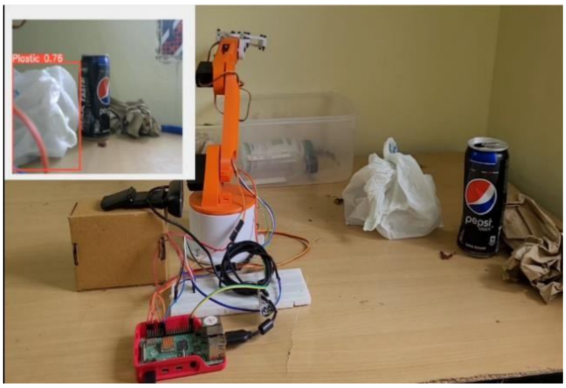


(b)

Fig 8. (a) F1confidence curve (b) Labels correlogram




(a)




(b)

Fig 9. Plastic segregation (a) Before (b) After

To evaluate the system's performance in object localization, the distance between the arm and the detected object was measured using an ultrasonic sensor. The 3D position of the object was calculated using the normalized bounding box coordinates and the measured distance. The system's ability to accurately locate the object in 3D space was demonstrated by its ability to manipulate the object using the robotic arm's end effector.
The robotic arm's ability to manipulate the detected plastic waste items was evaluated by measuring the successrate of grasping the objects. The system achieved a grasping success rate of 87.5%.
Overall, the results indicate that the developed robotic waste separation system can accurately detect, locate and manipulate plastic waste items in real-time. The system has the capacity to greatly advance waste disposal and recycling practices, ultimately contributing to a cleaner and safer environment.

## V. CONCLUSION

In this paper, a system is proposed for the detection and segregation of plastic waste using YOLOv5 and Raspberry Pi. The proposed system can effectively detect and segregate plastic waste based on colour with high accuracy. The proposed system can be used in various applications, such as waste management and recycling. The system can also be expanded to detect and segregate other waste materials such as glass, metal, and paper.
In conclusion, a robotic waste separation system is developed that utilizes YOLOv5 object detection algorithm, Raspberry Pi, and a robotic arm with an end effector. Our system is capable of accurately detecting plastic waste items in real-time, locating their position in 3D space, andmanipulating them using the robotic arm.
The YOLOv5 algorithm is trained on a custom plastic waste dataset, which significantlyimproved the object detection performance. The system's ability to accurately detect plastic waste items and manipulate them using the robotic arm is a significant step towards improving waste disposal and recycling practices. By automating the waste separation process, human error can be reduced and increase efficiency, ultimately leading to a cleaner and safer environment.
Furthermore, a hyperparameter evolution technique is implemented to optimize the YOLOv5 algorithm's performance, which resulted in a faster and more accurate detection process. The combination of YOLOv5,

Raspberry Pi, and the robotic arm with an end effector provides acomprehensive waste separation solution that can significantly improve recycling efforts.

In summary, this robotic waste separation system is a novel approach to tackle the global issue of plastic waste and is a great illustration of advanced technology can be used to address issues in theactual world. With further development and improvement, this system can make a significant contribution to creating a more sustainable future.

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