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Automated Waste Sorting with Delta Arm and YOLOv8 Detection

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Abstract

In the midst of rapid urbanization and industrialization, accurate and efficient waste classification has become an essential task due to the increased emphasis on environmental preservation. Several issues arise from the lack of efficient waste management, such as contamination of the air and water and the spread of disease. Developing nations often face challenges due to limited resources and infrastructure, highlighting the need for effective waste separation. Recent advancements in robotics and machine learning have significantly impacted the waste management sector. This study integrates a robotic arm for effective waste sorting with the most recent version of the You Only Look Once (YOLO) concept, known as YOLOv8. The waste is separated into four categories: paper, plastic, metal, and biodegradable. Inverse kinematics is applied to determine the joint angles needed for the robotic arm to reach a desired position. The results demonstrate that YOLOv8 outperforms state-of-the-art algorithms in waste detection and classification with better precision, recall, and F1 score, emphasizing its potential as a useful tool for enhancing waste management procedures.

Keywords: Inverse kinematics, Machine Learning, Object Detection, Robotics, YOLO

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1. Introduction

1.1 Background

Recycling and waste management are becoming important for sustainable development in today's society. It is anticipated that trash creation would almost quadruple by 2050, with a 40% increase per capita expected in low- and middle-income nations [1]. As a result, effective waste sorting systems are essential to minimizing environmental impact and maintaining resource recovery. Conventional techniques that depend on physical effort frequently result in labor-intensive procedures and irregular sorting procedures.

The goal of the "Automated Waste Sorting with Delta Arm and YOLOv8 Detection" is to create an automated system that can intelligently classify and sort different kinds of waste items to revolutionize waste management. The system makes use of the Delta arm's agility and precision, which is well-known for its speed and accuracy in handling waste. It also uses a vacuum suction pump to collect and transfer various waste materials precisely. The incorporation of cutting-edge deep learning algorithms, such YOLO (You Only Look Once), is essential for the success of the research. The system can efficiently identify and categorize common waste categories such as paper, plastic, glass, metal, and biodegradable materials by training on a customized dataset. The device smoothly integrates with the Delta arm by using a camera module for image processing to record and handle waste item coordinates. Using software frameworks such as TensorFlow, OpenCV, and Python guarantees effective integration and communication between all the parts of the system. This method creates a dependable and effective trash management system by combining robotics, deep learning, and accurate waste classification.

1.2 Problem Statement

Resource conservation and environmental sustainability depend on the effective recycling of waste products. However, due to insufficient trash separation, only 4.1% of Nepal's total waste is properly recycled [2]. This poor recycling percentage reveals serious flaws in waste management procedures that squander resources and pollute the environment.

The present waste management techniques encounter significant obstacles in attaining maximum recycling rates and tackling the escalating environmental issues associated with inappropriate disposal of waste. The volume of waste being produced worldwide is growing, and traditional human sorting methods are ineffective, unreliable, and unable to handle it. These techniques frequently lead to decreased recycling efficiency and cross-contamination.

Furthermore, the efficient separation of waste containing paper, plastic, glass, metal, and biodegradable materials is made more difficult by the absence of automated technologies. As a result, recyclables usually find their way into regular waste streams, decreasing their general recycling rates and possibilities for reprocessing.

To maximize resource recovery, minimize environmental effect, and improve recycling efficiency, it is imperative to improve waste sorting technologies and implement automated solutions.

1.3 Objectives

The main objectives of the" Automated Waste Sorting with Delta Arm and YOLOv8 Detection" paper is:

- To build and utilize a Delta arm to pick up waste items and place them in their respective place.

2. Related Work

2.1 Waste Classification Methods

Research by Zhang et al. [3] explores the application of deep learning algorithms, including YOLO, in waste detection and classification. Their work demonstrates the effectiveness of these algorithms in accurately identifying different waste categories. The commonly used waste classification and recycling standards are often too complex for the public to follow. Integrating industrial cameras and robotic arms enables real-time waste identification and tracking, representing a significant advancement in intelligent waste management and contributing to sustainable urban development.

2.2 Robotic Systems in Waste Management

Satav et al. [4] demonstrated the successful implementation of robotic waste sorting systems, emphasizing their potential to increase recycling rates while reducing human labor requirements. Their research highlights the use of robotics and AI in sorting materials such as glass, paper, plastic, and metals from other waste.

Pierrot et al. [5] highlighted the use of the delta arm in various applications. The study shows that delta arms are more efficient than other robotic arms because the motors are attached to the main body rather than the arms. This configuration allows the delta robot's arms to move quickly, making it ideal for lightweight pick-and-place operations.

2.3 AI Algorithms for Object Detection and Classification

Artificial intelligence, specifically deep learning algorithms, has transformed object detection and classification tasks. Convolutional neural networks (CNNs) have demonstrated exceptional performance in accurately detecting and categorizing objects in images and videos. Aishwarya et al [6]. demonstrated the successful implementation of the You Only Look Once (YOLO) algorithm for waste classification, achieving high accuracy and efficiency in identifying and categorizing various waste materials.

An intelligent municipal solid waste sorter (IMSWS) system was developed to pick and place solid waste from the conveyor belt. YOLOv3 or YOLOv4 is used to detect the plane location of solid waste, and the arm of the delta robot is moved to that specific location to absorb and place the waste in the respective bin. Implementing advanced technologies like deep learning and sensor-based approaches for automated waste segregation can significantly enhance the efficiency and effectiveness of waste management, leading to a cleaner and safer environment [7].

Nandhini S. et al. [8] suggests that implementing a robotic assembly with machine learning-based classification for automated waste collection and segregation can significantly improve waste management efficiency and safety by reducing human exposure to hazardous materials. The integration of computer vision and neural networks in intelligent robots for waste management demonstrates high accuracy and efficiency, with the YOLO model being preferred for real-time detection due to its balance between speed and performance. F Raptopoulos et al. [9] introduced the Pick-and-Toss approach using Delta robots, which represents a significant advancement in waste sorting technology. This new method outperforms the traditional Pick-and-Place method in terms of speed and efficiency, demonstrating superior accuracy and robustness in both simulation and real-world waste sorting environments, particularly with the ABB-IRB360 Delta robot.

A YOLO model modified with a Variational Autoencoder (VAE) was introduced by Anbang Ye et al. [12] to reduce model size and improve detection accuracy, making it appropriate for edge devices. A dataset from the 2020 Haihua AI Challenge (2020 HAC), a trash sorting competition, was utilized to train the model. In a similar vein, Andhy Panca Saputra et al. [13] introduced the waste identification models YOLOv4 and YOLOv4-tiny, which were trained on an altered TrashNet dataset that included more photos but fewer classifications. Using a customized waste dataset, Deep Patel et al. [14] compare five object detection techniques and conclude that YOLOv5M is the best accurate. On new benchmark datasets with seven trash types, Sylwia Majchrowska et al. [15] employed EfficientDet-D2 for waste localization and EfficientNet-B2 for classification.

3. Proposed Work

For precise and effective waste classification, the developed a system consists of two parts: a waste detection and classification module and a robotic arm integrated with vacuum suction grip

3.1 The Waste Detection Module

The waste detection module is responsible for real-time object detection through high-throughput image streams. For this, the YOLOV8 is utilized, as it offers improvements over its predecessors with a more complex network architecture and deeper, and more effective convolutional layers. YOLOv8 is anchor-free, predicting fewer boxes, and has a faster Non-Maximum Suppression (NMS) process [8]. This streamlines the detection process, simplifying waste management and encouraging more environmentally friendly practices.

3.1.1 Data Collection

The dataset includes approximately 8,200 images of various waste products, providing a wide range of examples to ensure accurate detection and classification. These waste materials have been divided into four main classes: paper, metal, plastic, and biodegradable waste. The images in the dataset reflect real-world scenarios where various types of waste coexist. The histogram of object counts per image offers a clear visualization of the distribution and variability in the number of objects depicted within each image, highlighting this complexity. The primary data sources include several highly well-regarded public datasets that are available on Kaggle and Roboflow.

These platforms provide an abundance of varied images, which have been very helpful in building a solid and extensive dataset. To improve the generalizability of our dataset, a wide range of waste items and contexts were considered during the selection process for these images. We have greatly enhanced our dataset with over 300 images created from household waste collected in Nepal, in addition to these publicly sourced images. This data subset offers a distinct and regional context, encapsulating the specific characteristics and variety of waste products commonly encountered in a Nepalese household. Figure 1 shows the object count per image.

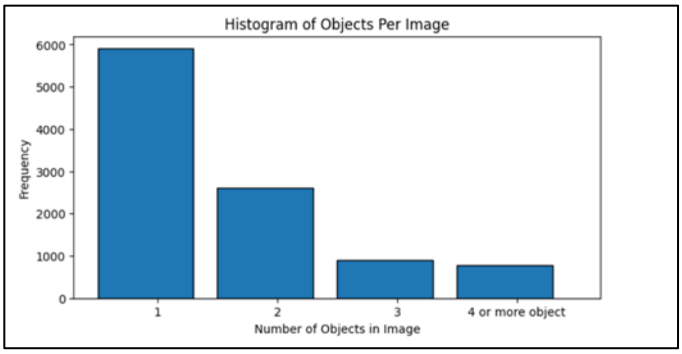

Figure 1. Object Count per Image

3.1.2 Preparing and Annotating Data

To label the objects in the images, bounding boxes were made during the dataset preparation stage. To facilitate supervised learning, each image in the collection underwent a thorough process of labeling and annotation. Trash items were identified and categorized in each image as paper, plastic, metal, or biodegradable materials. This annotation process ensures accurate ground truth labels, which is essential for effectively training and evaluating the waste classification algorithm.

The images underwent standard augmentation techniques, including flipping, rotating, resizing, adjusting brightness and contrast, adding noise, and cropping. The dataset included approximately 2,923 biodegradable, 2,589 plastic, 1,837 paper, and 1,001 metal images across four classes. The dataset was expanded to 20,840 annotated images, ranging in size from 0.03 megapixels to 16.04 megapixels, with a typical resolution of 512x384 pixels. This balanced representation of each waste type, enhances the dataset's resilience, improving its effectiveness in training the classification algorithm. The Figure 2 depicts the few annotated images.

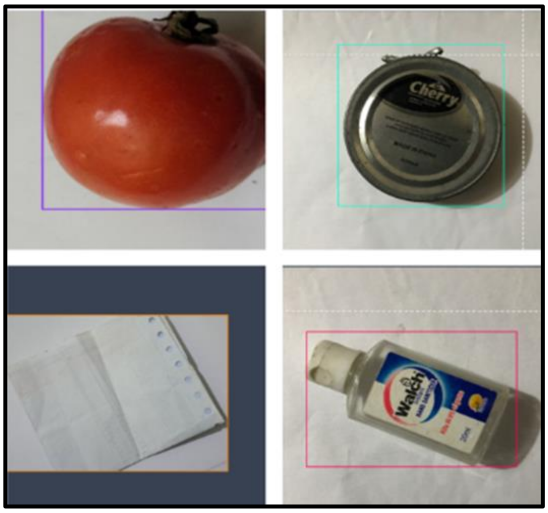

Figure 2. Image Annotation

3.1.3 Training

The proposed research began with the selection of Ultralytics YOLOv8, known for its rapid object detection capabilities. We selected the YOLOv8, and enhanced it with TensorFlow and OpenCV. As soon as the annotated datasets were prepared, model training began. To ensure the model could swiftly and accurately distinguish between different types of waste, we carefully adjusted the settings. The primary objective was to develop a waste recognition model that is fast and accurate. The following block diagram in Figure 3 demonstrates the complete training process using YOLOv8, over 70 epochs with groups the batch size of 32 images.

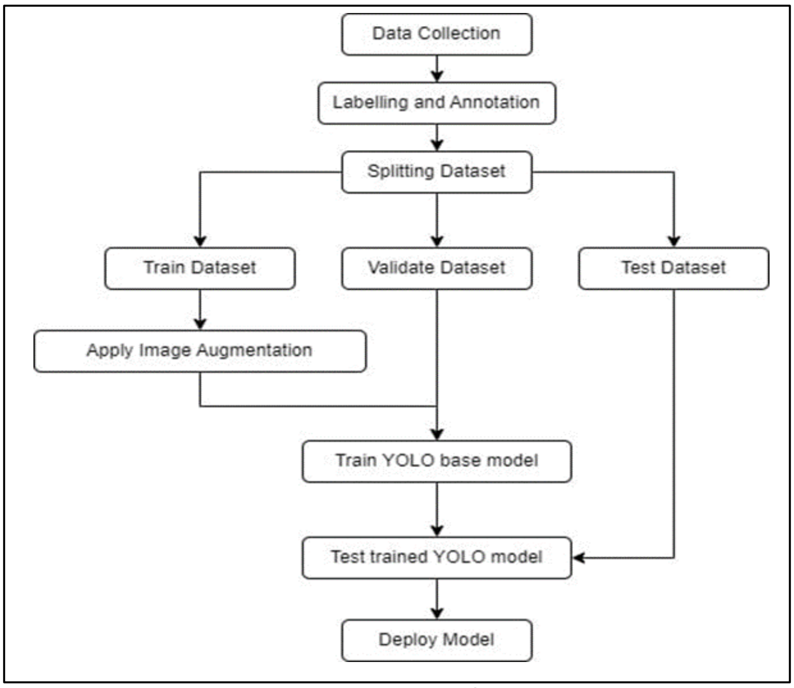

Figure 3. Block Diagram of Training Model

3.2 The Robotic Arm

The increasing amount of waste produced by population increase, urbanization, industrialization, and changing consumer patterns has become a major global concern. Effective waste management strategies are essential to preserve resources, reduce pollution, and safeguard the environment as waste levels continue to increase. Recently, there have been significant advancements in waste management, especially with the integration of robotics. In 2016, the first sorting robot was placed in a recycling center in the United States.[10]. Since then, efforts to help with waste management activities have led to an acceleration in the development of pick-and-place robots. Among these, the Delta arm robot with its delta or triangular configuration is unique because of its streamlined design components, which facilitates movement along x, y, and z axis. The Delta arm robot improves force distribution, and accuracy through the parallel action of its arms [9]. The robotic arms careful scheduling is shown in Figure 4 below with complete pick and place cycle movements essential for its optimal efficiency.

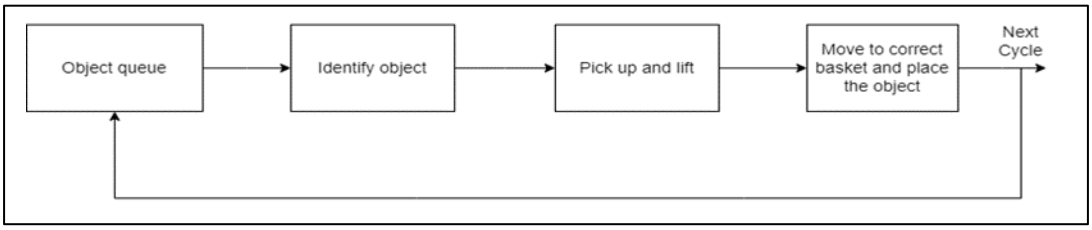

Figure 4. Complete Robotic Arm Task

The delta arm, which is responsible for picking and positioning things, is depicted in the Figure 5 and 6. The destination of the robot is dynamically modified according to the nature of the object. The relationship between the end-effector, the intended destination, and the object's current position are among the many aspects that are taken into consideration when creating the motion plan. The Delta robot's parallel kinematic structure, with arms attached to both the base and end effector, enables swift and accurate movements, This design ensures proper load distribution and reduced inertia. With its three degrees of freedom, the end effector can be precisely maneuvered within a three-dimensional workspace. Inverse kinematics (IK) plays a pivotal role in this process by determining the exact motions required for the robot's joints, particularly its stepper motors, to position the end effector, equipped with a vacuum suction pump, at a specified location and orientation in space. As part of the research workflow, waste materials are captured thorough a camera module, and the YOLOv8 algorithm identifies and provides their coordinates. After adjusting for the camera's position and orientation relative to the arm, these coordinates, initially in the camera's frame of reference, are transformed into the Delta arm's coordinate system. Subsequently, inverse kinematics translates these modified coordinates into precise motor movements. By calculating the necessary angles and positions for the arms to place the end effector at the target coordinates, complex equations relating the end effector's position to the robot's arm angles are solved. Upon completion of inverse kinematics calculations, the resulting stepper motor steps are transmitted to the Delta arm's motor controllers. These controllers then translate the computed steps into exact motor motions, ensuring the efficient retrieval of each recognized waste item. The integration of image processing, coordinate transformation, and inverse kinematics allows for efficient and accurate waste sorting with the Delta arm.

Figure 5. Delta Arm for Automated Waste Sorting

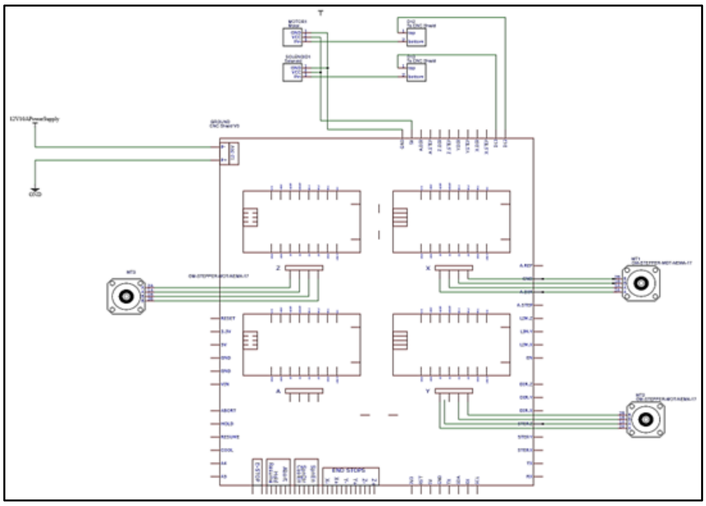

Figure 6. Schematic Diagram of Delta Arm

The formula for one of the arm's angles using inverse delta-kinematics is given below:

$$\Theta 1 = arctan\,(z * J1\,/y * F1 - y * J1)$$

Likewise using similar formula, the corresponding angle Θ2 and Θ3 is determined as shown in Figure 7.

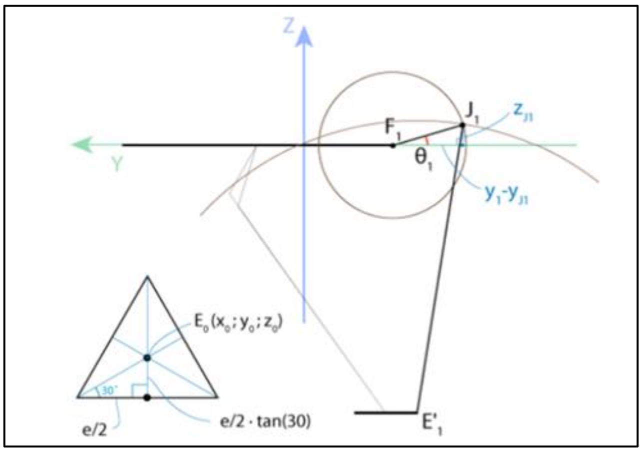

Figure 7. Inverse Delta Kinematics and its Parameters [11]

The suggested delta arm waste classifier's architecture combines software and hardware elements to allow for automated waste sorting. Figure 8 shows the detailed overview of overall architecture and connectivity among the components.

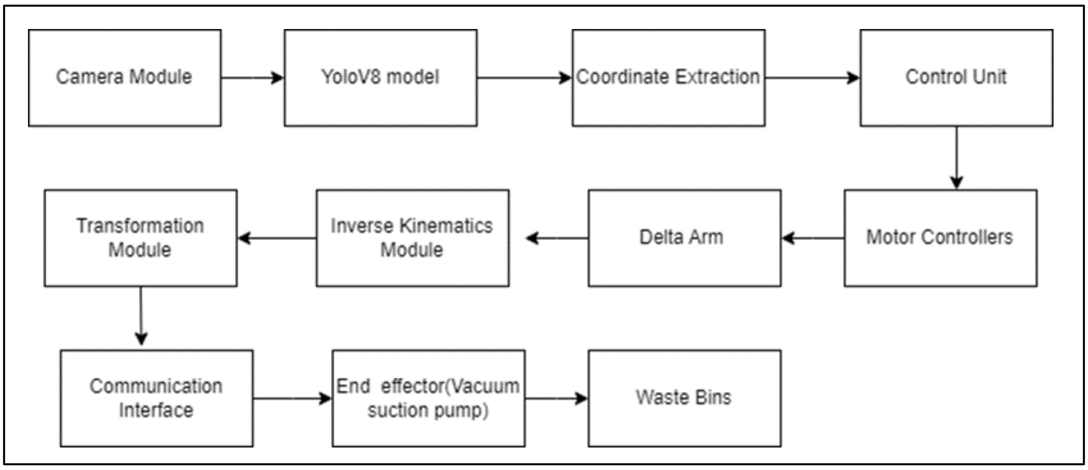

Figure 8. Overall System Architecture

4. Experimental Results

Apart from Mean Average Precision (mAP), precision, recall, and F1 score measures offered significant understanding of the waste categorization system's performance. The measurements for Mean Average Precision (mAP) at 50% Intersection over Union (IoU) and between 50% and 95% (mAP@50-95) were essential for assessing how well the model was performing. These results were obtained using the YOLOv8 model during both training and testing phases. The precision of the model is demonstrated by its ability to appropriately identify waste things without mislabeling unrelated objects. Precision is defined as the ratio of true positive cases to the total number of cases classified as positive. Conversely, recall highlights the ability of the model to identify and incorporate all pertinent waste items in its predictions, hence reducing false negatives, by calculating the ratio of true positive cases to the total number of actual positive cases. The F1 score offers a balanced evaluation of a model's performance by combining recall and precision into a single metric. Mathematically Precision, Recall and F1 score can be calculated as:

$$Precision = (TP / TP + FP)$$

$$Recall = (TP / TP + FN)$$

$$F1\,Score = (2 \times Precision \times Recall) / (Precision + Recall)$$

where TP represents true positives, FP represents false positives, and FN represents false negatives. The model was trained over with 32 batch size over 70 epochs, the following outcomes in Table 1 and 2 illustrates the loss observed during training and classification respectively and the overall performance score of YOLOv8 for classification is illustrated in Table 3.

Table 1. Training Loss

Parameters	Values
Box Loss	0.30762
Classification Loss	0.23631
Distribution Focal Loss	0.92997

Table 2. Classification Loss

Parameters	Values
Box Loss	0.34798
Classification Loss	0.27666
Distribution Focal Loss	0.97204

Table 3. Performance Evaluation Metrics

Metric	**Value**
Precision	0.94118
Recall	0.96622
F1 Score	0.95240
mAP@50	0.98252
mAP@50-90	0.92723

The model exhibited outstanding recall (0.96622), precision (0.94118), and F1 score (0.95240), showcasing its precision and accuracy in waste type detection. With a high mAP@50 score of 0.98252, it excelled in recognizing items with moderate overlap. However, the somewhat lower mAP@50-90 score of 0.92723 indicates some difficulty in categorizing items with significant overlap. Despite this challenge, the model’s overall proficiency in identifying and classifying the waste products remains evident, facilitating precise placement by the Delta arm into the correct bin. The Figure.9 and 10 illustrates the classification loss and box loss respectively. AS the epochs size is increased the loss is decreases gradually. The model's classification accuracy for each category is displayed in the normalized confusion matrix (Figure 11); higher accuracy is indicated by darker colors metal (0.97) and plastic (0.96). Correct classifications are represented by diagonal values, and incorrect classifications are shown by off-diagonal values.

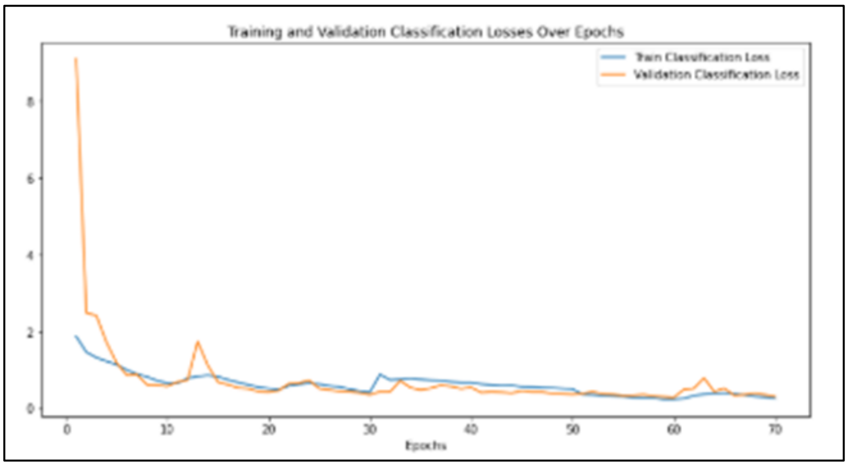

Figure 9. Classification Loss Over Epochs

Figure 10. Box Loss Over Epochs

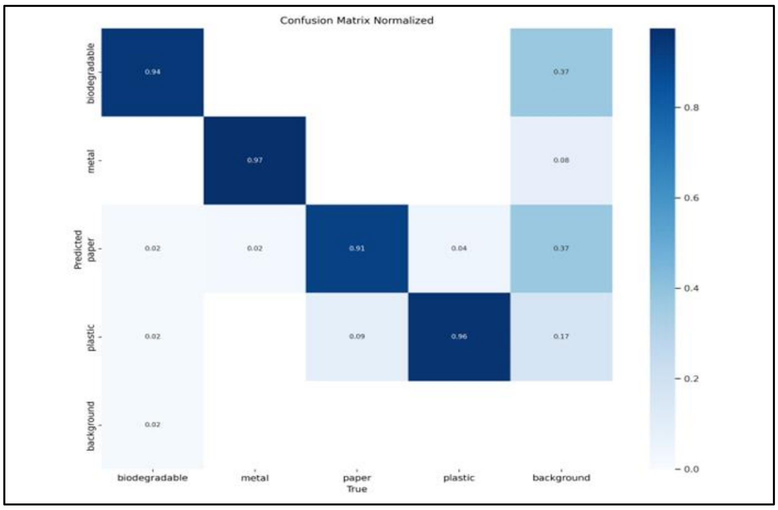

Figure 11. Normalized Confusion Matrix

The classification performance for five categories—biodegradable, metal, paper, plastic, and background—is displayed in the confusion matrix. With 94% accuracy for biodegradable, 97% for metal, 91% for paper, and 96% for plastic, the model does well in the majority of the categories. Nonetheless, there are some noteworthy misclassifications: 37% of the time, biodegradable is mistakenly labeled as background, and 37% of the time, paper is incorrectly classified as background. Plastic has the least amount of misclassification—only 17% of it is mistaken for background. Darker blues indicate more accuracy in the matrix, which exposes the classification strengths and flaws through color intensity.

5. Discussions

The system's efficiency in identifying waste materials with a high degree of confidence is demonstrated by the attained mAP scores, especially the mAP@50 value of 0.98252, even with considerable overlap between predicted and ground truth bounding boxes. This underscores the system's performance, indicating its ability to correctly classify the majority of trash objects in the test set and placing them. Additionally, the mAP@50-95 score of 0.92723 showcases the system's versatility in handling detections within a slightly smaller IoU range (50% to 95%), implying its capability to efficiently classify waste materials and potentially capture a wider range of waste goods in real-world circumstances where bounding boxes may not align precisely. Furthermore, the system's competence in classifying waste materials is highlighted by the F1 score of 0.95240, which strikes a balance between recall and precision. Together, these metrics emphasize the stability and dependability of the system in correctly recognizing and classifying waste materials across various situations, facilitating their placement into respective bins using the Delta arm.

6. Future Scope

There are some limitations that needs to be addressed before the completion of the research. The research drawbacks include the high upfront cost, and potential challenges in integrating the system with existing infrastructure, which requires advanced knowledge of robotics and sensor technology. The future development in autonomous delta arm waste classifiers will involve the implementation of the model with appropriate camera modules and other components, and offer multi-stage sorting for finer separation and the integration of cutting-edge sensors like 3D scanning for improved waste detection and classification. Streamlining operations and facilitating scaling can be achieved by adopting a modular architecture and improving interface with the current waste management infrastructure. Reducing environmental effect can be achieved by implementing energy-efficient components and sustainable materials. Predictive maintenance and remote monitoring will reduce downtime, while collaborative robotics and better human-robot interaction will increase the usefulness and safety of the system.

7. Conclusion

In conclusion, this study presents a novel strategy to expedite waste sorting procedures by fusing the most recent version YOLOv8, with a robotic arm. The study presents improvements in precision, recall, and F1 score for waste item detection and classification, indicating the superiority of YOLOv8 over existing methods. These results demonstrate the potential of YOLOv8 along with parallel movements of robotic delta arm as a useful instrument for streamlining waste management procedures and providing increased efficacy and precision in waste sorting processes. In the future, this research paves the way for greater developments in automated waste management systems, which will promote more efficient and sustainable waste management practices globally.

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