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Waste Segregation using YOLO v8 based Object Detection and Robotics

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Abstract : The growing demand for plastic in India highlights the necessity of shifting towards sustainable approaches to tackle the mounting waste and pollution challenges. However, the manual collection and segregation of waste present substantial obstacles, impeding the efficacy of waste management endeavours. To address this, our project proposes the development of an advanced waste segregation system leveraging YOLOv8-based object detection technology for real-time identification and classification of diverse waste items. By accurately discerning recyclables, non-recyclables, and other waste types, our system enhances waste management efficacy. Integrated with ByteTrack for multi-object tracking, our solution ensures precise waste detection and continuous monitoring of waste movement dynamics. Moreover, employing a Delta arm equipped with a suction pump facilitates efficient pick and place operations, optimizing waste segregation processes. The Delta arm's parallel-linkage structure promises swift and accurate movements that can accommodate a wide range of waste types and sizes, ensuring adaptability throughout the segregation process. Our innovative approach promises to revolutionize waste management practices, fostering sustainable solutions for India's burgeoning plastic consumption.

***IndexTerms* - Waste Segregation, Object Detection, Computer Vision, Deep learning, YOLOv8, Delta arm.**

I. Introduction

As of 2021-22, India's plastic demand has reached 20.89 million tonnes, and it is projected to continue growing to 22 million tonnes by 2023. The onus is on the industry to embrace circular economy principles, aiming not only to reduce waste and pollution but also to unlock new opportunities for growth and innovation. This responsibility underscores the imperative for a comprehensive and sustainable waste management system, emphasizing the need for effective segregation, and recycling processes. It is within this context that this initiative gains significance.

The omnipresence of plastic in our daily lives is undeniable, with the world producing an alarming 400 million tonnes of single-use plastic annually, constituting 47 percent of total plastic waste. Shockingly, only 9 percent of this plastic is estimated to be recycled globally. In the Indian context producing a staggering 9.3 million tonnes of plastic annually, waste management emerges as a critical concern, especially with the relentless growth of consumerism across the nation. Developing a sustainable model for plastic waste management becomes imperative, given that India generates 15 million tonnes of plastic waste annually, yet only one-fourth of this is recycled, primarily due to the absence of a functional solid waste management system. Consequently, this leads to the burning of waste in landfills, contributing to the poor socioeconomic conditions of waste pickers.

A major hurdle in waste recycling is the manual collection and segregation process, where mixed-up waste complicates the already cumbersome task of separating different types of waste. To address this challenge, introducing a system or machine capable of efficiently segregating waste emerges as a solution. Such a machine, leveraging data obtained directly from the site, can significantly enhance recycling efficiency by improving accuracy and speed. The journey we embark on encapsulates a commitment to responsibility, innovation, and impactful change. It envisions a future where waste transforms from being a challenge into a catalyst for positive change, creating sustainable landscapes and thriving communities.

II. Literature Review

[1] compared their proposed four layer CNN model performance with the AlexNet and Res-Net model which include ResNet having different numbers of layers to evaluate the impact of the model size on the efficiency and accuracy metrics. [2] explores the comparisons between different Machine Learning algorithms such as Support Vector Machine, Random Forest, Decision Tree and Convolutional Neural Network, to find the optimal algorithm for the waste classification. Multi Object tracking is a crucial task in computer vision and [3] presents a novel approach to multi-object tracking using submodular optimization that has applications in surveillance systems and sports analytics. [4] presents a multi-scale detector designed to enhance the accuracy of vehicle detection in traffic surveillance data. Leveraging the YOLO-v3 framework as a base network, the authors introduce additional prediction layers and Spatial Pyramid Pooling (SPP) networks to improve vehicle detection performance, particularly in varying scales. [5] suggests an optimized waste classification using a DenseNet121 CNN model on the TrashNet dataset. In addition to which they used data augmentation and genetic algorithms to refine the model and improve its classification accuracy. Grad-CAM visualization highlights dominant features in waste images. The paper suggests potential applications in waste sorting machines and calls for further research on multi-object detection and classification in waste images.[6] introduces two innovative approaches, G-RCNN

(Granulated RCNN) and MCD-SORT (Multi-Class Deep SORT), designed for multiple object detection and tracking in videos. These methods incorporate granulation and deep learning techniques to enhance object localization and tracking accuracy in video data.

The proposed work [7] compares CNN, YOLO, and faster RCNN-based classification methods to detect different types of waste at the collecting point. They propose a dustbin that employs these methods with the help of a Raspberry Pi microcontroller and camera module. [8] presents a multilayer hybrid deep-learning system (MHS) for waste classification in urban public areas. The MHS combines image processing and sensor data to sort waste items as recyclable or non-recyclable. A convolutional neural network (CNN) is employed to extract image features, while multilayer (MLP) consolidate the image features and sensor data for waste classification. In [9], a comprehensive investigation of garbage classification using a state-of-the-art computer vision algorithm, such as Convolutional Neural Network (CNN), as well as pre-trained models such as DenseNet169, MobileNetV2, and ResNet50V2 has been presented. [10] focuses on waste management and the classification of waste materials using Convolutional Neural Network (CNN) based on transfer learning. The objective is to classify waste materials into seven categories: cardboard, glass, metal, organic, paper, plastic, and trash. The authors employ pre-trained CNN models such as InceptionV3, InceptionResNetV2, Xception, and DenseNet201 to achieve accurate waste classification.

[11] implements an intelligent waste management system that combines deep learning with IoT technology. It begins with an overview of waste classification using CNN and waste identification using deep learning mechanisms like ResNet-18. [12] focuses on an intelligent waste management system that combines deep learning with IoT technology. It begins with an overview of related contributions in the field, highlighting previous studies that utilized machine learning and IoT for waste management and later discusses a system that can classify and segregate wastes into two different categories. [13] presents a framework for automatically classifying trash using deep neural networks. The authors address the importance of trash classification in the context of smart waste sorter machines and propose a robust model called DNN-TC. The work aims to compare the performance of DNN-TC with state-of-the-art methods on both the VN-trash dataset and the Trashnet dataset. [14] explores the application of deep learning for real-time 3D multi-object detection, localization, and tracking, with a focus on its relevance to smart mobility. The document discusses the use of the Simple Online Real-Time Tracking (SORT) algorithm for object tracking and YOLOv3 for object detection, highlighting its performance and computational efficiency.[15] develops a transfer learning-based model for solid waste classification using Faster RCNN with ResNet-50+RPN, trained on a dataset of 2000 recyclable solid waste images, the model excels in challenging conditions. [16] suggests a waste sorting system using vision detection and deep learning which does real-time detection, tracking, and sorting on a conveyor belt. The YOLOX object detection model is enhanced for better accuracy and speed. DeepSORT enhances tracking. The system uses Intel RealSense D435 and a robotic arm based segregation unit.

III. PROPOSED SYSTEM

The paper centers on the development of a robust object detection model utilizing YOLOv8, empowering the system to accurately identify and classify various waste items in real-time. This capability is pivotal for the precise categorization of recyclables, non-recyclables, and other waste types, thus significantly enhancing waste management effectiveness. In conjunction with YOLOv8, we have seamlessly integrated ByteTrack for multi-object tracking functionality. This combination not only ensures accurate waste detection but also enables continuous tracking of identified objects over time, providing valuable insights into waste movement dynamics for optimized management processes.

Furthermore, we have opted for the Delta arm equipped with a suction pump for pick and place operations, offering an optimal solution for efficient waste segregation. The streamlined mechanical design of Delta arms, coupled with the suction pump, results in reduced maintenance requirements and enhanced reliability, further enhancing the overall efficiency of the waste segregation unit.

IV. METHODOLOGY

4.1 Data collection and Preprocessing

The project aims to create a comprehensive dataset of waste items in public areas, ensuring a balanced representation of waste classes to prevent biases in training. Images of PET bottles, HDPE, aluminum cans, and tetra packs are collected, along with datasets from online resources like Roboflow. The dataset is then preprocessed to enhance the model's generalization to new examples. Data augmentation techniques, such as rotations, flips, and changes in brightness and contrast, are applied to create variations of the original images, exposing the model to a broader range of scenarios and preventing overfitting. The dataset contains 29231 images, covering all types after the augmentation process.

4.2 YOLO Model Training, Testing and Deployment

The model uses bounding box coordinates and class labels to classify waste objects. After training, it undergoes rigorous testing on a separate dataset to ensure reliability. The focus then shifts to integrating the trained YOLO model into the system's software backend. The model receives input from a camera module, performs real-time object detection, and applies post-detection refinement steps to improve accuracy. The coordinates of detected materials are processed to match input requirements of the delta arm unit.

4.3 Delta Arm Kinematics

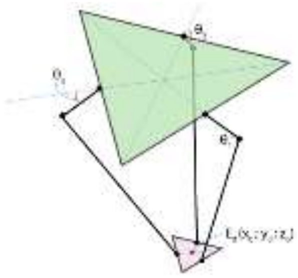

Figure 1 Delta Arm Kinematics

When tasked with constructing our own delta arm, we encountered two primary challenges. Firstly, we needed to address the issue of inverse kinematics, where given the desired position of the end effector, we must determine the corresponding angles of each of the three arms (joint angles) to position the motors correctly and thereby place the end effector accurately for picking. Secondly, in forward kinematics, if we know the joint angles, we must determine the position of the end effector, enabling us to make any necessary corrections to its current position. The setup consists of two equilateral triangles: a fixed green triangle housing the motors, and a movable pink triangle carrying the end effector. The joint angles are denoted as theta1, theta2, and theta3, while point E0 represents the end effector position with coordinates (x0, y0, z0). To solve the inverse kinematics problem, we referred [17] and developed a function with the coordinates of E0 (x0, y0, z0) as parameters, returning the corresponding (theta1, theta2, theta3) values. Similarly, the forward kinematics function takes (theta1, theta2, theta3) as inputs and returns the corresponding (x0, y0, z0) coordinates.

4.4 Delta Arm Development and Calibration

As an integral part of the waste segregation process, this paper introduces the Delta arm equipped with a suction pump for pick and place operations. This phase involves the development and calibration of the hardware components to ensure precise and coordinated movements of the delta-arm for efficient waste segregation. The Delta arm's streamlined mechanical design and suction pump capabilities are optimized to handle various waste types effectively while minimizing maintenance requirements.

4.5 Software-Hardware Integration

Finally, the various software and hardware components of the system are integrated to create a cohesive and functional solution. This phase focuses on establishing seamless communication and coordination between the YOLO model, camera module, Delta arm, and control system. By integrating these components, this system aims to achieve efficient waste segregation processes that leverage advanced technologies for improved waste management effectiveness.

V. SYSTEM ARCHITECTURE

5.1 Camera Module

The waste segregation system uses a webcam to capture high resolution live video of waste, facilitating precise detection, classification, and decision-making. The camera module ensures optimal performance by mounting securely, setting up resolution, and initializing parameters.

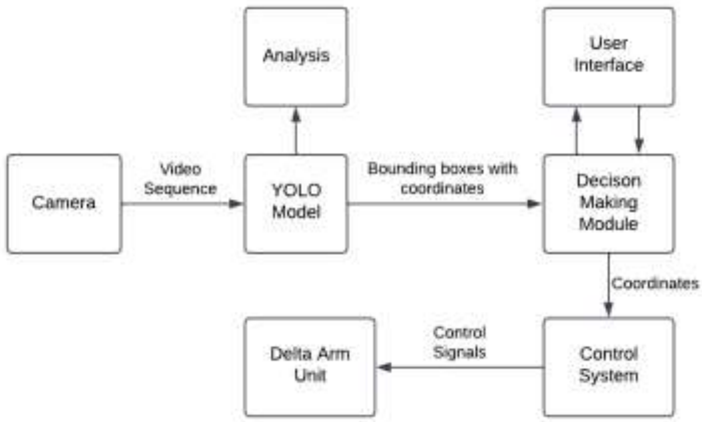

Figure 2 System Architecture

5.2 YOLO Module

The YOLO model is integrated into the Python backend for efficient waste object detection. The model is trained on a diverse dataset of waste images, annotated with bounding box coordinates and class labels. Optimization techniques, such as adjusting learning rates and applying regularization, improve model performance.

5.3 Analysis Module

The analysis module assesses waste detection and classification accuracy using a rigorous methodology involving and testing phases. The training phase involves iteratively adjusting model parameters and data augmentation techniques to optimize performance. The training progress is monitored using metrics such as loss functions and validation accuracy to ensure convergence.

5.4 Decision Making Module

The Decision Making module serves as the backbone of the waste segregation system, utilising analysis results from the YOLO model to determine actionable decisions for waste sorting. It employs sophisticated decision-making algorithms to interpret the output of the YOLO model, identifying various waste objects within the captured video feed. These instructions are then communicated to the Arduino-based control system for execution.

5.5 UI Module

The React-based User Interface (UI) is a vital tool for user interaction within the waste segregation system, providing seamless integration of real-time video feed display and waste object highlighting. Manual intervention options provide flexibility, enabling users to override automated decisions when needed.

5.6 Delta Arm Unit

An Arduino-based control system serves as the central hub for managing the movements of the delta arm by controlling the servo motor rotating movements, ensuring precise and coordinated actions for waste segregation. The Delta arm, coupled with a suction pump, emerged as the preferred choice for facilitating pick and place operations in automated waste segregation systems due to its practical benefits. Its parallel-linkage structure enabled swift and accurate movements, crucial for the efficient identification and manipulation of waste items.

VI. Experimentation And Results

The model's domain would be to detect and classify commonly found wastes in public areas like PET bottles, plastic wrapper, HDPE plastics, aluminium cans, tetrapaks. The dataset contains 29231 images comprising all the types after the augmentation process like Flip: Horizontal, Vertical and 90° Rotate: Clockwise, Counter-Clockwise, Upside Down. The dataset was trained for 200 epochs completed in 11.75 hours, the mAP50 for all classes obtained was 0.983.

Table 1 Dataset Split

Dataset	No. of Images
Train Set	20461
Valid Set	1985
Test Set	991

Figure 3 Waste Detection and Segregation

VII. Conclusion

In conclusion, the imperative of waste segregation for responsible garbage disposal in the face of modern society's substantial waste production cannot be overstated. The surge in plastic consumption, driven by escalating demands for new products and technology over the past two decades, accentuates the obstacle posed by the manual collection and segregation processes in efficient waste recycling.

The integration of YOLOv8 for object detection in our system proves to be advantageous due to its speed and simplified pipeline, surpassing other real-time systems in mean Average Precision (mAP) by more than double. This positions YOLOv8 as a superior choice for real-time processing, offering robust object detection and better generalization for new domains. The incorporation of ByteTrack for object tracking further enhances our system's capabilities, ensuring accurate tracking even in challenging environments with multi-object scenarios. EcoSift, with its adoption of advanced technologies, aligns seamlessly with sustainable development goals, particularly contributing to India's waste recycling endeavors. The delta arm's precision and dexterity enable it to physically separate detected waste materials with unparalleled accuracy and efficiency. This ensures that recyclables are properly sorted, thereby maximizing the yield of valuable materials for recycling and reducing contamination in the waste stream.

Moreover, the synergy between the delta arm and YOLOv8 fosters a seamless workflow, where objects are swiftly identified and precisely handled in real-time. This not only accelerates the recycling process but also minimizes the need for human intervention, thereby reducing labor costs and potential errors.

REFERENCES

[1] Mallikarjuna Gowda C. P., Sachin Yadav, Aditi Shanmugam, Hima V., Niharika Suresh. Waste Classification and Segregation: Machine Learning and IOT Approach. IEEE (2021).

[2] Khan Nasik Sami, Zian Md Afique Amin, Raini Hassan. Waste Management Using Machine Learning and Deep Learning Algorithms. InternationalJournal on Perceptive and Cognitive Computing (IJPCC) 6 (22020).

[3] J. Shen, Z. Liang, J. Liu, H. Sun, L. Shao and D. Tao. Multiobject Tracking by Submodular Optimization. IEEE Transactions on Cybernetics 49, 1990–2001 (2019).

[4] Kwang-Ju Kim, Pyong-Kun Kim, Yun-Su Chung and Doo-Hyun Cho. Multi-Scale Detector for Accurate Vehicle Detection in Traffic Surveillance Data. IEEE Access 7,78311–78319 (2019).

[5] Wei-Lung Mao, Wei-Chun Chen, Chien-Tsung Wang, Yu-Hao Lin.Recycling Waste Classification Using Optimized Convolutional Neural Network. Resources, Conservation and Recycling 164 (2021):105132(2020)

[6] A. Pramanik, S. K. Pal, J. Maiti and P. Mitra. Granulated RCNN and Multi-Class Deep SORT for Multi-Object Detection and Tracking. IEEE

[7] Neeraja Narayanswamy, A. R. Abdul Rajak, Shazia Hasan. Development of Computer Vision Algorithms for Multi-class Waste Segregation and Their Analysis. Emerging Science Journal 6 (2022).

[8] Yinghao Chu, Chen Huang, Xiaodan Xie, Bohai Tan, Shyam Kamal, Xiaogang Xiong. Multilayer Hybrid Deep-Learning Method for Waste Classification and Recycling. Computational Intelligence and Neuroscience in Neurorobotics 2018 Nov 1 (2018).

[9] Mohammed Imran Basheer Ahmed, Raghad B. Alotaibi, Rahaf A. Al-Qahtani, Rahaf S. Al-Qahtani, Sara S. Al-Hetela, Khawla A. Al-Matar, Noura K. Al-Saqer, Atta Rahman, Linah Saraireh, Mustafa Youldash and Gomathi Krishnasamy. Deep Learning Approach to Recyclable Products Classification: Towards Sustainable Waste Management. MDPI (2023).

[10] Sujan Poudel and Prakash Poudyal. Classification of Waste Materials using CNN Based on Transfer Learning. ACM (2023).

[11] Qiang Zhang, Xujuan Zhang, Xiaojun Mu, Zhihe Wang, Ran Tian, Xiang-wen Wang, Xueyan Liu. Recyclable Waste Image Recognition Based on Deep Learning. Resources, Conservation and Recycling 171 (2021).

[12] Md. Wahidur Rahman, Rahabul Islam, Arafat Hasan, Nasima Islam Bithi,Md. Mahmodul Hasan, Mohammad Motiur Rahman. Intelligent Waste Management System Using Deep Learning with IoT. Journal of King Saud University – Computer and Information Sciences 34 (5 2022).

[13] A. H. Vo, L. Hoang Son, M. T. Vo and T. Le. A Novel Framework for Trash Classification Using Deep Transfer Learning. IEEE Access 7, 178631–178639 (2019).

[14] A. Mauri, R. Khemmar, B. Decoux, N. Ragot, R. Rossi, R. Trabelsi, R. Boutteau, J. Y. Ertaud, X. Savatier. Deep Learning for Real-Time 3D Multi-Object Detection, Localisation, and Tracking: Application to Smart Mobility. MDPI (2020).

[15] Yayu Chen, Jisheng Sun, Shijun Bi, Cairu Meng, Fei Guo. Multi-Objective Solid Waste Classification and Identification Model Based on Transfer Learning Method. Journal of Material Cycles and Waste Management 23, 2179–2191 (2021).

[16] Shengping Wen, Yue Yuan, Jingfu Chen. A Vision Detection Scheme Based on Deep Learning in a Waste Plastics Sorting System. MDPI (2023).

[17] Alex. Delta Robot Tutorial. hypertriangle.com.https://hypertriangle.com/ alex/delta-robot-tutorial/