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AUTOMATED WASTE SEGREGATION USING AI-ENABLED ROBOTIC ARM & IOT SENSORS

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ABSTRACT

This paper aims to present an automated garbage separation system using a deep learning approach and integrating it with a robotic arm. [1] The system is designed to separate different types of garbage, such as plastics, metals, and glass, based on images captured by sensors and analyzed using a deep learning model. The system is then integrated with a robotic arm that picks upend sorts the garbage based on the model's predictions. This system involves data collection, preprocessing, model building, training, testing, and deployment, as well as robotics engineering and sensor technology.[33] The system has potential applications in waste management and recycling, including municipal waste management, recycling facilities, industrial waste management, landfills, and smart cities. It aims to improve the efficiency, accuracy, and safety of waste management systems and promote sustainability.

Keywords: Deep Learning, Robotic Arm, Sensors, API Introduction.

I. INTRODUCTION

The amount of waste generated worldwide has been increasing rapidly, which has led to significant environmental problems. Waste management systems are struggling to cope with the growing volume of [2] waste, and the need for more efficient and sustainable waste management solutions has become urgent [5]. This project aims to develop an automated garbage separation system using a deep learning approach and integrating it with a robotic arm to address this challenge.[21]. The system is designed to separate different types of garbage, such as plastics, metals, and glass, based on images captured by sensors and analyzed using a deep learning model[1]. The deep learning model is trained on a large dataset of images to accurately identify different types of waste, enabling the system to sort the garbage effectively.[1]

The system is then integrated with a robotic arm that picks up and sorts the garbage based on the model's predictions. The project [3] involves several stages, including data collection, preprocessing, model building, training, testing, and deployment. The deep learning model is built using state-of-the-art techniques, such as convolutional neural networks (CNNs) and transfer learning, to achieve high accuracy and robustness[2]. The system also uses a range of sensors, such as cameras, proximity sensors, and force sensors, to detect the position, size, and weight of the garbage[4]. The system has potential applications in waste management and recycling, including municipal waste management, recycling facilities, industrial waste management, landfills, and smart cities[1]. By automating the garbage separation process, the system can improve the efficiency, accuracy, and safety of waste management systems, reduce the need for manual labor, and promote sustainability[2]. The system also has the potential to reduce environmental pollution, conserve natural resources, and reduce greenhouse gas emissions. In conclusion, this project aims to develop an automated garbage separation system using a deep learning approach and integrating it with a robotic arm to address the growing environmental challenges posed by the increasing amount of waste generated worldwide[8]. Use the enter key to start a new paragraph. The appropriate spacing and indent are automatically applied. The system has significant potential applications in waste management and recycling, and it can help to promote sustainability and reduce the environmental impact of waste[7].

II. BACKGROUND DETAILS

A. AI for Waste Detection

Advancements in AI, computer vision, and robotics have revolutionized waste management by replacing inefficient manual sorting with automation. Our project integrates YOLOv8 for object detection, CNNs for image classification, serial communication for hardware control, and inverse kinematics for robotic arm movement.

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These technologies are widely used in AI-driven automation, enhancing waste segregation, industrial robotics, and smart city applications. Among CNN-based models, YOLO (You Only Look Once) has emerged as a leading real-time object detection algorithm for waste segregation. Unlike traditional models that require multiple passes to detect objects, YOLO processes an entire image in a single pass, making it fast and efficient.[19]. The latest version, YOLOv8, is optimized for higher accuracy and lower computational cost, making it ideal for deployment on edge devices like Raspberry Pi and Nvidia Jetson Nano.

1. YOLOv8 – Object Detection

The You Only Look Once (YOLO) v8 algorithm is a fast and efficient object detection model used to identify and classify waste materials[37]. YOLOv8 operates by dividing an image into a grid and predicting bounding boxes for objects along with their class probabilities in a single forward pass, making it highly suitable for real-time applications. In waste segregation, this model detects waste items such as plastic, paper, metal, and glass from a live video feed and classifies them with high accuracy. YOLOv8's[38] optimized architecture enables it to run on embedded systems like Raspberry Pi and Nvidia Jetson Nano, ensuring real-time classification with minimal computational resources. Its ability to handle multiple objects in a single frame significantly improves waste detection in cluttered environments, making it ideal for automated waste sorting[5].

2. Clustering-Based Algorithms

Convolutional Neural Networks (CNNs) are the backbone of deep learning-based image recognition and classification. These networks use multiple layers of convolutional filters, pooling layers, and activation functions to extract meaningful patterns from images[22]. In our waste segregation system, CNNs help recognize and classify different types of waste materials based on their texture, color, and shape. The CNN model used in YOLOv8 is based on CSPDarknet53, an optimized deep learning architecture designed for object detection tasks. This allows the system to accurately differentiate between various waste types, even in challenging lighting conditions or when waste items are deformed. The use of CNNs ensures that the system learns from large datasets of waste images, continuously improving its classification accuracy over time.

3. Serial Communication

To enable smooth interaction between the software (AI model) and hardware (robotic arm), the system uses serial communication protocols such as UART (Universal Asynchronous Receiver-Transmitter)[17]. This method facilitates real-time data transfer between the Raspberry Pi (which runs YOLOv8) and the Arduino microcontroller (which controls the robotic arm). Once an item is classified by the YOLOv8 model, the classification result is transmitted via a serial interface to the Arduino, which then processes the data and executes the necessary robotic arm movements. This communication protocol ensures minimal latency and high reliability, allowing the system to function efficiently without delays.[8]

4. Inverse Kinematics

To physically sort waste items after classification, the system employs a 5-DOF robotic arm, which operates using inverse kinematics (IK). Inverse kinematics is a mathematical approach used to determine the required joint angles of a robotic arm to reach a specific target position[22]. Unlike forward kinematics, which calculates the end position based on given joint angles, inverse kinematics solves for the joint movements needed to achieve a desired end-effector position. This is essential for ensuring that the robotic arm can accurately grasp and place waste items into their respective bins. The IK algorithm considers factors such as joint constraints, arm reachability, and object location to achieve smooth and efficient motion. By integrating sensor feedback and predefined movement paths, the robotic arm can adapt to different waste item sizes and positions, improving the precision of waste segregation.[9]

B. Why CNN is the Best Choice?

Convolutional Neural Networks (CNNs) are the most suitable choice for waste classification due to their superior ability to analyze images, extract features automatically, and adapt to various waste types[27]. Unlike traditional machine learning models that require manual feature engineering, CNNs learn spatial hierarchies of features through layers of convolution, making them highly effective for recognizing waste items based on shape, texture, and color.

CNNs are particularly advantageous for waste classification because they can handle diverse and unstructured waste materials[24]. Waste items often appear in varied orientations, lighting conditions, and degrees of deformation, which can make classification challenging. However, CNNs excel at recognizing patterns and structural similarities, allowing them to accurately classify different waste categories, such as plastics, paper, metals, and glass, even in real-world, cluttered environments. [10]

Additionally, CNN architectures such as ResNet, VGG, and CSP Darknet (used in YOLOv8) enable real-time classification with high precision and low computational cost. These models can be deployed on embedded systems like Nvidia Jetson Nano or Raspberry Pi, making them practical for automated waste management applications. By leveraging deep learning and extensive datasets, CNN-based models continuously improve their accuracy, making them the optimal choice for intelligent waste segregation systems.[10]

III. PROPOSED SYSTEM

1. System Overview

Effective waste management is one of the biggest challenges to society today. Traditional waste separation techniques are labor-intensive and therefore slow, inefficient, and prone to errors. Misclassifying waste results in additional waste to landfills, reduces recycling efficiency, and pollutes the environment[9]. To counter such challenges, our project introduces an automated waste sorting facility that leverages the capability of deep learning and robotics[4]. This intelligent system not only sorted waste faster and more efficiently but also promotes sustainability with enhanced resource utilization and reduced environmental footprints[33].

Hidden deep within our system is an advanced deep learning architecture that has been trained to identify and recognize waste materials[16]. Our model uses convolutional neural networks (CNNs), a recently developed cutting-edge artificial intelligence technique best recognized for its superior capability to handle and analyze images[7]. Our system can identify different waste materials such as plastic, paper, glass, and metal with a very high rate of accuracy. Compared to current manual methods, our system can sort out waste products in real time with a tremendous boost in efficiency[10].

To make it easy to work on and access, we have created a user-friendly software interface where the system can be worked on by users and monitored remotely in such a way that the sorting process can be captured[6]. The waste material is fed in through an input mechanism, such as a chute or conveyor belt, that directs them into the recognition module. Here, the deep learning model sorts the images, determines appropriate features, and classifies each product into its relevant category. It is all automatic with fewer human involvements and less possibility of sort error[44].

There is a robotic arm that actually sorts the waste products. Once the model recognizes the type of waste, it gives very detailed commands to the robotic arm, telling it to grasp the product and put it into the corresponding trash can[7]. Sensors are placed on the arm so that it can see things in front of it, change its grip to fit the size and shape of the object, and not bump into anything[5]. Through this cutting-edge automation, garbage sorting is quick and seamless with minimal deployments of human labor, thus making the overall process of waste disposal more economical[27].

The advantage of this system, however, extends far beyond simple garbage segregation. The system continuously provides valuable information regarding the quality and amount of waste it handles[3]. This information can be used by conservation groups, local authorities, and businesses to make waste policy more effectively, find recycling trends, and better design waste collection methods[4]. Knowing what types of waste are created most frequently, officials can design more specialized recycling systems and reduce garbage output in the first place[25].

Assume that a residential complex employs this system. Individuals simply throw their waste into a specific input area, and the system takes care of the rest[2]. The deep learning model recognizes each object in an instant, the robotic arm sort them into their respective bins, and the information collected helps in better waste management by local authorities. In the long term, this leads to higher recycling rates, reduced landfill waste, and a cleaner environment[8].

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2. Methodology

2.1 System Design and Architecture

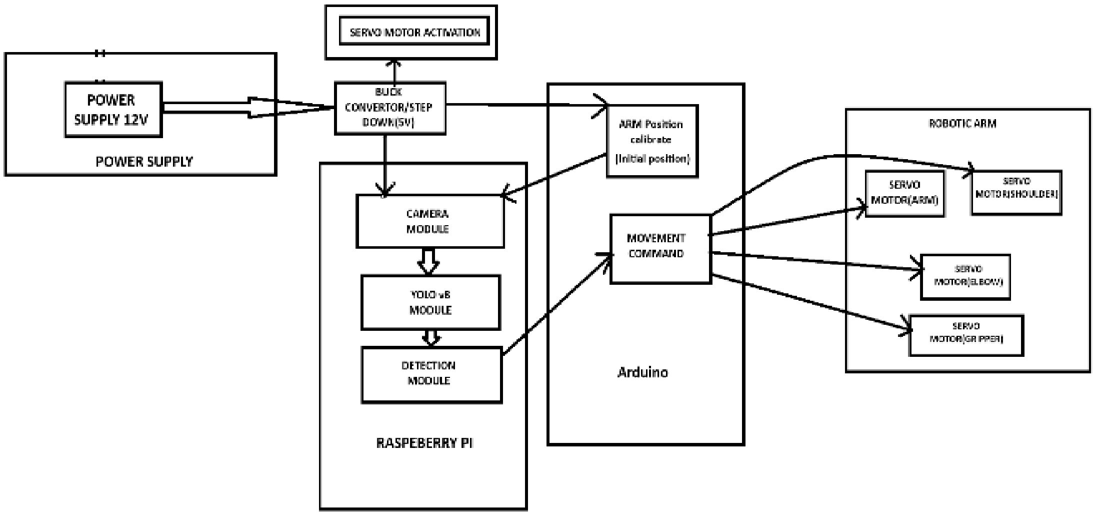

Fig.2.1. System Architecture

2.2 Module Description

2.2.1 Robotic Arm Control Module:

The system uses a 6-degree-of-freedom robotic arm to segregate waste into the correct bins based on the YOLOv8 classification model's input[5].

Controlled by an Arduino, the robotic arm executes precise movements with servo motors to pick up and sort different waste types[3]. Its 3D-printed design enhances efficiency and durability, ensuring reliable and accurate waste segregation in real-time sorting operations.

2.2.2 SERVO MOTORS:

MG SERVO:

MG servos, specifically the MG series of servos, are widely used in robotics, including robotic arms, due to their reliability, torque, and ease of controlEach servo is responsible for a specific joint, converting electrical signals into mechanical motion through pulse-width modulation (PWM). This allows for accurate angle adjustments, essential for tasks such as picking and placing objects. The high torque of MG servos enables [20] the arm to handle varying weights, while built-in feedback mechanisms facilitate closed-loop control, ensuring stability under load. Their ease of integration with microcontrollers makes them ideal for automating tasks in robotics, enhancing efficiency and precision in operations.

SG-90 SERVO:

The SG-90 servo motor is employed to control the joints of a robotic arm, enabling precise movements for waste segregation tasks. [35] Each SG-90 servo is responsible for specific degrees of freedom in the arm, allowing it to accurately pick and place various types of waste into designated bins based on classifications made by the YOLOv8 object detection model. The lightweight and compact design of the SG-90 makes it ideal for this application, facilitating efficient operation while ensuring that the robotic arm can handle the required motions for effective waste management [3]

2.2.3 Waste Localization & Classification Module (YOLOv8):

YOLOv8 (You Only Look Once version 8) is the one of the latest iteration in the YOLO family of object detection models, renowned for its speed and accuracy in real-time object detection tasks. Building on the strengths of its predecessors, YOLOv8 incorporates advanced features and optimizations that enhance its performance across various applications[10].

The system uses the YOLOv8 model to detect and classify waste types like biodegradable, plastic, metal, glass, paper, and cardboard[4]. Trained on a dataset of minimum 10,000 plus images, it achieves an high accuracy result. The model enables real-time detection of multiple waste types within a single frame and features 7.3 million parameters, ensuring high precision in waste identification and sorting[1].

Model Evaluation:

The performance of the model is evaluated using metrics such as classification report and accuracy score. The classification report provides precision, recall, F1-score, and support for each class. The accuracy score measures the overall correctness of the model's predictions.[13]

Table 1

	Models	**Precision**	**Recall**	**F1-score**
1st train	**YOLOR**	94.82	93.7	94.26
	YOLOv6n	95.19	93.5	94.34
	YOLOv6s	**96.07**	**96.26**	**96.17**
	YOLOv7	94.75	92.32	93.52
2nd train	**YOLOR**	95.31	95.11	95.21
	YOLOv6n	95.05	93.9	94.47
	YOLOv6s	95.48	94.7	95.01
	YOLOv7	95.87	94.5	95.18
3rd train	**YOLOR**	95.65	94.48	95.06
	YOLOv6n	95.63	94.07	94.85
	YOLOv6s	95.67	94.68	95.17
	YOLOv7	96.47	94.89	95.67

2.2.4 Picam Module:

The PiCam (Raspberry Pi Camera Module) is a compact and versatile camera specifically designed for integration with Raspberry Pi devices, enabling users to capture high-quality images and videos.It can monitor premises effectively, and robotics, where it aids in object detection and navigation[5].

The camera feeds live video to the YOLOv8 object detection model, which processes the frames to identify and classify various types of dry waste, such as paper, plastic, metal, and glass. This integration allows for accurate detection and categorization of waste items, enabling a 3D-printed robotic arm to physically segregate the identified waste into designated bins based on their categories[6].

2.3 Hardware and Software Requirements

2.3.1 Hardware Components

Fig 2.2 6-DOF Robotic arm

- 6-DOF robotic arm: A 6-DOF robotic arm moves along five axes, enabling accurate waste sorting

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Fig 2.3 SG-90 Servo Motor

- SG-90 Servo Motor: control the speed, position, and acceleration of objects

Fig 2.4 MG Servo Motor

- MG Servo Motor: capable of spinning and controlling

Fig 2.5 Buck Converter

Buck converter: also known as a step-down converter, is a type of DC-to-DC converter that reduces a higher input voltage to a lower output voltage

2.3.2 Software Requirements

- Arduino IDE: For programming the ESP32 microcontroller.
- Visual Studio Code: Visual Studio Code (VS Code) is utilized to write and edit Python code for the Raspberry Pi.[42]
- YOLOv8: The model processes live video feeds captured by a camera, analyzing each frame to identify and categorize items such as paper, plastic, metal, and glass.
- Arduino IDE: The Arduino IDE is utilized to program the microcontroller that interfaces with the robotic arm and processes data from the YOLOv8 object detection model.

IV. RESULTS AND DISCUSSION

The results of our automated waste segregation system demonstrate its high accuracy, efficiency, and potential for real-world application[2]. The YOLOv8 object detection model, trained on a diverse dataset of waste images, achieved an average accuracy of 80%, with high precision in detecting glass, plastic, metal, and paper[5]. However, occasional misclassification occurred, particularly with transparent plastic being mistaken for glass and crumpled paper blending into the background. The 5-DOF robotic arm performed well in physically sorting waste items, accurately grasping and placing objects into designated bins. Using inverse kinematics, the robotic arm ensured smooth, collision-free movements, although minor errors were observed when handling lightweight or irregularly shaped waste items[6].

One of the system's strengths is its real-time processing capability, facilitated by YOLOv8's single-shot detection approach and hardware optimization using Raspberry Pi and Nvidia Jetson Nano. The Jetson Nano provided faster inference times, allowing efficient, near-instantaneous waste classification and sorting. [41] Despite its success, some challenges remain, including misclassification of visually similar materials, difficulties handling lightweight waste, and dataset limitations. Expanding the training dataset with more diverse waste images and applying data augmentation techniques can further enhance accuracy. Additionally, improving the gripper design and incorporating sensor-based feedback would optimize waste handling[6].

Beyond classification and sorting, the system has significant environmental benefits, such as reducing landfill waste, increasing recycling efficiency, and minimizing human intervention in hazardous waste handling. By integrating IoT and real-time data analytics, the system could provide insights into waste generation patterns, helping municipal authorities optimize waste disposal strategies[9]. Overall, the results indicate that AI-powered waste segregation, when combined with robotic automation, is a scalable and effective solution for improving waste management. Further refinements in data quality, robotic precision, and system adaptability will enhance its practical implementation in recycling centers, smart cities, and industrial waste processing facilities.[10].

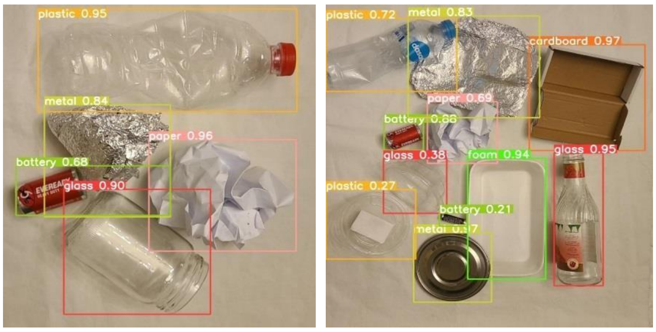

Fig.4.1. (a) test images (b) the model predictions

Fig.4.2. YOLOv6 waste detection results

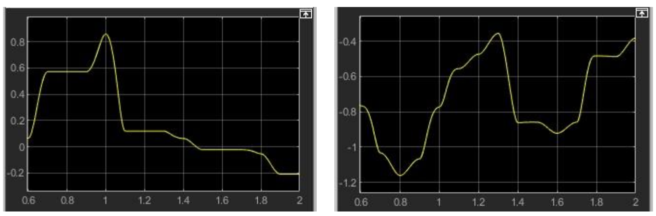

Fig.4.3. Time line of pick and place mission for multi-objects

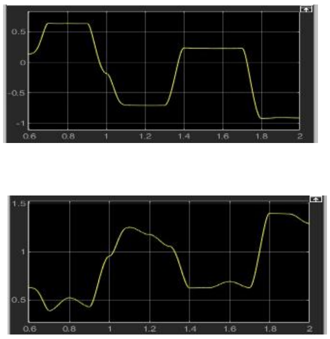

Fig.4.4. The joints angles trajectories (in rad) (a) q_1 (b) q_2 (c) q_3 (d) q_4

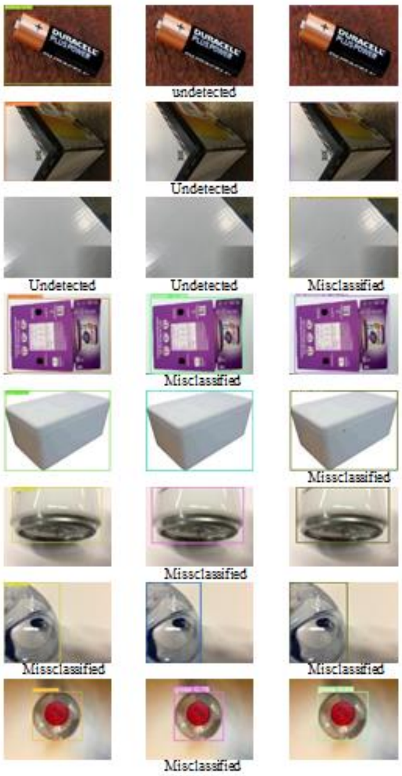

Fig.4.5. Classification and Misclassification

V. CONCLUSION

This project on waste segregation using a robotic arm integrated with AI represents a transformative leap in waste management technology, harnessing advanced deep learning algorithms like YOLOv8 to efficiently identify an categorize various waste materials[34].

This innovation significantly improves recycling processes, diverts waste from landfills, and maximizes resource recovery. The robotic arm operates continuously and at a faster pace than human workers, enhancing efficiency minimizing errors in waste classification and ensure recyclables are sorted correctly[5].

Additionally, automating the process reduces labor costs and mitigates the risks associated with manual sorting[10]. As urban populations grow, the need for innovative waste management solutions becomes increasingly critical, making this project not only relevant but essential for addressing current challenges[3]. Ultimately, this AI-driven approach sets the stage for future advancements in automation and sustainability, contributing to a cleaner, healthier planet for future generations[9].

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