A Robotic Arm Solution for Smarter Waste Handling

1st Abhishek Kudari
Department of Computer Science and Engineering
KLS Gogte Institute of Technology
Belagavi, India
abhishekkudari444@gmail.com

2nd Bhanu Kamble
Department of Computer Science and Engineering
KLS Gogte Institute of Technology
Belagavi, India
bhanukamble1249@gmail.com

3rd Chandrakant Acharatti
Department of Computer Science and Engineering
KLS Gogte Institute of Technology
Belagavi, India
chandrakantacharatti@gmail.com

4th Chetan Ingali
Department of Computer Science and Engineering
KLS Gogte Institute of Technology
Belagavi, India
chetaningali018@gmail.com

5th Arati Shahapurkar
Department of Computer Science and Engineering
KLS Gogte Institute of Technology
Belagavi, India
asshahapurkar@git.edu

***Abstract*—The efficiency and safety of automated waste handling systems are vital for modern smart cities, particularly in environments that require fast and reliable waste sorting. This project presents a real-time waste detection and robotic sorting setup that integrates a YOLOv8n object detection model with a 6-DOF robotic arm on a Raspberry Pi platform. The system is trained to identify common waste types—such as metal, glass, and paper—using a deep learning classifier. After classification, the robotic arm, operated through an Arduino and a PCA9685 servo driver, carries out the sorting task with precise pick-and-place movements.**

In this approach, YOLOv8n processes live camera input to detect waste items and sends the corresponding commands to the Arduino, which then performs the mechanical sorting operations. For every object recognized, the system displays the predicted label, confidence value, and triggers a coordinated robotic motion to ensure the item is placed in its appropriate bin. By combining real-time object recognition with automated actuation, this solution significantly enhances the speed, accuracy, and safety of waste segregation. Experimental evaluations confirm the system's effectiveness in classification and robotic manipulation, highlighting its suitability for intelligent waste management and recycling applications.

***Index Terms*—Waste Segregation, YOLOv8n, Raspberry Pi, Robotic Arm, Object Classification, PCA9685, Arduino UNO, Machine Learning.**

I. Introduction

Automation, smart city development, and intelligent environmental management have seen rapid advancement in recent years, driven by the global demand for efficiency, sustainability, and reduced human involvement in hazardous tasks [1]. A key requirement for such intelligent systems is the ability to perceive their surroundings in real time and make informed decisions that enable autonomous operation. Within the domain of waste management, real-time object classification plays a crucial role in identifying different categories of waste materials, thereby supporting efficient recycling workflows. Accurate detection of materials such as metal, glass, and paper significantly enhances the effectiveness of waste segregation while minimizing dependence on slow, labour-intensive, and often error-prone manual sorting processes.

Traditional waste segregation approaches typically rely on manual sorting or centralized cloud-based computation, both of which introduce delays, increase operational costs, and hinder scalability in high-volume environments. However, recent progress in edge computing has made it feasible to deploy intelligent waste classification models directly on low-power embedded platforms, such as the Raspberry Pi. With the ability to perform on-device machine learning inference, these edge devices offer an efficient balance of performance, cost, and energy consumption—making them well-suited for real-time automation tasks in modern smart waste management systems.

The YOLO (You Only Look Once) family of deep learning models is widely recognized for achieving an effective balance between detection accuracy and real-time performance in object recognition tasks [4]. Among its variants, YOLOv8n—a lightweight and optimized version—offers reliable detection accuracy with fast inference speeds, making it particularly suitable for embedded devices. This efficiency makes YOLOv8n ideal for real-time waste classification scenarios where rapid decision-making is critical. While visual recognition enables accurate identification of waste materials, it alone cannot complete the segregation process without an accompanying physical actuation system.

To overcome this limitation, modern robotic systems increasingly employ multi-module integration and sensor-driven automation techniques [5]. By combining robotic manipulation with computer vision, fully autonomous waste sorting solutions can be developed. In this system, a 6-DOF robotic arm driven through an Arduino–PCA9685 control architecture is integrated with YOLOv8n-based classification running on a Raspberry Pi. The Raspberry Pi performs on-device inference to categorize each waste item, while the Arduino executes precise pick-and-place operations tailored to each category. Through this coordinated approach, the system autonomously detects, selects, and sorts waste materials into their respective bins, completing the entire waste segregation workflow.

This integrated framework is particularly suitable for applications such as intelligent recycling stations, industrial sorting lines, smart waste management systems, and autonomous material-handling platforms. With its compact design, low power requirements, and ability to perform real-time processing, the proposed system presents a practical and scalable solution for efficient automated waste segregation within modern smart city infrastructures.

II. LITERATURE REVIEW

A. Maintaining the Integrity of the Specifications

Duan et al. [1] present a deep-learning-based waste classification approach using the DenseNet-121 architecture. Their model processes waste images and classifies them into 12 categories, achieving an accuracy of 94.17

Lahoti et al. [2] propose a real-time waste segregation framework that integrates YOLOv5 with a 5-DOF robotic arm controlled through a Raspberry Pi and Arduino. Their system detects common waste types from live camera feeds and directs the robotic arm for corresponding sorting actions, achieving nearly 91

Elsayed et al. [3] develop an advanced robotic sorting solution using YOLOv6 for waste identification along with a 4-DOF robotic arm designed through CAD modeling and inverse kinematics. Their system demonstrates strong robustness to object variations and achieves superior F1-scores compared to earlier YOLO versions. Targeted at industrial recycling environments, the method integrates precise trajectory planning with real-time detection to support highly automated workflows. Despite its high accuracy and reliability, the system relies on comparatively expensive hardware like the Jetson Nano and a complex mechanical structure, which makes it less suitable for low-budget implementations.

Deeksha More et al. [4] introduce one of the earlier automated waste segregation systems using a rule-based approach rather than deep learning. Their setup employs basic sensors such as infrared, moisture, and metal detectors to classify waste into dry, wet, and metallic categories, with the sorting process executed through a mechanism driven by an LPC2148 microcontroller. While the design is inexpensive and simple to deploy, it lacks the adaptability of modern AI-based methods and struggles with complex or ambiguous waste types.

To cover a broad spectrum of existing solutions, multiple studies related to robotic sorting, waste classification, and embedded automation were reviewed [1]–[13].

III. HARDWARE SPECIFICATIONS

The hardware setup for the proposed automated waste segregation system consists of the robotic arm, microcontroller units, sensing modules, and computational hardware. The essential specifications of the 6-DOF robotic arm and associated electronics are outlined below.

A. Robotic Arm Specifications

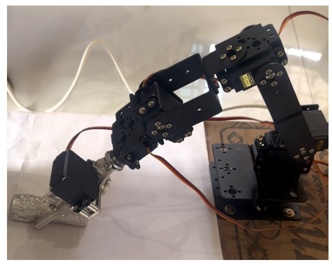

Fig. 1. Robotic arm performing a grasp during testing.

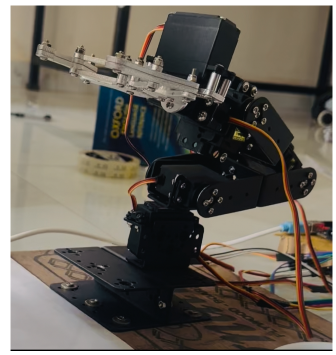

Fig. 2. Robotic arm extended into pick position prior to lifting.

- **Degrees of Freedom:** Six-axis articulated arm.
- **Reach Radius:** Approximately 355 mm.
- **Joint Rotation:** Up to 180° at primary joints.
- **Gripper Opening Range:** Maximum spread of 98 mm, suitable for medium waste items.
- **Servo Configuration:**
  - MG996R motors used on joints requiring higher torque.
  - MG995 motors used where lower torque is sufficient.
- **Frame Material:** Durable aluminum alloy construction.
- **Base Support:** Mounted on a rigid platform for stability during operation.

B. Control Electronics

- **Microcontroller:** Arduino UNO powered by ATmega328P.
- **Servo Controller:** PCA9685 PWM driver with 16 independent channels.
- **Communication Interface:** USB serial link between Raspberry Pi and Arduino.
- **Power Requirements:**
  - External 5V supply (3A–5A) dedicated for servo operation.
  - Shared ground connection among Arduino, PCA9685, and Raspberry Pi.

C. Processing Unit

- **Board:** Raspberry Pi 4 Model B.
- **Processor:** Quad-core Cortex-A72 clocked at 1.5 GHz.
- **Memory:** 2GB/4GB RAM, adequate for YOLOv8n inference.
- **Camera Module:** Raspberry Pi Camera or USB-based webcam.
- **Operating System:** Raspberry Pi OS (recommended 64-bit).
- **Software Stack:** Ultralytics YOLOv8, OpenCV, NumPy, PySerial.

D. Mechanical and Functional Characteristics

- **Payload Capacity:** Designed for lightweight waste items such as cans, paper, and small glass components.
- **Motion Accuracy:** Smooth and precise joint actuation enabled through PCA9685 control.
- **System Coordination:** Robotic actions synchronized with real-time detection outputs.
- **Operational Stability:** Consistent performance during extended sorting cycles.

IV. METHODOLOGY

The methodology used in this project is a systematic integration of machine learning-based object detection with robotic actuation to perform real-time waste classification and automated sorting. The complete workflow is broken down into various stages, such as dataset preparation, model training, input acquisition, pre-processing, detection, serial communication, and mechanical execution via a 6-DOF robotic arm.Each page of this site explains in detail each step and the technical operations that were followed in the development of the system.

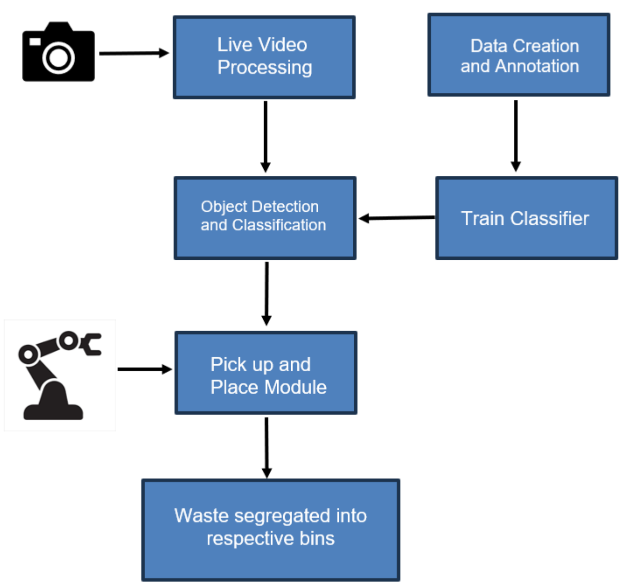

Fig. 3. Overall methodology workflow for automated waste detection and robotic sorting.

A. Dataset Preparation

Dataset preparation forms the foundation of the object detection model used in this system. Images representing the three waste categories—metal, glass, and paper—were gathered from multiple sources, including a mobile phone camera, the Raspberry Pi camera module, and publicly available datasets from Kaggle. To ensure good model generalization, the images were captured under varied lighting conditions, from different angles, and with intentionally cluttered backgrounds to test robustness.

All collected images were annotated using Label Studio, where each waste item was enclosed with a bounding box and assigned its corresponding class label. After annotation, the dataset was exported in YOLO format, generating image–label pairs that are directly compatible with the YOLOv8 training pipeline.

B. Model Training

The annotated dataset was uploaded to Google Colab, where the YOLOv8n model was trained for 60 epochs using an input resolution of 640×640 pixels. The YOLOv8n (nano) variant was selected due to its lightweight architecture, making it highly suitable for real-time inference on the Raspberry Pi. During training, the pipeline incorporated data augmentation, optimization techniques, and continuous monitoring of performance through evaluation metrics such as Precision, Recall, and mAP. After training, the model's best-performing weights file (best.pt) was exported and deployed on the Raspberry Pi for on-device inference.

C. Input Acquisition

The system processes inputs from two main sources:

- **Raspberry Pi Camera Module:** Live video frames are captured using OpenCV, preprocessed through resizing and normalization, and then fed into the YOLOv8n model for detection. The model outputs bounding boxes, predicted class labels, and confidence values for each identified waste item.
- **Serial Communication to Arduino:** After classification, the Raspberry Pi transmits the detected waste category ("metal", "glass", or "paper") to the Arduino using USB serial communication. This signal instructs the robotic arm to execute the appropriate sorting motion.

D. Data Pre-Processing

Before a captured frame is sent to the detection model, essential pre-processing operations are applied:

- **Resizing:** All incoming frames are resized to 640×640 pixels to match the input requirements of the YOLOv8n network.
- **Normalization:** Pixel values are scaled from the range [0, 255] down to [0.0, 1.0] to ensure compatibility with the model and to maintain stable inference behaviour.

These steps help improve inference speed and contribute to more consistent performance on the Raspberry Pi.

E. Detection and Post-Processing

After pre-processing, the YOLOv8n model performs object detection and returns predicted classes along with confidence scores. Post-processing includes:

- Removing detections that fall below the defined confidence threshold.
- Improving reliability by confirming detections across multiple consecutive frames.
- Converting numerical class IDs into human-readable waste labels.

Only the class with the highest confidence value is selected and forwarded for robotic action.

F. Serial Communication

Final predictions are sent from the Raspberry Pi to the Arduino Uno using a USB-based serial interface. A simple string message (e.g., "metal") is transmitted, which instructs the Arduino to initiate the corresponding sorting routine. Once the pick-and-place operation is completed, the Arduino sends back an acknowledgment message ("Cycle complete. Back to hold.") to signal readiness for the next detection.

G. Robotic Arm Control

The Arduino manages a 6-DOF robotic arm through the PCA9685 PWM servo driver. Each servo—base, shoulder, elbow, wrist pitch, wrist roll, and gripper—is assigned its own PWM channel. The firmware defines a set of predefined poses, including:

- Pick position
- Lift position
- Category-specific placement positions
- Home/hold position

The arm performs smooth, interpolated joint movements to grasp the detected object, move it to the appropriate bin (metal, glass, or paper), release it, and return safely to the home position.

H. System Integration

The entire workflow runs in a synchronized manner, ensuring that only one object is handled at a time. The Raspberry Pi pauses further detections until an acknowledgment is received from the Arduino, preventing mechanical conflicts and ensuring consistent operation. This coordinated integration of deep learning and robotic control enables a fully autonomous waste sorting system.

V. RESULTS AND DISCUSSION

The waste classification and robotic sorting system built around the YOLOv8n model on a Raspberry Pi demonstrates reliable and efficient real-time performance. The setup successfully identifies objects belonging to three waste categories—metal, glass, and paper—and communicates the classification results to a 6-DOF robotic arm controlled by an Arduino for automated pick-and-place operations. The system was tested using live video streams and physical sample objects to evaluate accuracy, stability, and overall responsiveness.

The Raspberry Pi processed incoming frames smoothly and produced consistent detection results with stable confidence values. Only predictions exceeding the predefined confidence threshold were accepted as valid, and a frame-based debouncing technique was incorporated to minimize false detections. On the actuation side, the Arduino correctly executed all serial commands sent from the Raspberry Pi, carrying out each sorting cycle without interruptions. The robotic arm performed the pick, transfer, and placement actions reliably, returning to its home position after each operation, ensuring continuous and error-free functioning of the entire system.

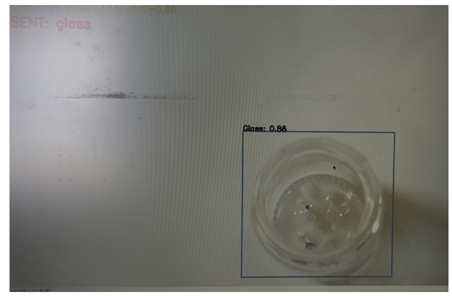

Fig. 4. YOLOv8n detection of glass waste (confidence = 0.86).

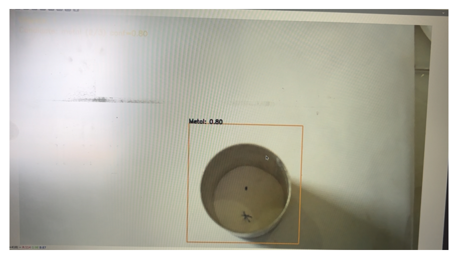

Fig. 5. YOLOv8n detection of metal waste (confidence = 0.80).

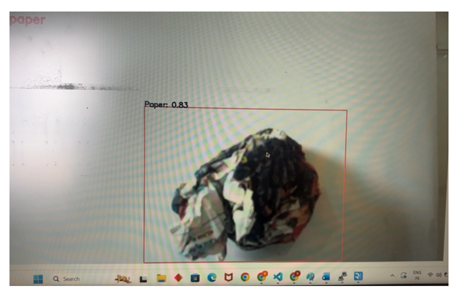

Fig. 6. YOLOv8n detection of paper waste (confidence = 0.83).

A. Pre-Optimization

The initial training phase was carried out using a small dataset of nearly 75 images representing the three waste categories. With this limited dataset, the model achieved an average detection accuracy of approximately 60%. Although the system was able to recognize objects and trigger the robotic arm, the confidence scores fluctuated noticeably under changing illumination and object orientations. Despite these variations, the robotic component performed consistently, indicating that the synchronization between the Raspberry Pi and Arduino was functioning correctly.

B. Post-Optimization

To improve the overall performance, the dataset was expanded to more than 130 images that included diverse lighting conditions, cluttered backgrounds, and varied object orientations. After retraining the YOLOv8n model for 60 epochs on this enriched dataset, detection accuracy improved significantly, reaching approximately 85–90%. Confidence scores became more stable, and false detections decreased substantially. The robotic arm responded more accurately to the high-confidence predictions, performing category-specific sorting without misalignment. The PCA9685-driven servo movements produced smooth transitions between pick, lift, place, and home positions, minimizing jerk and ensuring reliable operation.

C. System Performance Summary

The integrated system was evaluated for accuracy, real-time responsiveness, and operational stability. Key findings include:

- YOLOv8n consistently delivered real-time inference speeds on the Raspberry Pi. the Raspberry Pi.
- Detection accuracy increased markedly after expanding the dataset.
- Serial communication between Raspberry Pi and Arduino remained stable with no packet loss.
- The 6-DOF robotic arm executed pick-and-place routines with high precision.

Overall, the results validate the capability of the combined YOLOv8n, Raspberry Pi, and Arduino-based robotic system in performing automated waste classification and sorting. The system demonstrates strong potential for deployment in small-scale waste management and recycling environments.

VI. CONCLUSION AND FUTURE SCOPE

The automated waste classification and sorting system developed through the integration of YOLOv8n-based object detection and embedded robotic control demonstrates strong real-time performance in waste segregation. After expanding and optimizing the dataset, the lightweight YOLOv8n model running on the Raspberry Pi was able to identify metal, glass, and paper waste with high confidence.

The Raspberry Pi efficiently processed live video streams, while the Arduino-driven 6-DOF robotic arm accurately executed pick-and-place motions based on the detected category. The communication link between the Raspberry Pi and Arduino remained stable throughout testing, ensuring seamless coordination between machine learning inference and mechanical actuation.

With an enhanced dataset and retrained model, the detection accuracy increased to approximately 85–90%, demonstrating that edge AI models combined with low-cost hardware provide a practical and energy-efficient solution for small-scale automated waste management. The robotic arm performed sorting operations consistently and reliably, indicating strong potential for deployment in recycling and material segregation environments.

Future Scope

Several avenues exist for improving and expanding the capabilities of the proposed system:

- **Larger and more diverse datasets** can further increase classification accuracy and allow the system to operate under a wider range of lighting conditions, object shapes, and background complexities.
- **Incorporating additional sensors**, such as depth cameras or infrared modules, can enhance environmental awareness and enable more sophisticated sorting strategies.
- **Supporting more waste categories** (e.g., plastics, cardboard, organic waste) can extend the applicability of the system in modern waste management workflows.
- **Using wireless communication interfaces** like ESP32 or LoRa can support remote monitoring and IoT-based smart segregation setups.
- **Mechanical upgrades** to the robotic arm can improve speed, payload capacity, durability, and overall efficiency.
- **Scaling to industrial environments** by integrating conveyor mechanisms and continuous detection pipelines can facilitate fully autonomous recycling stations.

Overall, the system illustrates the effectiveness of combining deep learning, embedded processing, and robotics to produce a low-cost intelligent waste segregation solution with promising potential for real-world implementation and future enhancement.

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