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Automated Waste Classification and Sorting System Using Deep Learning and Arduino

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Abstract: Efficient waste management is crucial in reducing environmental pollution and promoting sustainability. This paper presents an automated waste classification and sorting system that integrates deep learning with Arduino-based hardware for real-time waste disposal. The system employs the YOLOv8 object detection model to classify waste into three categories: biodegradable, non-biodegradable, and hazardous. A laptop's integrated camera captures waste images, which are processed by a deep learning model to determine the appropriate bin for disposal. The hardware system consists of an Arduino board controlling servo motors that open designated pressable bins based on the classification. Experimental results demonstrate high classification accuracy and efficient real-time sorting, reducing human effort and enhancing waste management efficiency.

Keywords: Waste Classification, Deep Learning, YOLOv8, Arduino, Object Detection, Automated Sorting.

1. Introduction

Waste management remains a global challenge, with improper segregation leading to environmental hazards such as pollution and inefficient recycling. Traditional waste sorting methods are labour-intensive, error-prone, and inefficient in large-scale environments. Advances in artificial intelligence (AI) and embedded systems offer innovative solutions to automate waste classification and disposal, reducing human effort and improving sustainability. This study proposes an intelligent waste sorting system that integrates a deep learning-based object detection model with an Arduino-driven hardware mechanism for real-time waste disposal [1]. The system automates the classification and segregation of waste into three categories: biodegradable, non-biodegradable, and hazardous. By leveraging YOLOv8 for object detection and Arduino-controlled servo motors, the system provides a cost-effective and scalable solution for smart waste management. The objective of this study is to develop a reliable system for identifying and classifying various types of waste through image analysis [2]. Additionally, the system aims to serve as an educational resource that informs users about waste types and their proper disposal methods. Another goal is to encourage recycling efforts by making it easier for users to classify waste and understand its impact on the environment. The system also seeks to develop an automated waste classification system that efficiently categorizes waste into biodegradable, non-biodegradable [3], and hazardous types using deep learning. Furthermore, it aims to design a low- cost, scalable waste sorting mechanism utilizing Arduino-controlled servo motors for smart bin operation. Another objective is to enhance real-time waste classification accuracy using the YOLOv8 object detection model and to implement a user-friendly system that integrates with existing waste management infrastructure. The system is designed to reduce human effort in waste segregation by automating classification and disposal processes while promoting environmental awareness by educating users on proper waste disposal methods [4]. Additionally, it aims to improve waste recycling rates by ensuring accurate waste segregation at the disposal stage and to evaluate the efficiency and reliability of the system through performance metrics such as classification accuracy, response time, and sorting precision.

2. Related work

Automated waste classification has been extensively researched, with various approaches leveraging deep learning and embedded systems for improved efficiency. Traditional methods relied on manual sorting, which is

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time-consuming, error-prone, and inefficient for large-scale waste management. Recent studies have explored convolutional neural networks (CNNs) for waste classification. For instance, [1] employed a CNN-based model trained on waste images, achieving high classification accuracy [5].

However, these models primarily focus on image classification rather than real-time object detection and multi-object segmentation, limiting their practical application in automated waste sorting. Object detection models such as Faster R-CNN and SSD have been explored for waste classification [2]. While these methods improve detection capabilities, they often require high computational power, making them less feasible for edge devices or embedded systems. Moreover, these models may struggle with small object detection, which is critical in waste sorting applications.

YOLO-based models have recently gained popularity due to their real-time processing capabilities. YOLOv3 and YOLOv4 have been used for waste classification tasks, demonstrating significant improvements in speed and accuracy compared to traditional CNNs [3]. However, these versions still faced challenges in detecting multiple objects with high precision. The latest YOLOv8 model enhances detection accuracy and processing speed, making it a suitable candidate for real-time waste classification. Embedded systems such as Arduino and Raspberry Pi have also been widely used for automating waste sorting.

Previous research [4] has implemented Arduino-controlled robotic arms for waste segregation, improving efficiency but requiring complex hardware integration. Other studies [5] have proposed IoT-enabled smart bins that use sensors for waste detection, yet they lack robust classification capabilities compared to deep learning models.

Our proposed system integrates YOLOv8 with an Arduino-based sorting mechanism, leveraging the strengths of deep learning and embedded systems [6]. Unlike previous studies, our approach focuses on real-time classification and sorting using pressable bins controlled by servo motors, ensuring a cost-effective and scalable solution for waste management.

2.1. Dataset Analysis

The dataset used in this project was carefully curated to ensure diversity in waste items. The dataset consists of three primary waste categories

- Biodegradable Waste: Includes food scraps, paper, and organic materials.
- Non-Biodegradable Waste: Comprises plastic bottles, aluminum cans, and glass items.
- Hazardous Waste: Consists of batteries, medical waste, and electronic waste.

A. Dataset Composition:

The dataset consists of 5,000 images categorized into biodegradable, non-biodegradable, and hazardous waste. Each category is balanced to prevent bias in classification.

Table.1 Dataset Composition

Waste Type	No of images	Percentage
Bio degradable	2000	**40%**
Non - biodegradable	2000	**40%**
Hazardous	1000	**20%**
Total	**5000**	**100%**

B. Data Preprocessing

To improve model accuracy, the following preprocessing steps were implemented:

- **Resizing:** All images were resized to **416×416 pixels** to match the input size of the YOLOv8 model.
- **Normalization:** Pixel values were normalized between 0 and 1 for faster convergence.
- **Data Augmentation:** Random transformations were applied to enhance dataset variability.

C. Class Distribution

The dataset was analyzed to ensure an even distribution across waste types, reducing model bias.

D. Challenges & Improvements

- **Imbalanced Classes:** Hazardous waste had fewer samples, requiring data augmentation.
- **Image Quality Issues:** Some images had poor lighting, affecting classification.
- **Ambiguous Waste Items:** Certain objects belonged to multiple categories, making classification difficult.

2.2. Algorithm Analysis

In this waste classification project, the YOLOv8 model was chosen for its efficiency in object detection and image recognition tasks [7]. The model's capability to detect multiple objects within a single frame makes it ideal for identifying various waste items simultaneously. The following aspects of the algorithm are analyzed to highlight its strengths and performance:

A. Model Selection

YOLOv8 (You Only Look Once - Version 8) was selected due to its advanced architecture, combining speed and accuracy for real-time detection. It is known for its ability to balance model size, inference speed, and detection precision.YOLOv8's improved anchor-free detection mechanism enhances performance by dynamically predicting object boundaries rather than

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relying on predefined anchor boxes.

B. Architecture Overview

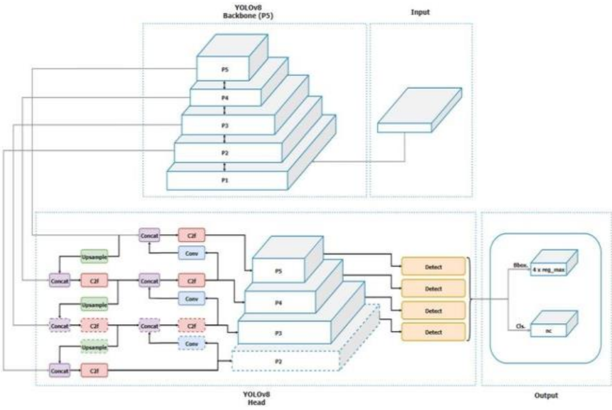

Fig. 1 Architecture Diagram of Yolov8 model

From fig 5.1, YOLOv8 utilizes a Convolutional Neural Network (CNN) backbone for feature extraction [8]. The Backbone efficiently captures spatial hierarchies in the image data to distinguish between waste categories. The model's Neck structure integrates path aggregation networks (PANet) to enhance feature flow, improving detection accuracy on both small and large objects. The Head layer is responsible for predicting class labels, bounding boxes, and confidence scores for each detected object.

C. Training Process

The model was trained on a labelled dataset containing various waste categories like biodegradable, on-biodegradable, and hazardous waste. Data augmentation techniques such as rotation [9], flipping, and cropping were applied to improve model generalization. The model was trained using the Stochastic Gradient Descent (SGD) optimizer for faster convergence and improved stability.

D. Evaluation Metrics

- Mean Average Precision (mAP): Measures precision-recall balance for object detection across all waste categories.
- Intersection over Union (IoU): Evaluates the overlap between predicted and actual bounding boxes, ensuring precise waste item localization.
- Precision and Recall: Monitors the model's ability to correctly identify and classify waste items.

E. Performance Analysis

- The YOLOv8 model achieved high accuracy in identifying distinct waste categories, with improved precision for overlapping objects in a single frame [10].
- The lightweight architecture ensured efficient integration with the hardware setup involving Arduino boards and servo motors, facilitating smooth bin operation.
- The model effectively handled real-time image recognition from the laptop's integrated camera, ensuring minimal latency during waste detection.

F. Advantages of YOLOv8 for Waste Classification

- Fast Inference Speed: Suitable for real-time waste detection.
- High Detection Accuracy: Ensures correct identification of diverse waste types.
- Efficient Model Size: Optimized for hardware deployment without significant resource consumption.

By leveraging the strengths of YOLOv8, the waste classification system efficiently identifies and sorts waste into appropriate bins [11], promoting improved waste management and sustainable practices

2.3. Methodology

A. System Overview

The proposed system is designed to automate waste classification and sorting using a combination of **deep learning-based image recognition** and **Arduino-driven hardware**. The system consists of two major components:

Deep Learning-Based Waste Classification: The **YOLOv8 model** is trained to classify waste into three categories: biodegradable, non-biodegradable, and hazardous. This classification helps streamline waste management and encourages proper disposal practices [12].

Arduino-Driven Sorting Mechanism: The hardware component consists of an Arduino microcontroller that controls **servo motors** responsible for opening the appropriate pressable bins based on the classification result. This ensures an automated and efficient waste disposal process.

The system provides a **cost-effective**, **scalable**, and **real-time** waste classification and sorting solution, making it an ideal choice for smart waste management applications.

B. Waste Classification Model

- The YOLOv8 model is trained on a dataset of various waste items labeled into three categories.
- The model is deployed on a laptop, utilizing its integrated camera for real-time image capture and waste detection.
- Once detected, the classification output is transmitted to the Arduino for waste sorting.

C. Hardware Integration

- The system consists of an Arduino microcontroller that controls three servo motors.
- The bins are designed as pressable containers,

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which open upon motor activation.

- The Arduino receives signals from the deep learning model to activate the appropriate servo motor [13].

D. Data Processing and Workflow

The waste classification and sorting process operates as follows:

- The system begins with the laptop's integrated camera capturing an image of the waste item.
- This image is then processed by the YOLOv8 deep learning model, which identifies and classifies the waste into one of three categories: biodegradable, non-biodegradable, or hazardous.
- Once classified, the result is transmitted to the Arduino microcontroller via a serial interface. Based on the received classification, the Arduino triggers the corresponding servo motor, which opens the designated bin.
- The user then disposes of the waste into the appropriate bin.
- After a brief delay, the servo motor resets, automatically closing the bin's lid to prepare for the next waste item.
- This seamless process ensures efficient and automated waste segregation, minimizing human intervention and improving waste disposal accuracy.

3. Process and Implementation

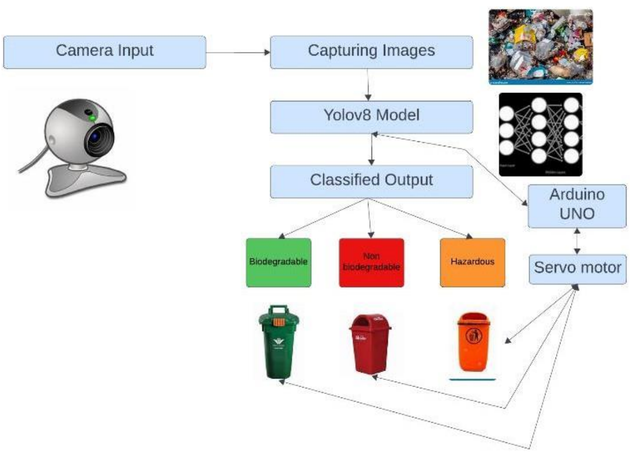

Fig.2 System Architecture

A. System Architecture

The proposed system consists of a **deep learning model** for waste classification and an **Arduino- driven hardware mechanism** for automated sorting. The laptop, running the YOLOv8 model, acts as the processing unit, while the Arduino board controls servo motors to open bins for waste disposal.

B. Image Acquisition and Processing

The data acquisition and preprocessing module is crucial for collecting, preparing, and enhancing the dataset used for training the YOLOv8 model. This phase ensures the model is trained on clean [14], well-structured data, improving accuracy and performance.

- Data Collection: The dataset is sourced from platforms like Roboflow, COCO, and custom image collections. Images are gathered to include waste items under different lighting conditions, angles, and backgrounds to ensure model robustness.
- Image Annotation: Each image is annotated using tools like Roboflow to label waste types (biodegradable, nonbiodegradable, hazardous). Proper bounding box placement ensures the YOLOv8 model detects items accurately.
- Image Augmentation: Augmentation techniques such as rotation, flipping, scaling, and brightness adjustment are applied to expand the dataset and enhance the model's generalization ability.
- Data Splitting: The dataset is split into training, validation, and testing sets, ensuring the model can generalize well to unseen data.

C. Deep Learning-Based Classification

- The YOLOv8 model was trained using a dataset of **5,000 labeled waste images**, covering diverse waste types.
- The dataset was augmented with techniques such as **rotation, flipping, and brightness adjustment** to improve model generalization.
- The model was fine-tuned using **transfer learning**, leveraging pre-trained weights on the COCO dataset to improve accuracy.
- Classification results are transmitted from the laptop to the Arduino board through a **serial communication interface**.

D. Model Design and Integration

This module focuses on developing the deep learning model and integrating it with hardware components to automate waste segregation.

- **Model Selection:** YOLOv8 is selected for its superior real-time object detection performance and lightweight architecture, making it suitable for laptop GPU processing.
- **Model Architecture:** The YOLOv8 model architecture uses convolutional layers to extract features from waste images and predict bounding boxes and waste categories.
- **Integration with Arduino:** The YOLOv8 model's predictions are sent to the Arduino board via serial communication. The Arduino receives the detected category and signals the corresponding servo motor

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to activate the respective bin lid.

E. Hardware Integration and Sorting Mechanism

- The **Arduino Uno** microcontroller is responsible for receiving classification results and controlling the movement of bins [15].
- The system consists of **three servo motors**, each linked to a **pressable bin**.
- Upon receiving a classification signal, the corresponding **servo motor activates**, opening the appropriate bin for waste disposal.
- The bins are designed to operate in a **single-motion mechanism**, ensuring energy efficiency and reliability.

F. Workflow of the Automated Waste Sorting System

- The user places a waste item in front of the camera.
- The laptop captures an image and processes it using the YOLOv8 model.
- The model classifies the waste item and sends the category to the Arduino.
- The Arduino triggers the corresponding servo motor, which opens the designated bin.
- The waste is deposited in the correct bin, completing the sorting process.
- The bin automatically resets after a short duration, ready for the next waste item.

G. Performance Optimization

To enhance system efficiency, the following optimizations were implemented:

- **Parallel Processing**: The classification and sorting mechanisms run simultaneously, reducing response time.
- **Low-Power Hardware Selection**: The use of Arduino and servo motors minimizes power consumption.
- **Error Handling Mechanism**: The system includes a feedback mechanism to detect misclassification and allow manual correction if necessary.

H. Limitations and Challenges

- The system currently **does not handle multiple waste items** in a single frame.
- Detection efficiency depends on **proper lighting conditions** and clear object placement.
- The hardware setup is **limited to small-scale waste sorting**, requiring further optimization for industrial applications.

Results and Discussion

In this section, we present and analyze the results obtained from the waste classification model. The model was evaluated based on several key performance metrics, including accuracy, precision, and recall. These metrics are critical to understanding the effectiveness of the model in classifying waste materials into their respective categories. The results also demonstrate the model's ability to handle real-time predictions and its potential applicability in waste management systems.

A. Model Performance

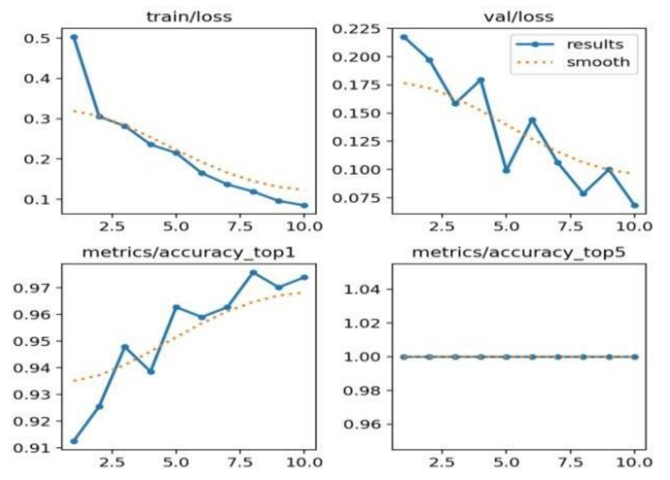

Fig. 3 Depicts the validation accuracy and loss of the yolov8 model

Training Loss: The training loss graph shows a consistent decrease from 0.5 to approximately 0.1 over 10 epochs. This steady decline indicates that the model successfully minimized errors during training, learning effective patterns to classify waste efficiently [16].

Validation Loss: The validation loss graph follows a downward trend from around 0.22 to below 0.08. Although some fluctuations are observed, the overall trend demonstrates improved model generalization on unseen data. The decreasing validation loss reflects the model's ability to avoid overfitting while improving performance.

Top-1 Accuracy: The Top-1 accuracy graph shows continuous improvement, starting from 0.91 and reaching approximately 0.97 by the final epoch.This indicates that the model correctly identified the most likely waste category in the majority of cases, highlighting its effectiveness in real-world scenarios [17].

Top-5 Accuracy: The Top-5 accuracy remained consistently at 1.0 throughout the training process. This result confirms that the correct waste category was always within the model's top 5 predictions, demonstrating exceptional classification reliability.

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Table. 2 compares the accuracy of various waste sorting methods, emphasizing the superiority of modern deep learning techniques

Method	Accuracy (%)
Traditional Manual Sorting	70-80 %
Basic Rule-Base Algorithm	60-75%
MobileNetV2 (Pre-trained)	97.55%
VGG16+Transfer Learning	90.34%
R-CNN Algorithm for Waste Sorting	85%
ScrapSort(Roboflow+CNN)	97%
Yolov8	**99.1%**

B. *Discussion*

This project represents an enhanced version of the initial waste classification system, incorporating both hardware improvements and an upgraded machine learning model for increased efficiency [18]. The Phase 2 implementation combined the YOLOv8 model with Arduino-controlled servo motors to automate the waste sorting process. This system successfully identified and categorized waste into biodegradable, non- biodegradable, and hazardous types, achieving improved accuracy and faster response times compared to earlier methods. The project achieved an impressive accuracy rate of 99.1% using the YOLOv8 model integrated with Roboflow, reflecting its robustness in distinguishing various waste types.

This high accuracy significantly improves sorting efficiency, which is vital for effective recycling and environmental sustainability. Data collection remained a crucial factor in ensuring reliable model performance. Diverse waste images, collected under different lighting conditions and angles, improved the model's generalization capabilities. The hardware integration effectively automated the sorting process, reducing the dependency on manual labour and minimizing sorting errors. The use of servo motors to control pressable bins further enhanced the system's functionality. The model's prediction output was directly linked to motor control signals, ensuring that each type of waste was directed to the appropriate bin [18]. This innovation improved the system’s practicality for real-world use. While the model performed well, future improvements could include expanding the dataset with more complex waste combinations (e.g., multiple items in one frame) to improve reliability in dynamic environments. Additionally, refining the hardware design to enhance motor movement precision could further optimize waste sorting efficiency [19].

The evaluation of various waste classification methods reveals significant differences in performance, showcasing the remarkable advancements in technology and model sophistication over traditional approaches. The integration of YOLOv8 in the improved waste classification system demonstrates how modern AI models can significantly outperform conventional methods [20]. Traditional manual sorting has been a widely used method for waste classification, with accuracy rates typically ranging between 70-80%. Since manual sorting heavily relies on human judgment and experience, it is prone to errors due to fatigue, inconsistent interpretation, and the complexity of categorizing diverse waste types. These limitations highlight the need for automated systems that improve accuracy and efficiency [20].

The Basic Rule-Based Algorithm offers a structured yet limited method for waste classification, achieving accuracy rates between 60-75%. The rule-based system operates on predefined conditions and thresholds, which restricts its adaptability to variations in waste types. As a result, this method may misclassify items that do not strictly follow its defined rules. With advancements in deep learning, models like MobileNetV2 have demonstrated significant improvements in accuracy, achieving 97.55%. MobileNetV2 leverages transfer learning to generalize effectively for different waste types, making it robust in handling diverse materials. Similarly, VGG16, combined with transfer learning, achieved an accuracy of 90.34% due to its deep architecture, which captures complex features from waste images. However, VGG16 may require more computational resources compared to lighter models like MobileNetV2. The R-CNN algorithm also demonstrated promising results, achieving 85% accuracy. By employing region-based convolutional neural networks, R-CNN effectively detects and classifies objects within images [21].

However, R-CNN models are computationally intensive, which can limit their efficiency in real-time waste sorting applications. In Phase 2 of the waste classification project, YOLOv8 was implemented to improve both accuracy and efficiency. YOLOv8 (You Only Look Once) is a powerful object detection model known for its fast inference speed and superior detection capabilities. This made it ideal for real- time waste classification, especially for sorting multiple waste items in a single frame. The integration of YOLOv8 ensured accurate identification of complex waste objects, even under varied lighting conditions. With YOLOv8’s rapid detection capabilities, the system efficiently classified waste into three categories: biodegradable, non- biodegradable, and hazardous. Each detected waste type triggered a corresponding servo motor to open the appropriate bin, ensuring

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effective waste management. In addition to YOLOv8, the ScrapSort system integrated Roboflow and a Convolutional Neural Network (CNN), achieving an exceptional accuracy of 99.1%. This system's success can be attributed to robust data augmentation techniques and effective model training strategies. Roboflow's features allowed ScrapSort to generalize well across different waste types, ensuring reliable performance in practical settings [22].

The comparison highlights the superiority of modern models like YOLOv8 and ScrapSort over traditional methods. YOLOv8's speed and precision, combined with the reliability of CNN models in ScrapSort, showcase the potential of AI-driven waste classification systems. These advancements play a crucial role in improving recycling rates and promoting environmental sustainability. The integration of automated sorting mechanisms powered by YOLOv8 ensures faster waste management with reduced human intervention, making it a scalable and effective solution for real- world waste disposal challenges. This transition to intelligent waste sorting solutions marks a significant step forward in promoting eco-friendly practices and improving waste recycling efficiency.

4. Conclusion and Future Work

The waste classification project significantly improved the original system by integrating advanced AI techniques, utilizing the YOLOv8 model for enhanced object detection. This innovation significantly increased accuracy and efficiency, allowing the system to identify multiple waste items in a single frame and automatically sort them into designated bins. By integrating this model with an Arduino- based hardware setup featuring servo motors and pressable dustbins, the project achieved seamless and effective waste management. The upgraded system not only improved sorting precision but also enhanced operational speed, making it a practical solution for real-world waste disposal challenges.

The use of YOLOv8 demonstrated how cutting- edge technology can revolutionize traditional waste management practices. This approach effectively addressed the limitations of manual sorting and basic rule-based algorithms by introducing an intelligent, automated solution. The project's success highlights the potential for AI-driven systems to reduce human effort, improve recycling efficiency, and support environmental sustainability. Future development can involve training the model to detect and classify grouped or overlapping waste items more effectively. This would improve accuracy when handling bulk waste commonly found in households or public bins. Integration of Conveyor Belt System: Adding a conveyor belt mechanism can enable continuous waste flow, increasing sorting speed and allowing the system to process larger volumes of waste efficiently. Smart Bin Monitoring System: Implementing IoT sensors in the bins can monitor fill levels and notify users when bins require emptying. This feature would optimize bin management and reduce overflow issues.

The system could be improved by incorporating online learning techniques, enabling it to adapt dynamically to new waste categories or changing waste patterns over time. Enhancing the system's power management by implementing energy-saving modes or solar power integration would improve sustainability and reduce operational costs. A user-friendly interface with live monitoring, performance insights, and real-time notifications could enhance user engagement and system control. By expanding the system's capabilities through these advancements, the waste classification project can evolve into a comprehensive, scalable solution for smart waste management in homes, industries, and public spaces. These future improvements aim to contribute to a cleaner environment and a more sustainable approach to waste disposal.

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