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Implementation of Internet of Things (IoT) in Smart Garbage Using an Inductive Proximity Sensor and Computer Vision

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A B S T R A C T

The increasing volume of waste in Indonesia is a major environmental challenge due to poor source segregation. This study develops a Smart Garbage system based on IoT and computer vision to classify waste into metal, organic, and inorganic categories with real-time monitoring. The system integrates an ESP32 microcontroller, inductive proximity sensor, webcam, Teachable Machine, Python, and the Blynk platform. The sensor detects metal waste while image classification distinguishes organic and inorganic waste. Results are sent to ESP32 via serial communication to control the sorting mechanism. Testing evaluated detection accuracy, confidence threshold, lighting conditions, and communication delay. The inductive sensor achieved 100% accuracy for metal detection. The optimal confidence threshold was 0.8 with 90% classification accuracy. The average confidence score reached 0.89 under good lighting and latency averaged 4.26 seconds. The Blynk platform enabled real-time monitoring. Overall IoT and computer vision improve waste sorting efficiency and system performance effectiveness overall improved.

INTRODUCTION

Waste management has become one of the major environmental challenges faced by many countries worldwide. Rapid population growth, urbanization, and increasing consumption patterns have contributed significantly to the rise in municipal solid waste generation. According to the World Bank, global waste generation is projected to continue increasing and may reach more than 3.4 billion tons annually by 2050 if no effective management strategies are implemented [1]. In Indonesia, waste management remains a significant concern due to the large volume of waste produced every day and the limited effectiveness of waste sorting practices at the source. Data from the National Waste Management Information System (SIPSN) indicate that a substantial portion of municipal waste still ends up in landfills without proper segregation, reducing recycling efficiency and increasing environmental pollution [2].

One of the primary challenges in waste management is the lack of proper waste segregation. Waste sorting is commonly performed manually, requiring human involvement to separate waste into different categories such as organic, inorganic, and metal waste. Manual sorting is often inefficient, time-consuming, and susceptible to human error. Improper waste segregation can negatively impact recycling activities, increase landfill accumulation, and reduce the economic value of recyclable materials. Therefore, the development of intelligent waste sorting systems capable of automatically identifying and classifying waste is essential to improve waste management effectiveness.

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Recent advancements in the Internet of Things (IoT), machine learning, and computer vision technologies have created opportunities for developing smart waste management systems. IoT enables devices to communicate and exchange information through internet-based platforms, allowing real-time monitoring and control of waste management processes [3]. Meanwhile, machine learning and computer vision technologies have demonstrated promising capabilities in object recognition and classification tasks, including waste identification applications [4].

Several studies have investigated automatic waste sorting systems using different approaches. Agustya and Fahruzi [5] developed an automatic waste sorting system using inductive and capacitive proximity sensors to distinguish metal, organic, and inorganic waste. However, the system relied primarily on sensor-based detection and lacked intelligent image classification capabilities. Nugroho and Aria [6] designed a waste sorting device using the ATmega328P microcontroller for wet, dry, and metal waste classification, but the system utilized conventional sensing techniques with limited adaptability. Velmurugan et al. [7] proposed an IoT-based smart garbage monitoring system focusing on waste monitoring and navigation rather than automatic classification. Damayanti and Sidik [8] developed a PLC-based waste sorting model that demonstrated reliable industrial control performance but required relatively expensive hardware components. Furthermore, Wulandari et al. [9] investigated the application of inductive proximity sensors in smart trash systems and reported effective metal detection performance; however, the classification of non-metal waste remained limited.

Based on the literature review, most existing studies utilize conventional sensors or programmable controllers and focus primarily on monitoring functions. The integration of machine learning-based image classification, metal detection prioritization, and real-time IoT monitoring in a single waste sorting platform remains relatively limited. In addition, many systems still depend on specialized industrial hardware, which may increase implementation costs and reduce accessibility for wider applications.

To address these limitations, this study proposes an IoT-based Smart Garbage system integrating an ESP32 microcontroller, inductive proximity sensor, webcam, Teachable Machine image classification model, and Blynk monitoring platform. The inductive proximity sensor is employed as the primary detector for metallic waste, while computer vision techniques are used to classify organic and inorganic waste. The classification results are transmitted to the ESP32 through serial communication, enabling automatic control of sorting actuators and real-time monitoring through IoT services.

Therefore, the objective of this research is to design, implement, and evaluate the performance of an IoT-based Smart Garbage system capable of automatically sorting waste into metal, organic, and inorganic categories. The performance evaluation includes metal detection testing, classification accuracy assessment, threshold optimization, lighting condition analysis, actuator response evaluation, system latency measurement, and IoT monitoring verification.

METHOD

Research Method

This study employed an engineering research method with an experimental approach. The research focused on designing, developing, and testing a Smart Garbage system capable of automatically classifying waste into metal, organic, and inorganic categories using Internet of Things (IoT) technology and computer vision.

The research stages consisted of research preparation, system design and development, software programming, equipment testing, system testing, data analysis, and conclusion. The overall research procedure is illustrated in Figure 1.

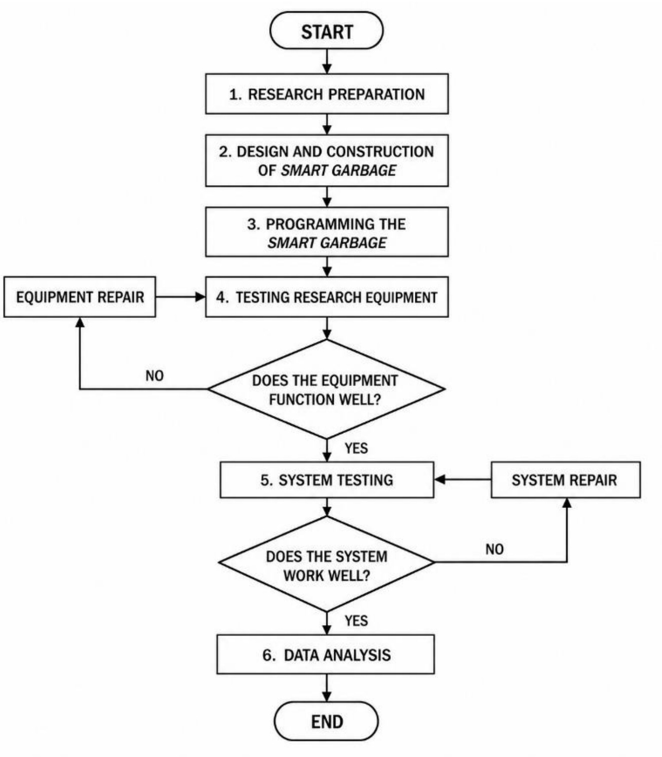

Figure 1. Research Flowchart

System Architecture

The proposed Smart Garbage system consists of three main subsystems: the sensing subsystem, the processing subsystem, and the actuation subsystem.

The sensing subsystem includes an inductive proximity sensor and a webcam. The inductive proximity sensor is utilized to detect metallic waste directly, while the webcam captures images of non-metal waste objects for classification purposes.

The processing subsystem consists of a computer running Python and OpenCV, a Teachable Machine classification model, and an ESP32 microcontroller. The classification model processes image data obtained from the webcam and determines whether the object belongs to the organic or inorganic waste category. The classification result is then transmitted to the ESP32 through serial communication.

The actuation subsystem comprises a NEMA 17 stepper motor, an SG90 servo motor, and a waste sorting mechanism. Based on the classification result, the ESP32 controls the actuators to direct waste into the corresponding disposal container. Simultaneously, classification information and system status are transmitted to the Blynk IoT platform for real-time monitoring.

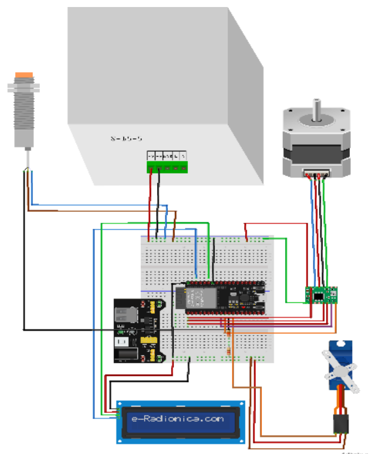

Figure 2. System Architecture of Smart Garbage

The interaction among hardware and software components is represented through the block diagram shown in Figure 3.

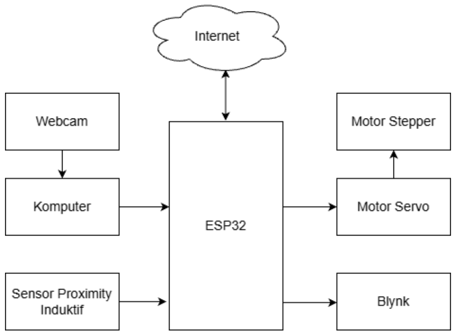

Figure 3. Smart Garbage Diagram Block

Hardware and Software Specification

The Smart Garbage prototype was developed using a combination of hardware and software components to support waste detection, classification, actuation, and monitoring processes.

Table 1. Hardware Components

Component	Function
ESP32 Development Board	Main controller and IoT communication
Inductive Proximity Sensor LJ12A3-4-Z/BX	Metal detection
USB Webcam 720p	Image acquisition
NEMA 17 Stepper Motor	Rotating sorting mechanism
SG90 Servo Motor	Waste release mechanism
LCD 16×2 I2C	System status display
A4988 Driver	Stepper motor control
Power Supply 12V	System power source
Waste Containers	Final waste storage

Table 2. Software Components

Software	Function
Arduino IDE	ESP32 programming
Python 3	Classification processing
OpenCV	Image acquisition and processing
Teachable Machine	Machine learning model generation
Blynk IoT Platform	Real-time monitoring
TensorFlow/Keras	Model execution
NumPy	Numerical processing
PySerial	Serial communication

Smart Garbage Workflow

The operational workflow of the Smart Garbage system begins when a waste object is inserted into the input compartment. The inductive proximity sensor first determines whether the object contains metallic material.

If metal is detected, the ESP32 immediately categorizes the object as metal waste and activates the sorting mechanism without performing image classification. The stepper motor rotates the waste container toward the metal compartment, while the servo motor releases the object into the designated bin.

If no metal is detected, the webcam captures an image of the object. The image is then processed using OpenCV and passed to the Teachable Machine model for classification. The model predicts whether the object belongs to the organic or inorganic waste category and generates a confidence score.

To improve classification reliability, a confidence threshold of 0.8 was implemented. Classification results below the threshold are ignored and categorized as unknown objects. When the confidence score exceeds the threshold, the classification result is transmitted to the ESP32 through serial communication.

The ESP32 subsequently controls the stepper motor and servo motor to direct the waste into the appropriate container. The classification result, confidence score, and system status are displayed on the LCD and transmitted to the Blynk platform for real-time monitoring.

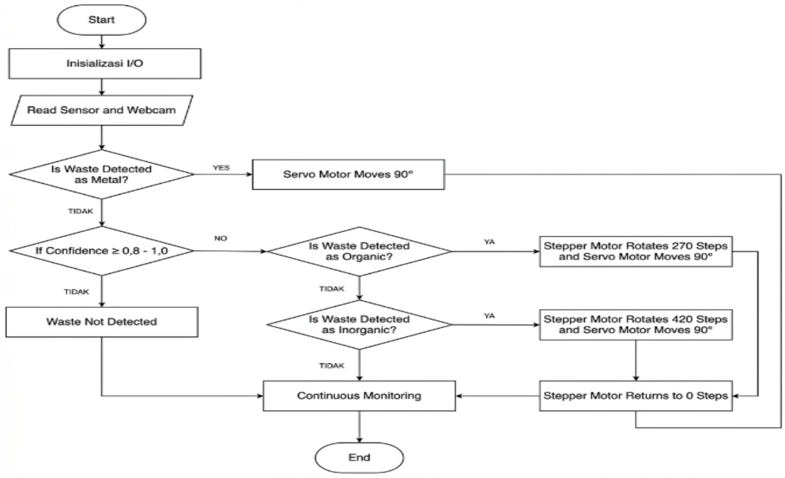

Figure 4. Smart Garbage Workflow

The operational procedure is described as follows:

1. Waste is inserted into the input chamber.
2. The inductive proximity sensor detects the presence of metal.
3. If metal is detected, ESP32 immediately classifies the waste as metal.
4. If no metal is detected, the webcam captures the waste image.
5. The captured image is processed using a Teachable Machine model through Python.
6. The classification result is evaluated using a confidence threshold of 0.8.
7. If the confidence value exceeds the threshold, the classification result is sent to ESP32.
8. ESP32 activates the stepper motor and servo motor to direct the waste into the corresponding container.
9. Classification results and confidence values are displayed on the LCD and transmitted to the Blynk platform.

Testing Procedure

System testing was conducted to evaluate the performance of the proposed Smart Garbage system in terms of detection capability, classification accuracy, actuator response, communication reliability, and real-time monitoring functionality. The testing process consisted of several stages, including metal detection testing, threshold optimization testing, image classification testing, lighting condition testing, latency testing, actuator testing, LCD testing, and IoT monitoring testing.

Metal Detection Testing

Metal detection testing was performed using several metallic objects such as beverage cans, spoons, forks, and iron materials. The objective was to verify the capability of the inductive proximity sensor in identifying metallic waste before image classification.

Threshold Optimization Testing

Threshold optimization testing was conducted by comparing confidence thresholds of 0.7, 0.8, and 0.9 using ten waste samples. The objective was to determine the optimal confidence threshold for classification performance.

Teachable Machine Classification Testing

Classification testing was performed using ten waste samples consisting of organic and inorganic waste categories. Confidence values and classification results were recorded and analyzed.

Lighting Condition Testing

Lighting performance was evaluated under two environmental conditions:

- Low illumination (15 lux)

- Normal illumination (350 lux)

The objective was to determine the influence of lighting intensity on classification accuracy.

Latency Testing

Latency testing measured the response time from object placement until classification information appeared on the Blynk application.

The average latency was calculated using:

$$Latency_{avg} = \frac{\sum_{i=1}^{n} t_i}{n}$$

where:
t_i= response time of each trial (seconds)
n= number of observations

Actuator Testing

The functionality of the NEMA 17 stepper motor and SG90 servo motor was evaluated to ensure proper waste sorting operation.

Blynk Monitoring Testing

IoT monitoring testing was performed to evaluate real-time data transmission between ESP32 and the Blynk cloud platform.

RESULTS AND DISCUSSION

Smart Garbage System Implementation

A Smart Garbage ystem based on Internet of Things (IoT) technology was successfully designed and implemented to automatically sort waste into three categories: metal, organic, and inorganic waste. The proposed system integrates computer vision technology, machine learning, embedded systems, and IoT communication into a single platform.

The developed system consists of two main subsystems: a computer vision subsystem and a hardware control subsystem. The computer vision subsystem utilizes a USB webcam and a Teachable Machine classification model running on a personal computer. The classification results are transmitted to the ESP32 microcontroller via serial communication. Meanwhile, the hardware subsystem executes the sorting process through the coordination of an inductive proximity sensor, a NEMA 17 stepper motor, a servo motor, and an LCD display.

The operational sequence begins when a waste object is placed into the input compartment. The inductive proximity sensor first determines whether the object contains metallic material. If metal is detected, the object is directly categorized as metal waste without image classification. Otherwise, the webcam captures the object's image and forwards it to the machine learning model for classification into either organic or inorganic categories. The final classification result is transmitted to the ESP32, which subsequently activates the stepper motor and servo motor to direct the waste toward the appropriate storage compartment. Simultaneously, monitoring data are sent to the Blynk platform for real-time visualization.

Figure 5. Hardware Implementation of Smart Garbage System

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Metal Detection Performance

The metal detection experiment was conducted to evaluate the effectiveness of the inductive proximity sensor in identifying metallic waste objects. Ten metallic objects were tested under identical operating conditions.

Table 3. Metal Detection Results

NO	Object	Detection Result	Status
1	Refreshment Can	Detected	Success
2	Blade	Detected	Success
3	Iron Hanger	Detected	Success
4	Spoon	Detected	Success
5	Juice Can	Detected	Success
6	Beverage Can	Detected	Success
7	Fork	Detected	Success
8	Hemaviton Can	Detected	Success
9	Used Nail	Detected	Success
10	Sardine Can	Detected	Success

The experimental results demonstrate that the inductive proximity sensor successfully detected all tested metallic objects, yielding a detection success rate of 100%. The sensor effectively identified metallic materials regardless of object shape or thickness. However, reliable detection was only achieved when objects were positioned within approximately 4–8 mm of the sensing surface. This limitation is consistent with the operational characteristics of inductive proximity sensors.

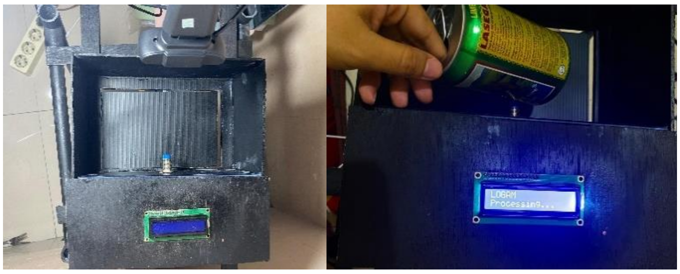

Figure 6. Metal Detection Experiment

Threshold Optimization Analysis

Threshold optimization was performed to determine the most suitable confidence threshold for the classification model. Three threshold values were evaluated: 0.7, 0.8, and 0.9.

Table 4. Threshold Optimization Results

Confidence Threshold	Samples	Successful Sorting	Failed Sorting
0.7	10	6	4
0.8	10	9	1
0.9	10	6	4

The results indicate that a threshold value of 0.8 produced the highest sorting accuracy. Lower thresholds allowed uncertain predictions to be accepted, increasing misclassification rates. Conversely, higher thresholds rejected several valid classifications, reducing overall system effectiveness.

Therefore, a confidence threshold of 0.8 was selected as the optimal value because it provided the best balance between classification accuracy and decision reliability.

Teachable Machine Classification Performance

The performance of the Teachable Machine model was evaluated using ten waste samples consisting of organic and inorganic materials.

Table 5. Waste Classification Results

No	Waste Object	Classification Result	Confidence Score	Status
1	Corn Husk	Organic	0.86	Success
2	Candy Wrapper	Inorganic	0.94	Success
3	Banana Leaf	Organic	0.81	Success
4	Oil Bottle	Inorganic	0.99	Success
5	Snack Wrapper	Inorganic	0.87	Success
6	Cardboard	Organic	0.90	Success
7	Food Paper	Inorganic	0.89	Success
8	Tissue	Organic	0.88	Success
9	Yogurt Bottle	Inorganic	0.83	Success
10	Plastic Waste	Inorganic	0.95	Success

Average Confidence Score = 0.89

The classification model achieved an average confidence score of 0.89, indicating strong recognition capability for distinguishing organic and inorganic waste. All test samples exceeded the predefined threshold value of 0.8, demonstrating stable and reliable classification performance.

These findings indicate that the Teachable Machine model is suitable for waste classification applications under controlled environmental conditions.

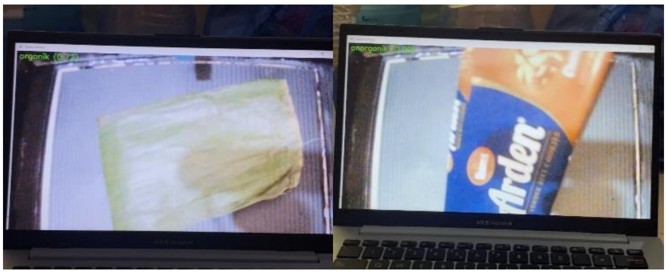

Figure 7. Webcam-Based Waste Classification Interface

Effect of Lighting Conditions

Lighting intensity significantly influenced the performance of the computer vision subsystem.

Table 6. Lighting Condition Evaluation

Waste Type	Environment	Illumination (Lux)	Confidence Score	Status
Metal	No Lamp	15	-	Success
Organic	No Lamp	15	0.58	Failure
Inorganic	No Lamp	15	0.70	Failure
Metal	LED Lighting	350	-	Success
Organic	LED Lighting	350	0.99	Success
Inorganic	LED Lighting	350	1.00	Success

The results reveal that adequate lighting is essential for successful image classification. At 15 lux, the camera failed to capture sufficient visual features, resulting in low confidence scores below the classification threshold.

Conversely, under LED illumination of 350 lux, classification confidence reached 0.99 and 1.00 for organic and inorganic waste, respectively. Metal detection remained unaffected because the proximity sensor operates independently of lighting conditions.

System Latency Evaluation

System latency was measured from object placement to successful visualization of classification results on the Blynk dashboard.

Table 7. Latency Measurement Results

Waste Type	Trial	Response Time (s)
Metal	1	2.50
Metal	2	2.29
Organic	1	4.19
Organic	2	4.52
Inorganic	1	5.83
Inorganic	2	6.28

Average Latency = 4.26 seconds

Metal waste exhibited the fastest response because classification was performed directly through the proximity sensor. Organic and inorganic waste required additional image processing and serial communication, resulting in longer response times.

Despite this delay, the overall average response time of 4.26 seconds remains acceptable for prototype-scale automatic waste sorting applications.

Actuator Performance Evaluation

The actuator subsystem was evaluated to verify synchronization between classification results and mechanical movements.

Table 8. Actuator Testing Results

Input Category	Stepper Motor	Servo Motor	Status
Metal	Active	Active	Success
Organic	Active	Active	Success
Inorganic	Active	Active	Success

The results confirm that both actuators responded correctly to all classification commands. The stepper motor successfully rotated the sorting container to the designated position, while the servo motor consistently released waste into the corresponding compartment.

Blynk Monitoring Results

The Blynk platform successfully displayed the waste classification results in real time. Information such as waste type, confidence score, and system status was transmitted from the ESP32 to the Blynk cloud server and subsequently displayed on both desktop and smartphone interfaces. The monitoring system enabled users to observe the Smart Garbage operation remotely without significant delay.

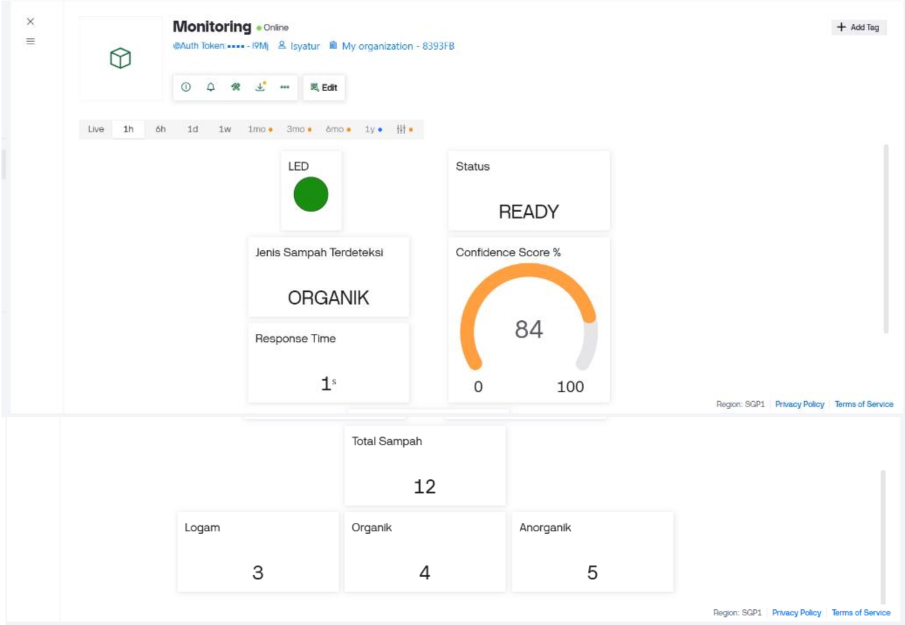

Figure 8. Blynk Monitoring Interface on Desktop

Figure 9. Blynk Monitoring Interface on Smartphone

CONCLUSION

This study successfully developed a Smart Garbage system based on Internet of Things (IoT) and computer vision technologies for automatic waste classification. The proposed system integrates an ESP32 microcontroller, an inductive proximity sensor, a webcam, a Teachable Machine classification model, and the Blynk IoT platform to classify waste into metal, organic, and inorganic categories.

Experimental results showed that the inductive proximity sensor achieved a 100% detection success rate for metallic waste, enabling direct classification without requiring image processing. For organic and inorganic waste classification, the Teachable Machine model achieved an average confidence score of 0.89, indicating satisfactory classification performance under appropriate lighting conditions. Threshold optimization experiments demonstrated that a confidence threshold of 0.8 provided the best balance between classification reliability and detection consistency. Furthermore, the system achieved an average response time of 4.26 seconds from waste detection to monitoring display on the Blynk application.

The implementation of IoT technology enabled real-time monitoring of waste classification results through smartphones, improving system accessibility and usability. Although the prototype performed effectively, its performance was influenced by environmental lighting conditions and the limitations of open-loop motor control. Future studies may improve the system through larger training datasets, enhanced imaging devices, and wireless communication protocols to increase robustness and scalability.

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