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Garbage Classification of Real-Time Waste Detection with IoT

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Abstract: Managing waste efficiently has become a major issue in rapidly growing urban areas, creating the need for smart, automated systems that minimise manual effort and improve recycling processes. This project introduces an IoT-driven real-time waste classification and monitoring system that combines sensors, embedded hardware, and machine learning to identify and sort waste automatically.A camera module connected to an IoT- enabled microcontroller or single-board computer—such as a Raspberry Pi—captures images of disposed items. These images are processed using a lightweight deep- learning algorithm that categorizes waste into groups like biodegradable, non-biodegradable, plastic, metal, and paper. To complement image-based classification, ultrasonic and load sensors track the bin's fill level and weight, ensuring instant alerts whenever the bin approaches full capacity. The system transmits classification results and bin status to a cloud platform through Wi-Fi or MQTT, enabling real-time monitoring, analytics, and automated notifications. This approach improves segregation accuracy, reduces the amount of waste directed to landfills, and supports sustainable smart-city waste management initiatives. The overall solution is affordable, easy to scale, and capable of enhancing waste collection and recycling efficiency. By automating segregation and continuously observing bin conditions, the IoT-based system lowers human involvement, boosts recycling performance, decreases operational costs, and contributes to cleaner urban spaces. Its flexible design makes it suitable for residential areas, institutions, public locations, and large smart-city environments. The research confirms that integrating machine learning with IoT substantially improves the speed and accuracy of waste classification while promoting environmental sustainability.

1. Introduction

Waste classification plays a vital role in environmental sustainability, resource recovery, and public welfare. With rapid urbanization and expanding industrial production, the amount of solid waste generated worldwide has risen dramatically. Global reports indicate that billions of tons of waste are produced each year, and this number is expected to grow even further in the coming decades. A major challenge within this context is the lack of proper waste segregation at the source. When municipalities fail to separate waste effectively, mixed garbage ends up in landfills. Improperly sorted recyclable or biodegradable materials contaminate other waste streams, reduce recycling efficiency, increase landfill pressure, and contribute to environmental threats such as soil degradation, greenhouse emissions, and water pollution.

Traditional waste disposal methods rely heavily on manual labour for sorting and for monitoring bin levels. These practices are not only inefficient and time-consuming but can also be hazardous to workers who may come into contact with dangerous materials. Overflowing bins are another recurring issue, resulting in higher operational costs and significant public health concerns. As cities move toward smarter and more sustainable infrastructures, there is an increasing demand for automated, intelligent, and data-driven systems that can transform waste management.

The rise of the Internet of Things (IoT) has created new possibilities for modernizing waste-handling operations. IoT connects physical devices—such as sensors, controllers, and embedded hardware—to cloud platforms, enabling communication and data exchange. Through this connectivity, IoT technologies can track waste levels, classify disposal materials, and assist in real-time waste management. When combined with machine learning and deep learning methods, including computer vision, IoT systems can automatically identify different categories of waste—biodegradable items, plastic, paper, metal, glass, and even hazardous materials— with high accuracy.

An IoT-enabled real-time waste detection system typically includes sensors, cameras, microcontrollers like Adriano or Raspberry Pi, and cloud-based processing. Images captured from the system are analyzed using pre-trained classification models, which determine the appropriate waste category. Sorting at the point of disposal significantly enhances the overall efficiency of waste management. It reduces dependency on manual labor, improves the quality of recyclable materials, and promotes more eco-friendly handling of waste resources. Real-time platforms developed for this purpose help ensure accurate and timely waste segregation.

Manual waste sorting—common in many households and communities—involves separating items into broad groups such as wet and dry waste or recyclable and non-recyclable materials. While this method requires minimal infrastructure, it is slow, labor-intensive, and inconsistent. Errors in segregation often lead to contamination, reduced recycling rates, and excessive landfill use.

Smart bins equipped with IoT-based monitoring use sensors such as ultrasonic, infrared, or moisture sensors to measure fill levels. These systems generate alerts when a bin reaches capacity, improving collection scheduling and reducing overflow. However, many existing systems still have limitations: they may support only a few waste categories, require mechanical sorting components like servo-actuated lids, or still depend partly on human sorting. In many cases, actual classification is limited to fill-level monitoring while segregation remains manual.

Recent advances in edge computing have enabled smart bins to perform on-device computer vision for waste identification. Such systems can classify materials like paper, plastic, metal, cardboard, and glass with prediction accuracies reported to be around 97%, enabling automatic sorting without human involvement. Other solutions install cameras along conveyor belts in recycling plants, capturing images of moving waste to automate large-scale sorting operations.

Prototypes combining “smart bin, IoT, real-time sensor, classification, and actuation” include sensors for detecting fill levels and environmental data, cameras for capturing waste items, microcontrollers or embedded systems, AI models for image classification, and mechanical sorting using servo motors, rotating disks, or grippers. When waste is thrown in, the system detects the type of waste and sorts it into the right bin.

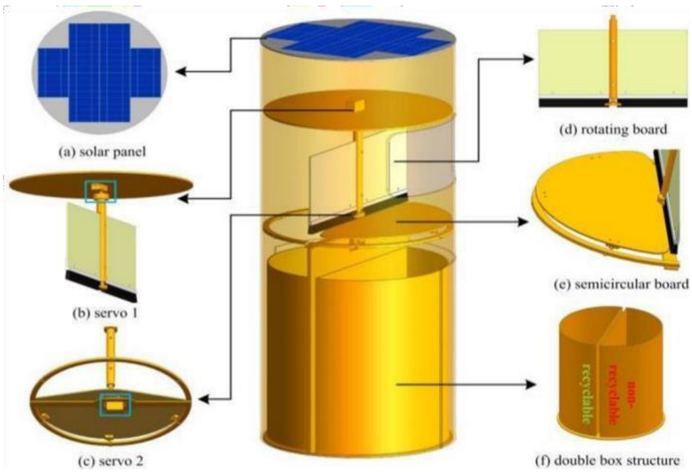


Figure 1. Structure of The Trash Bin.

Household waste management has become more complex with the increasing variety of products used in daily life. Although recent developments in the Internet of Things have made it possible to integrate computer vision into practical applications such as object detection and recognition, applying these technologies to waste classification remains challenging. With access to large, labelled datasets and advanced vision algorithms, deep learning models can accurately identify and categorise recyclable items. However, several obstacles still limit their performance, as illustrated conceptually in Fig. 1

Collecting and annotating sufficiently large datasets for training requires significant time and financial resources.

Waste images often contain clutter, irregular shapes, dirt, and low-quality visuals, making manual labelling difficult and increasing the likelihood of errors. These inconsistencies also reduce the accuracy of conventional recognition models. Furthermore, the number of waste categories continues to expand as new consumer products are introduced with varying textures, shapes, and packaging styles. Adding these new categories to existing neural networks often demands high computational power and extensive retraining, making models harder to scale. Together, these factors reduce the real-world effectiveness of current garbage-recognition systems.

An IoT-based solution typically incorporates sensors, cameras, microcontrollers such as Raspberry Pi, and cloud platforms to process the captured data. Using pre-trained image classification models, the system can automatically determine the type of waste and assign it to the appropriate category. Sorting at the point of disposal greatly improves overall waste-management efficiency. It reduces the need for labor-intensive manual sorting, enhances the quality of collected recyclables, and promotes more environmentally sound waste-handling practices. Such platforms enable real- time detection and reliable waste classification, supporting smarter and more sustainable waste-management processes.

Managing household waste is becoming increasingly complex, and although advances in the Internet of Things have enabled the integration of computer vision into practical applications such as object detection and recognition, applying these methods to waste sorting remains difficult. With access to large annotated datasets and mature vision algorithms, deep learning models can classify recyclables with high precision. However, several obstacles still make real-world garbage recognition challenging, as illustrated conceptually in Fig. 1. Creating extensive, well-labelled datasets is costly and time-consuming. Waste images typically contain noise, clutter, and irregular shapes, which complicate human annotation and often degrade the performance of conventional visual recognition systems. Moreover, the variety of waste items continues to expand as new products with diverse packaging and appearances enter the market. Updating an existing neural network to accommodate additional categories frequently requires substantial computational resources. These factors collectively reduce the effectiveness of current object-recognition approaches when deployed for real-world garbage classification.

Although research on automated waste-sorting systems has progressed significantly, many challenges remain related to accuracy, robustness, and processing speed. Only a limited number of studies focus specifically on deep learning–based waste classification. Deep neural networks have achieved remarkable success in general image classification tasks. For example, Reset—introduced by He et al. [10]—has achieved accuracies of 93.03% on CIFAR-10 and 95.51% on Image Net. Hong et al. [11] enhanced performance by combining residual and Inception blocks, reaching accuracies of 99.66% on MNIST, 98.04% on SVHN, and 95.32% on CIFAR-10.

While deep learning models can perform exceptionally well on public benchmark datasets, there is still considerable room for improvement when applied to messy, real-world garbage datasets.These observations highlight the need for more robust training techniques. First, transfer learning is essential: pertaining a model on a large and well-curated dataset allows the system to leverage learned representations and adapt them to a more limited garbage dataset. Second, the model must remain adaptable so it can recognize new categories with minimal retraining. Traditional approaches require large amounts of new training data for each additional class. In our proposed design, we draw inspiration from metric-based face recognition to create a unified learning framework for waste classification. This method enables the introduction of new waste categories simply by adding a few training examples and performing classification by measuring the distance between test samples and the new examples.

Another major issue is that garbage datasets often contain noisy labels due to unclear images, overlapping waste items, or ambiguous categories. Deep learning models generally suffer performance drops when trained on mislabeled or inconsistent data [8]. To address this, we adopt the mix-up technique, which mitigates the impact of incorrect labels by blending training samples and applying the principle of vicinal risk minimization. This strategy reduces over fitting and strengthens the model's ability to generalize, even when the dataset contains noise.

Figure 2. Challenges of Vision-Based Garbage Classification for Waste Recycling.

The main contributions of this work can be summarised as follows:

Comprehensive problem analysis: We present an in-depth review of the key difficulties associated with garbage classification and examine how current visual recognition and deep learning approaches address—or fail to address—these challenges.

Proposal of a unified learning framework (Garbage Net): To overcome existing limitations, we introduce *Garbage Net*, a unified learning framework designed to enhance classification performance. Our approach incorporates knowledge transfer from large-scale visual domains, supports effortless expansion to new waste categories through metric- learning strategies, and applies data-mining techniques to improve robustness in garbage classification tasks.

Creation of a dedicated dataset and benchmark: To the best of our knowledge, this study is the first to release a curated waste-classification dataset accompanied by a comprehensive benchmark specifically tailored for evaluating deep learning models in garbage recognition.

Extensive experimental validation: We carry out a wide set of experiments demonstrating that Garbage Net achieves superior performance compared to existing methods. Furthermore, our results show that the framework can effectively identify new waste categories using only a small number of training samples, thereby eliminating the need for costly and time-consuming retraining of deep neural networks when new classes are added.

2. Hardware Design

A. Structure Design

The first step is to construct a physical model of the smart garbage bin. Its design matches the overall form of a standard waste container. The system stands 915 cm high with an inner diameter of 390 cm and is divided into three functional layers: the upper, middle, and lower compartments.

The upper layer houses the electronic and power components, including a solar panel, rechargeable battery, LED strip, Raspberry Pi,and the camera module. The middle layer contains the mechanical sorting mechanism, which consists of two servo motors, a rotating plate, and a semicircular plate. To minimize friction with the circular track, a set of small balls is installed beneath the semicircular plate.

The bottom layer includes two separate bins, one dedicated to recyclable waste and the other to non-recyclable items.

Key components used in the structure include:

Solar power module: The system relies on solar energy for its power supply, making the bin energy-efficient and environmentally sustainable.

Servo motors: The DS3218 servo is used, offering a torque of 20 kg·cm, a lightweight design of 60 g, and an operating voltage between 5.0 and 6.5 V.

Rotating plate: Connected to Servo 1 (Fig. 1b), the plate is mounted on a central shaft. When activated, it rotates to direct recyclable waste into the designated container. A brush is attached to the bottom to reduce friction with the hardware components (Fig. 1d). The plate measures 150 cm in height and 380 cm in width.

Semicircular plate: Attached to Servo 2 (Fig. 1c), this plate is positioned perpendicular to the rotating plate. When it rotates, non-recyclable waste falls into its corresponding bin. Beneath it is a bearing seat connected to a circular track through several small balls, which helps reduce resistance during movement (Fig. 1e). The plate has a diameter of 384 cm.

Dual waste box: Located at the bottom of the bin, it accommodates two separate containers—one for recyclables and one for non-recyclables.

B. Selection of the Development Board

Considering these needs, the Raspberry Pi was selected as the core development board. As a single-board computer running a Linux-based operating system, it offers high versatility and supports a wide range of intelligent applications [32]–[34]. The Raspberry Pi 3B+ features a 1.4 GHz quad-core 64-bit CPU along with a Broadcom VideoCore IV GPU, providing adequate computational performance for real-time image processing tasks. Additionally, its camera serial interface is fully compatible with the camera module used in the system.

C. Object Classification Test

To evaluate the performance of the classification model, we conducted an object-recognition experiment. Fourteen representative waste items were selected: a book, plastic bottle, towel, paper box, metal piece, broken glass, crumpled paper, plastic item, light bulb, packaging box, battery, banana peel, leaves, and orange peel.

A large collection of images was captured for each object, with over 200 images per item, resulting in a dataset of 4,168 images used for training. After retraining the model on this custom garbage-classification dataset, the system was tested to examine its recognition accuracy and its ability to properly distinguish different waste types.

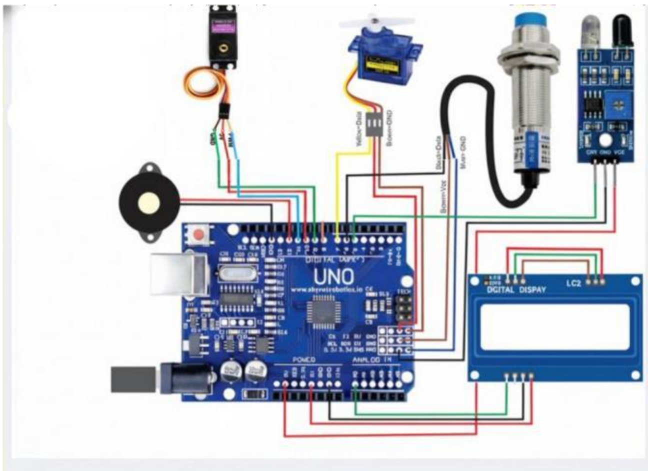


Figure 3: Architecture of Proposed Model

The diagram shows a project where an Arduino UNO controls:

1. **Arduino UNO:** The main microcontroller board used to control the sensors, display, servo motors, and buzzer. Provides digital pins, analogue pins, 5V power, and GND. Acts as the brain of the entire circuit.
2. **IR Sensor:** Used to detect objects or movement. Wiring: VCC → 5VGND →GND OUT → Arduino signal pin. 26
3. **Servo Motor:** A small servo used to rotate or move something. Wiring: Orange/Yellow (Signal) → Arduino digital pin Red

(VCC) → 5V, Brown/Black (GND) → GND Servo Motor (Blue Servo – SG90 Micro Servo) Purpose: Used to move or rotate objects (e.g., open/close a lid, sorting flap).
Connections: Brown → GND**,**Red → 5V**,**Yellow/Orange → Signal pin (Digital Pin – looks like D9 or D10)

4. Second Servo Motor :(Metal Gear Servo – MG995/MG996R type)
Purpose: A stronger servo is used for larger movements or lifting heavier objects.
Connections: Black → GND**,** Red → 5V**,** White/Yellow → Signal (Connected to another digital pin)

5.Inductive Proximity Sensor :(Metal Cylinder Sensor) this detects metal objects. Wire Colours (Typical Sensor): Brown → Vcc (5V), Blue → GND, Black → Signal output to Arduino. Purpose: Detects metal items for sorting garbage.

6.IR Sensor Module: Used for object detection (plastic/paper/clothes, etc.) Connections: Vcc → 5V, GND → GND, OUT → Digital Input Pin of Arduino Purpose:
Detects whether an object is present in front of the sensor.

7. Buzzer: Purpose: Gives beeping alerts when an object is detected or when an action is completed.
Connections: Red → Digital pin of Arduino, Black → GND

8. LCD Display: This is used to show messages such as: "Object Detected", "Metal Waste", "Plastic Waste", "Servo Activated" Connections: Pins of the LCD module are connected to Arduino digital pins: Vcc → 5V, GND → GND, RS, EN, D4, D5, D6, D7→Arduinodigitalpins the LCD is used to display real-time output, making the project user-friendly.

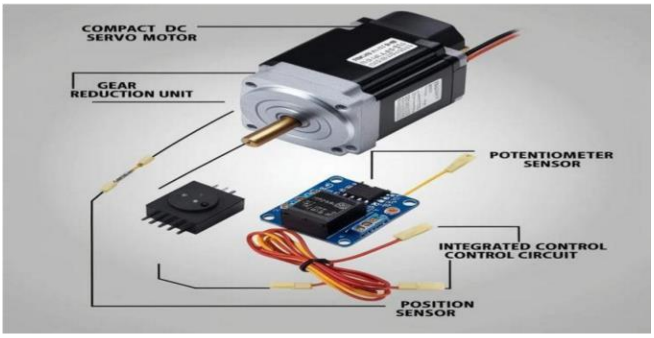
9. Wires / Jumpers Red wires → Power (5V)
Black wires → Ground (GND) Yellow/Green wires → Signal connections

1. **IR Sensor**

An IR sensor is an electronic device that detects infrared radiation (heat or light) from objects in its surroundings. It is mainly used to sense objects, distance, motion, or temperature.

2. **Microcontroller (ESP32)**

The ESP32 is a low-cost, low-power microcontroller developed by Espressif Systems. It is widely used in IoT (Internet of Things) applications due to its advanced features. The ESP32 comes with built-in Wi-Fi and Bluetooth, making.



1. **DC Motor:** Provides the rotational motion. Usually, a small DC motor is inside hobby servos.
2. **Gearbox:** Reduces speed and increases torque. Converts fast motor rotation into slow, powerful shaft rotation.
3. **Control Circuit:** Receives input signal (PWM). Compares actual shaft position with desired position. Adjusts motor rotation using feedback.

Feedback System (Potentiometer): Connected to the output shaft. Detects the current position. Provides feedback to maintain accuracy.

3. Servo Motor Works (Simple Explanation)

1. Controller sends a **PWM signal** (Pulse Width Modulation).
2. The **width of the pulse** determines the angle:
3.1 ms → 0°,1.5 ms → 90°,2 ms → 180°
The servo compares the pulse with feedback from the potentiometer.
Motor rotates until the **desired angle is reached**. When the position matches, the motor stops

4. Inductive Proximity Sensor

An Inductive Proximity Sensor is a non-contact metaldetecting sensor used to detect the presence of metallic objects without physical contact. It works based on the principle of electromagnetic induction**.**

Main Components of an Inductive Proximity Sensor modulating properties of liquid crystals combined with polarizer's to display information. Liquid crystals do not emit light directly[1] but instead use a backlight or reflector to produce images in color or monochrome. LCDs are available to display arbitrary images (as in a general-purpose computer display) or fixed images with low information content, which can be displayed or hidden: preset words, digits, and seven segment displays (as in a digital clock) are all examples of devices with these displays. They use the same basic technology, except that arbitrary images are made from a matrix of small pixels, while other displays have larger elements.

3. Methodology

The proposed methodology for real-time waste recognition and classification combines machine learning techniques with an IoT-enabled embedded system. The process begins with **Oscillator:** Generates an alternating magnetic field through the coil.

Coil: Creates the electromagnetic field used to detect metal.
Schmitt Trigger (Switching Circuit): Converts changes in the field into a clean digital ON/OFF signal.
Output Stage: Sends signal to external circuits (PLC, microcontroller, relays).
Working Principle (Simple Explanation)
The sensor generates a **high-frequency electromagnetic field**

Using an oscillator. When a metal object enters this field:

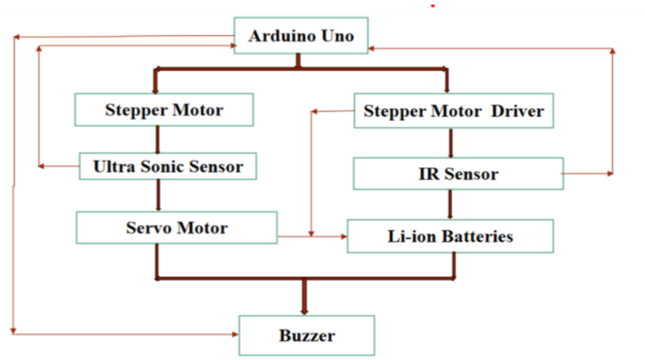
Eddy currents are induced in the metal. These eddy currents weaken (disturb) the electromagnetic field.
The sensor detects this disturbance. Image acquisition, where a camera connected to an IoT board—such as a Raspberry Pi or ESP32—captures photographs of incoming waste items. These images from both the training dataset and the input for real-time predictions. To ensure robust model learning, the dataset includes samples from multiple waste groups, including organic waste, plastics, metals, paper, and glass. Before training, the collected images undergo preprocessing steps such as resizing, normalization, and augmentation to increase variability and improve the model's ability to perform well in different lighting and environmental conditions.

The machine learning module is built around a convolutional neural network (CNN) or a compact transfer-learning architecture capable of extracting visual features and distinguishing between waste categories. During training, the network learns characteristic patterns—such as edges, shapes, textures, and colour distributions—that enable accurate classification. For deployment on IoT hardware, the trained model is optimized using techniques like quantization and model compression. These optimizations reduce computation time and energy consumption, making the model suitable for real-time execution on low-power embedded platforms without frequent reliance on cloud-based processing.

After deployment, the system operates in a continuous sensing–capturing–processing loop. Sensors such as ultrasonic or infrared modules detect the presence of an object and trigger the camera. The captured frame is immediately processed by the optimized neural network, which outputs the predicted waste category. Depending on the classification, the system may activate actuators—such as mechanical flaps or rotating bins—to sort the waste into the correct compartment. Real-time feedback through LEDs, LCD indicators, or audio alarms further enhances user interaction and system automation.In the final phase, IoT connectivity is utilized to transmit classification results, timestamps, device status, and bin fill levels to a cloud service such as Firebase, Blynk, or ThingSpeak. These platforms store the uploaded information and generate visual dashboards that help monitor waste generation trends and system performance. Alerts such as bin- full notifications can also be issued to assist waste management teams. Through this integrated approach, machine learning and IoT collectively provide a smart, automated, and data-centric solution for efficient real-time waste classification.

4. System Architecture

1. **Power Supply:** Lithium-ion batteries serve as the primary power source for the Adriano Uno and the other electronic modules in the system.
2. **Input Stage:** The ultrasonic sensor measures the distance to nearby objects. The IR sensor detects movement or the presence of items approaching the bin. Both sensors send their readings to the Adriano Uno for further processing.
3. **Processing Stage:** The Arduino Uno evaluates the sensor data and follows the programmed logic to determine which system components need to be activated. This decision- making process governs the automatic operation of the waste-sorting mechanism.
4. **Output Stage:** Based on the Arduino's analysis, the system: Operates the servo motor for angular rotation, Controls the stepper motor via its driver for precise mechanical movement, and activates the buzzer to provide audio alerts when an object is detected or when specific system events occur.



Input / Output Design

Input Design

a. **Image Acquisition:** A camera module captures images of waste items placed in front of the system. These images form the primary input for the classification model.
b. **Sensor Readings:** Inputs from various sensors— such as ultrasonic, weight, or moisture sensors—help detect object presence and provide additional physical information that supports classification.
c. **User Interaction:** Users may provide feedback regarding the correctness of the classification. This input can be used to improve system performance through retraining or calibration.

Output Design

1. **Classification Result:** The system outputs the detected category of waste, such as paper, plastic, metal, glass, or organic material.
2. **Confidence Level:** Along with the predicted label, the system displays a confidence score indicating how certain the model is about the classification.
3. **Alerts and Notifications:** The system generates alerts—such as incorrect disposal warnings, full-bin notifications, or maintenance prompts—through the IoT dashboard.

5.Result And Discussion

The project **"Real-Time Waste Detection and Classification Using IoT"** demonstrates an effective and intelligent approach to improving waste management processes. By combining machine learning, image processing, and IoT connectivity, the system is capable of automatically identifying waste items and monitoring bin conditions with minimal human involvement. This contributes to improved recycling practices, better waste segregation, and a reduction in manual sorting operations.

The developed system achieved promising performance. The classification model consistently identified multiple waste categories—including plastic, metal, paper, organic waste, and hazardous materials—with high accuracy. Additionally, sensors integrated into the system provided reliable fill-level monitoring, ensuring timely detection of overflowing bins. Data sent to the IoT platform allowed users and waste- management authorities to remotely track bin status, observe waste patterns, and take immediate action when needed.

The combination of hardware components—microcontroller, sensors, camera, and communication modules—worked cohesively with the software pipeline. This validated the practicality of deploying the system across various environments such as homes, schools, organizations, and smart-city infrastructures.

Overall, the system successfully delivered:

- Real-time waste identification
- Accurate detection of bin fill levels
- Push notifications for timely action
- Enhanced waste segregation efficiency
- Lower reliance on manual labour

The results highlight the system's potential to support cleaner, more efficient, and more sustainable waste-management practices. With further enhancements—such as more advanced AI models, improved mechanical sorting units, and large-scale IoT integration—the solution could play a key role in automated city-wide waste-handling operations.

6. Discussion

In this study, waste classification was performed using the physical characteristics of waste items or sensor-based data rather than relying solely on real waste samples. Despite this simplified approach, the system delivered strong accuracy and fast processing times. This performance is largely due to the inclusion of meaningful features such as weight, shape, moisture level, surface texture, and readings from additional sensors such as RFID or chemical detectors. These features enabled the model to reliably differentiate between categories such as organic, recyclable, hazardous, and mixed waste.

Machine learning techniques played a crucial role in enhancing system performance. By training on diverse datasets, the model learned subtle patterns and variations that may not be easily distinguishable by humans. Improvements in the model architecture—through the use of efficient layers, activation functions, and preprocessing strategies—further minimized misclassification errors and optimized runtime performance. Reducing the size of computationally heavy model components also helped lower memory usage, making the system suitable for embedded and low-power applications.

Ablation studies revealed how individual components influenced the overall performance. Small modifications in input handling, feature extraction, or model configuration produced noticeable improvements in accuracy and inference speed. The system also demonstrated resilience when processing noisy data or items with close visual similarity, emphasizing the effectiveness of sensor-based classification.

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