



ORIGINAL RESEARCH ARTICLE

DEVELOPMENT OF A MACHINE LEARNING-DRIVEN AUTOMATED WASTE SORTING SYSTEM

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ABSTRACT

The rapid growth of municipal solid waste presents environmental and health challenges, while manual sorting remains inefficient and hazardous. This study develops a prototype machine learning-driven automated waste sorting system designed for low-cost deployment. The system integrates an ESP32-CAM module for image capture, a MobileNetV2 convolutional neural network (CNN) transfer learning technique for classification, and a servo-actuated mechanical sorting mechanism. Waste items are classified into biodegradable and non-biodegradable categories, with system control managed through an ESP32 microcontroller and real-time communication via WebSocket. The model was trained on 90 live images with an additional 2356 images augmented from an online database. The system achieved an accuracy of 93.57% on the test set. While this result confirms the system's feasibility, its generalizability is currently restricted by lighting sensitivity, a limited dataset, and an inability to classify wet waste. The prototype highlights the potential of combining embedded AI and mechatronics for sustainable waste management, supporting circular economy goals. Future work should expand datasets aimed at mitigating overfitting and addressing high intra-class variance, incorporate synthetic data generation to enhance model robustness, and explore edge inference for reduced latency.

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1.0 Introduction

The increase in global population, urbanization, and industrialization has led to a significant rise in solid waste generation (Chiang et al., 2024). Improper waste management contributes to environmental degradation, groundwater pollution, and public health risks (Gude et al., 2024). Waste management systems involve sorting waste into different categories such as biodegradable and non-biodegradable wastes (Mookkaiah et al., 2022). Waste sorting processes are mainly traditional manual, automated or hybrid sorting. Traditional manual waste sorting processes face several critical challenges such as occupational health risks, operational inefficiencies and labour intensity (Imam and Rafizul, 2025). To address these challenges, automation and Artificial Intelligence (AI) are being increasingly adopted in smart waste management systems. AI and Machine Learning (ML) have emerged as powerful tools capable of transforming traditional waste management methods into intelligent, data-driven systems (Olawade et al., 2024). The integration of AI into waste sorting systems enables automatic identification and classification of materials, reducing human error and increasing efficiency (Fang et al., 2023).

Recent advances in embedded systems, such as the ESP32 microcontroller, combined with computer vision and machine learning, have opened new opportunities for developing cost-effective and intelligent waste sorting mechanisms (González et al., 2025) These systems leverage real-time image capture, sensor data, and trained neural network models to perform classification tasks similar to human perception (Anggrawan et al., 2022; Jin et al., 2023)

Despite previous efforts in automated sorting using sensors or mechanical separation, accuracy and flexibility remain challenging. Gude *et. al.* (2024) developed an intelligent waste processing framework, offering higher classification accuracy and addressing existing limitations in communication methods but there is potential vulnerability concerning data security and privacy on cloud stored data. Similarly, Agbehadji *et. al.* (2022) developed a neural network model for smart waste bins at edge/Internet of Things (IoT). They reported an accuracy of 80% over eight waste classes. The processing techniques (data augmentation, resizing and normalizing) enhanced the model's robustness, reduced over fitting by simulating diverse real-world conditions within the training set, but it cannot adapt to new waste categories and varying image condition. Additionally, Abdulkareem *et. al.* (2024) enhanced waste sorting performance through hybrid CNN models, they employed Deep learning models (ResNet50, GoogleNet, Inception and Xception) while Lakhout (2025) in a review on AI and IoT for urban waste, stated that while AI/IoT improve collection, sorting, and recycling, they face high initial costs, privacy concerns, and technical limitations, and explicitly advocated continued investment in innovative technologies and robust data-privacy solutions.

It can be seen from the aforementioned that there remains a lack of low-cost, embedded, and deployable waste sorting systems that balance classification accuracy, hardware simplicity, and real-time operation without reliance on powerful cloud infrastructure. This study addresses this gap by developing a low-cost, ESP32-based automated waste sorting prototype that integrates lightweight CNN inference with mechatronic actuation.

2. Materials and Method

2.1 System Description

The proposed machine learning–driven automated waste sorting system is designed to classify and separate waste into biodegradable and non-biodegradable categories. The overall architecture of the system is illustrated in the system block diagram shown in Figure 1, while the operational workflow is presented in the system flowchart in Figure 2.

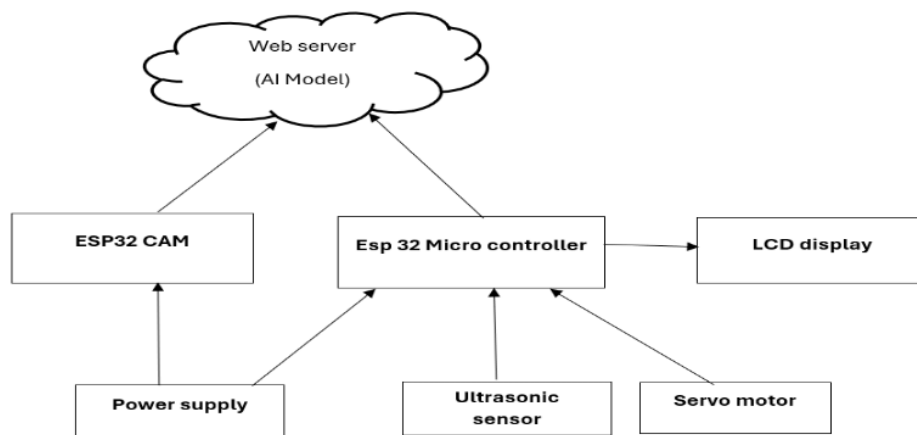


Figure 1: Block diagram of the waste sorting system

As depicted in Figure 1, the system consists of several key hardware and software components, including an ESP32-CAM module, an ESP32 microcontroller unit (MCU), an ultrasonic sensor, a servo motor, a liquid crystal display (LCD), a buck (step-down) converter module, and a cloud-based web server hosting the machine learning model. The ESP32-CAM is centrally mounted on the waste sorting frame to ensure optimal image capture of incoming waste items. The ultrasonic sensor, LCD, and servo motor are interfaced with the ESP32 MCU, which serves as the main control unit of the system. Both the ESP32-CAM and the ESP32 MCU are connected to the same web server via Wi-Fi, enabling seamless communication between the devices.

2.2 Operational Workflow

The system flowchart which describes the operational workflow is depicted in Figure 2. As shown in Figure 2, the system operation begins when the ultrasonic sensor detects the presence of a waste object. Upon detection of a waste object by the ultrasonic sensor, the ESP32-WROOM triggers the ESP32-CAM to capture an image of the waste items. The captured image is transmitted to the server hosting the machine learning model. The classification result is returned to the control microcontroller, which actuates the servo motor to direct the waste into the appropriate bin and updates the LCD display accordingly. Once the web server

receives the image, it forwards the data to the machine learning algorithm, where classification is performed to determine whether the waste is biodegradable or non-biodegradable. The prediction result is subsequently sent back to the ESP32 MCU for decision-making. If the waste is classified as biodegradable, the result is displayed on the LCD and a control signal is sent to the servo motor to allow the waste to enter the appropriate bin. Conversely, if the waste is identified as non-biodegradable, the classification result is displayed on the LCD and the servo motor restricts access to the bin, thereby preventing improper disposal.

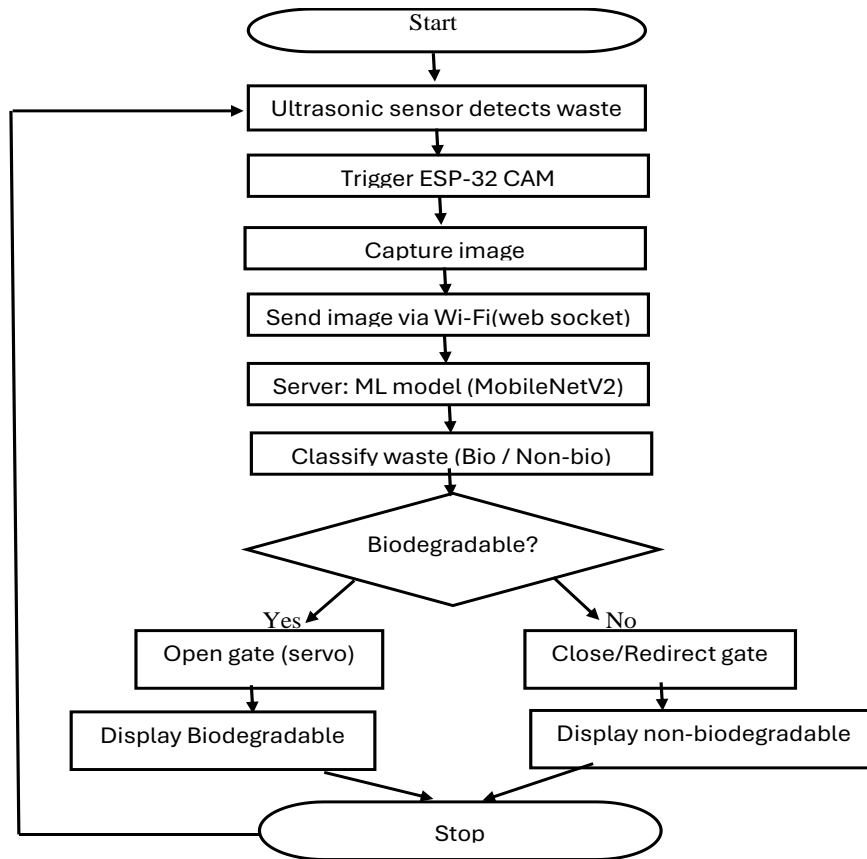


Figure 2: Waste sorting system flowchart

All communication between the web server and the two microcontroller clients is implemented using WebSocket technology to ensure low-latency, real-time data exchange. Power for the entire system is supplied through a regulated 5V power supply, provided by the buck converter module, ensuring stable operation of all components.

2.3 Hardware Component Selection and Mechanical Design

The design of a reliable sorting system requires the careful selection of components that balance performance, power consumption, and cost-effectiveness. The mechanical/mechatronic assembly must be capable of handling the physical load of various waste materials while maintaining electrical stability (Zamuragin *et al.*, 2024). The heart of the visual system is the ESP32-CAM, a low-cost module that integrates an OV2640 camera capable of 2-megapixel resolution. The dual-core 240 MHz processor of the board and its integrated Wi-Fi make it an ideal edge device for IoT applications requiring image streaming (Nowroz *et al.*, 2025). Complementing this is the ESP32-WROOM microcontroller, which manages low-level control logic and hardware interrupts for the ultrasonic sensor and servo motor, thereby ensuring precise timing, responsive actuation, and reliable overall system operation (Sayyad *et al.*, 2023). Table I outlines the primary hardware components and their technical justifications.

2.3.1 Mechanical design

The mechanical frame was designed to provide structural support for the entire waste sorting mechanism. A waste chute guides incoming materials toward the imaging section, where a camera captures images prior to the sorting process. The structural framework was modelled using Computer-Aided Design (CAD) software

to ensure mechanical stability, accurate alignment of components, and smooth movement of waste materials during operation.

The development process commenced with the creation of a detailed three-dimensional CAD model of the wooden platform. This model served as a design blueprint, specifying precise dimensions and component layouts to maintain consistency and accuracy throughout fabrication. By enabling thorough visualization of the platform before physical construction, the CAD model helped minimize design errors and facilitated an efficient transition from conceptual design to implementation.

Table I: Hardware Components Selection and Technical Justification

Component	Model	Technical justification	Specifications
Microcontroller (Camera)	ESP32-CAM	Integrated image capture and Wi-Fi streaming.	5V Input, OV2640 Sensor.
Microcontroller (Control)	ESP32-WROOM	High-speed GPIO for sensor and actuator management.	3.3V/5V Operation.
Ultrasonic sensor	HC-SR04	Non-contact proximity detection with 2cm-400cm range.	5V DC, 15mA Current.
Servo motor	MG946R	High-torque metal gear actuator for physical sorting.	13kg.cm Torque at 6V.
Display	LCD16x2	Real-time user feedback and status updates.	I2C Interface, 5V.
Power management	LM2596	Voltage stabilization for high-current actuators.	Bulk Converter Module.

The sorting gate mechanism is actuated by a servo motor controlled by the ESP32 microcontroller, allowing rapid and precise redirection of waste into the appropriate collection bins based on the classification outcome.

Figure 2 presents the CAD design images, which illustrate the systematic planning underlying the mechanical structure and form the foundation of the overall system. These images highlight the detailed geometry and dimensional accuracy of the design, thereby supporting the effective translation of the virtual model into a functional physical prototype.

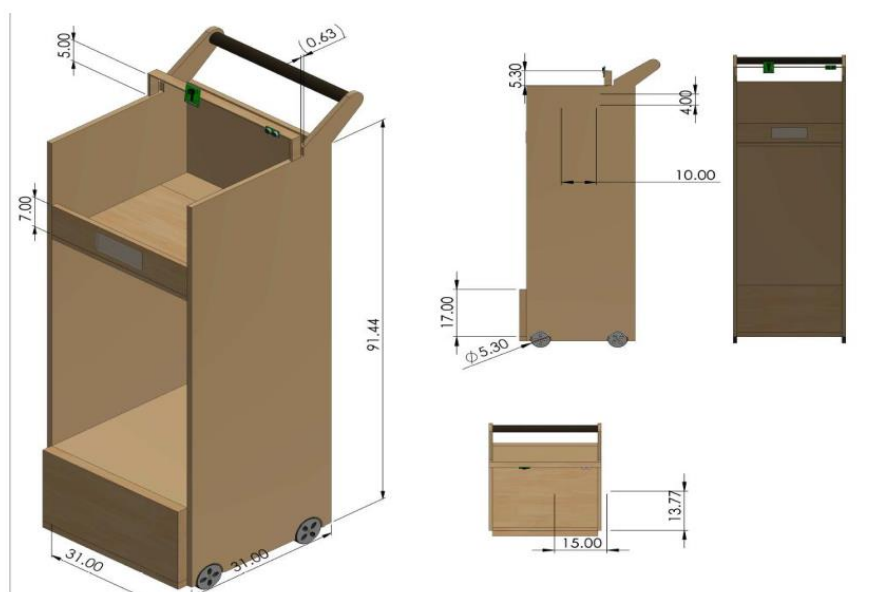


Figure 2: CAD design of the system frame

The physical platform for the sorting machine was fabricated using 4mm MDF plywood, providing a lightweight yet stable structure for prototyping. To ensure that the selected servo motor could reliably actuate the bin lid, kinematic calculations were performed to determine the required torque.

The lid of the bin, measuring $0.3\text{ m} \times 0.25\text{ m} \times 0.3\text{ m}$, has a calculated volume of $2.25 \times 10^{-4}\text{ m}^3$. Given the density of the MDF board (700 kg/m^3), the mass of the lid (m) is approximately 0.1575 kg . The torque (τ) required to rotate the lid is calculated as Equation 1:

$$\tau = m \cdot g \cdot \frac{L}{2}$$

Where: g = acceleration due to gravity, and L = length of the lid. Substituting the values:

$$\tau = 0.1575\text{ kg} \cdot 9.81 \frac{\text{m}}{\text{s}^2} \cdot \frac{0.3\text{ m}}{2} = 0.2317\text{ Nm}$$

With an extra load factor, the total required torque was determined to be 0.2802 Nm . The MG946R servo motor, which provides a stall torque of 0.981 Nm at 4.8 V , offers a significant safety margin, ensuring that the mechanism will not fail even under maximum load conditions.¹ Power is supplied via a $10,000\text{mAh}$ power bank, with the LM2596 bulk converter stepping the voltage down to a stable 5 V .

2.4 Electronic Design

The electronic circuit, designed using Proteus software, integrates the ESP32-CAM, ESP32-WROOM, ultrasonic sensor, servo motor, LCD, and LM2596 buck converter. A regulated 5 V supply ensures stable operation of all components, as shown in Figure 3.

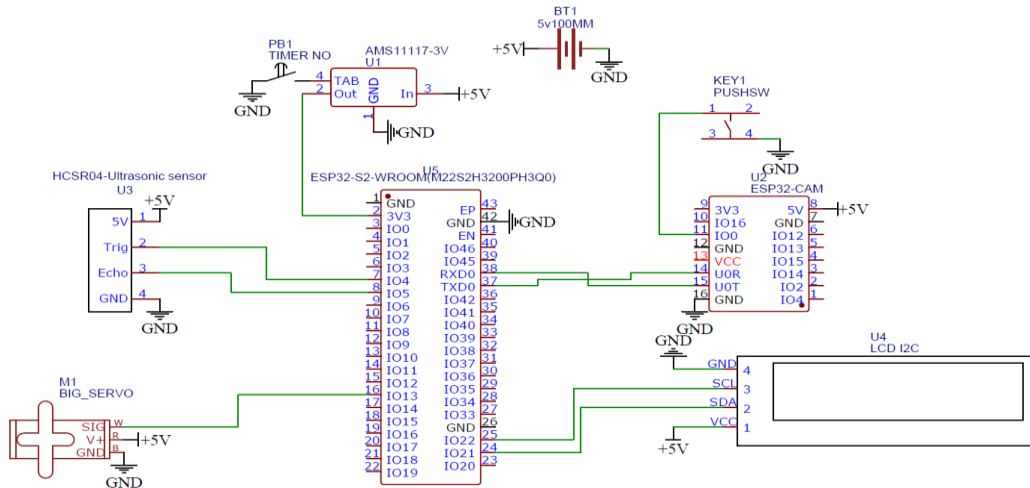


Figure 3: Electronic Circuit Diagram of Waste Sorting System

2.5 Dataset Description

The images were collected in a well-lit environment in broad day light. The waste items collected are grouped into biodegradable and non-biodegradable wastes. The biodegradable wastes consist of egg shell, yam peel, pineapple peels, vegetables, orange peels. Samples of these wastes are shown in Plate 1. The non-biodegradables consisted of metal cans and plastic bottles (See samples of the non-biodegradable wastes in Plate 2). In total there were 90 live images. We also augmented this dataset with an additional online dataset of 2356 images from Kaggle (Smarth, 2026). A transfer learning technique, specifically the MobileNetV2 model, was deployed to make the training robust. This choice is in conformity with the works of Gulzar (2023) and Pham et al., (2024). The MobileNetV2 model was trained on the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) 2012 dataset. This classification dataset consists of 1.2 million training images that are categorized into 1,000 different object classes. The dataset splits also include 50,000 validation images and 150,000 testing images.

2.6 Software Engineering and Predictive Analytics

The software component of this work involves the Arduino Integrated Development Environment (IDE) which is an open-source Arduino software used to program the Arduino microcontrollers. It is the main text editing program used for Arduino programming. It makes it easy to write codes and upload it to the board. The

program codes consist of the Arduino code written in C++ and the codes for training the machine learning algorithm written in Python.

The software architecture of the waste sorting system is divided into two distinct domains: the embedded firmware for real-time control and the server-side machine learning engine for image classification.



Plate 1: Sample dataset of biodegradable materials



Plate 2: Sample dataset of non-biodegradable materials

2.6.1 Embedded firmware and communication protocols

The ESP32 microcontrollers were programmed using Arduino IDE (C++). A finite-state machine architecture was implemented to manage detection, image capture, classification, and actuation states. A critical component of the software design is the use of WebSocket for communication. Unlike traditional HTTP requests, WebSocket maintain an open, persistent connection, allowing for full-duplex communication with minimal overhead. This is essential for minimizing the capture-to-actuation latency, which is a key performance indicator for real-time sorting systems.

2.6.2 Machine learning model development - CNN

The predictive heart of the system is the MobileNetV2 neural network. MobileNetV2 is an efficient convolutional neural architecture designed specifically for resource-constrained environments by significantly decreasing the number of required operations and memory usage (Noor *et. al.*, 2024).

The architecture is built upon an inverted residual structure with linear bottlenecks. Each basic building block consists of three layers:

- a) **Expansion Layer:** A 1×1 convolution that expands the low-dimensional input manifold to a higher dimension to allow the model to learn more complex patterns.
- b) **Depth wise Convolution:** A 3×3 depthwise separable convolution that performs spatial filtering with minimal computational overhead. This layer utilizes ReLU6 activation to restrict values to a range of $ReLU6(x) = \min(\max(0, x), 6)$, facilitating efficient quantization for mobile hardware.
- c) **Projection Layer:** A 1×1 convolution that projects the features back to a lower-dimensional bottleneck. This layer utilizes a linear activation to preserve the information encoded in the "manifold of interest" and prevent information loss during transformation.

Transfer learning was employed by utilizing pre-trained weights from the ImageNet dataset and fine-tuning the upper layers for binary classification of waste categories. Transfer learning generally involves utilizing the pre-trained weights of a model (Abou Baker *et. al.*, 2022). For our study, the MobileNetV2 model was trained to perform binary classification using a sigmoid activation function in the output layer. To further enhance model robustness, data augmentation techniques were applied, including random rotations, zooms, and horizontal flips, ensuring the model can recognize waste items regardless of their orientation or position on the platform

2.6.3 Optimization and loss functions

The training process utilized the Adam (Adaptive Moment Estimation) optimizer with a learning rate of 0.001. Adam is widely recognized for its ability to maintain per-parameter learning rates that adapt based on the mean and uncentered variance of the gradients, facilitating faster convergence. For the loss function, Binary Cross-Entropy (BCE) was selected to measure the dissimilarity between the actual labels (y) and the predicted probabilities (p). This is depicted in Equation 2:

$$BCE = -\frac{1}{N} \sum_{i=1}^N [y_i \log(p_i) + (1 - y_i) \log(1 - p_i)] \quad 2$$

Where N is the number of samples, y_i is the actual binary label for the i th sample (either 0 or 1), p_i is the predicted probability that the i th sample belongs to class 1. This mathematical approach ensures that the model is heavily penalized for confident but incorrect classifications, driving the system toward high precision.

2.7 Training and Validation

Table 2 shows the parameter for the training set-up of the model.

Table 2: Training Parameters

Parameter	Value
No of epochs	6
Batch size	32
Learning rate	0.001
No of hidden layers	5
Total training time	26 minutes

From Table 2, the number of hidden layers is set to 5 to allow for an in-depth training for the neural network. 80% of the dataset was used for training while 20 % of the dataset was used for testing. The data was trained with 6 epochs. Early Stopping callback was implemented. This was done so that the validation precision could be monitored. The early stopping was configured with a patience of 3 epochs to prevent overfitting, and it automatically restored the weights from the best performing epoch (the one with the highest precision) once training terminates. The training was performed using TensorFlow Version 2.17.0 which was run on Python programming language of Version 3.12.4.

2.8 Prototype Development

The development of the system was started by hardware prototyping on breadboard. This was followed by soldering onto permanent Vero boards and then integration into the MDF wooden platform. The fabrication process was begun by selecting plywood sheets and cutting them precisely according to the dimensions specified in the CAD model. Each piece was meticulously shaped and assembled to replicate the design, ensuring strength and stability in the final platform. The completed prototype is shown in Plate 3.



Plate 3: Completed waste-sorting system

3. Results and Discussion

3.1 Performance Metrics and System Evaluation

The effectiveness of the automated sorting system was validated using standard statistical metrics, focusing on precision and loss across both training and validation sets. The system achieved a classification accuracy exceeding 93.57%, confirming the efficacy of the MobileNetV2 transfer learning approach. Table 3 summarizes the critical performance evaluation values achieved during testing.

Table 3: Performance Metrics Values

Evaluation Metric	Achieved Value	Significance
Achieved Precision (Training)	0.9734	High training accuracy indicates effective feature extraction
Validation Precision	0.9357	Precision on unseen data confirms model generalizability.
Training Loss	0.0746	Low loss indicates successful optimization during training.
Validation Loss	0.01677	Low validation loss suggests minimal overfitting.

The recorded training loss of 0.0746 and a significantly lower validation loss of 0.01677 in Table 3 indicate a highly successful optimization process. The low training loss suggests that the Adam optimizer (learning rate = 0.001) successfully minimized the Binary Cross-Entropy (BCE) function, allowing the model to converge effectively. The proximity and low values of both loss metrics, specifically the validation loss being lower than the training loss suggest that the early stopping strategy (with a patience of 3 epochs) and the use of transfer learning were highly effective. These techniques prevented the model from simply memorizing the training data, which is a common risk when working with small datasets. These results make the system highly suitable for real-time deployment on low-cost IoT hardware like the ESP32-CAM, where memory and computational power are limited. While the statistical results are excellent, the slight drop between training and validation precision (3.7%) is typical and likely stems from real-world visual complexities such as varying object orientations or lighting inconsistencies.

3.2 Confusion Matrix Analysis

To further scrutinize the predictive performance of the model beyond simple precision, a confusion matrix was generated based on the validation dataset results. The matrix provides a detailed breakdown of correct and incorrect classifications across the binary categories: Biodegradable and Non-Biodegradable. The confusion matrix and a table explaining the evaluation metrics are shown in Figure 4 and Table 4 respectively.

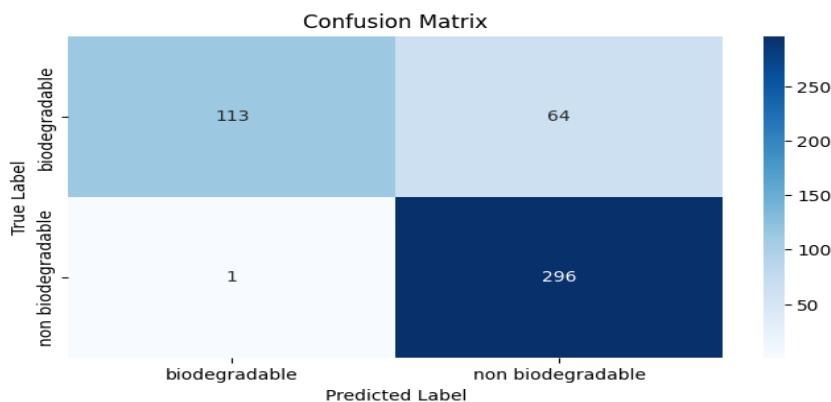


Figure 4: Confusion matrix

The confusion matrix shown in Figure 4 and its evaluation metrics in Table 4 confirmed that the 93.57% validation precision is a result of a highly concentrated diagonal of True Positives (TP) and True Negatives (TN). While the system demonstrated a strong ability to correctly identify biodegradable materials, the presence of isolated false detections highlights the system's sensitivity to visual contaminants in non-

biodegradable waste. In similar mechatronics-driven sorting studies using the ESP32-CAM, precision rates for biodegradable materials have reached as high as 97.74%, though such results often rely on highly controlled lighting environments. The current matrix serves as a tool for identifying specific misclassification trends, such as the system's occasional failure to distinguish between complex textures like paper and certain plastic films.

Table 4: Confusion Matrix Evaluation Metrics

Evaluation Metric	Achieved value	Significance
Precision (biodegradable)	0.99	A 99% of the predicted biodegradable items were actually biodegradable
Precision (non-biodegradable)	0.82	82% of the items predicted as non-biodegradable were correct.
Recall (biodegradable)	0.64	The model successfully identified 64% of all truly biodegradable items in the dataset.
Recall (non-biodegradable)	1.0	The model perfectly identified 100% of all truly non-biodegradable items (zero false negatives).
F1 score (biodegradable)	0.78	A strong score balancing the perfect precision and 78% recall for the biodegradable class.
F1 score (non-biodegradable)	0.90	An overall score reflecting the balance of perfect recall and high precision for this class

The results achieved by this system demonstrate its competitiveness when compared to contemporary research in the field of automated waste management. The achieved validation accuracy (>91%) significantly outperforms early MobileNetV2 applications for waste classification, such as the study by Yong *et. al.* (2023), which reported an absolute accuracy of 82.92%. While larger architectures like VGG-16 can achieve high accuracy, MobileNetV2 remains superior for real-time edge deployment. The work of Kumala *et. al.* (2025) indicated that MobileNetV2 achieved 95.6% accuracy, outperforming VGG16 (89.13%) and demonstrating much faster training times.

One of the most notable strengths of the system is its seamless real-time operation. The integration of the ultrasonic sensor with the WebSocket-enabled server resulted in a near-instantaneous response from detection to classification. The high precision rate demonstrates that CNNs are remarkably suited for waste classification, even when deployed on low-cost hardware. However, several limitations were identified during the testing phase. The classification accuracy was found to be sensitive to lighting conditions; poor illumination reduced the clarity of the captured images, leading to occasional misclassifications. Furthermore, the MDF platform, while excellent for prototyping, is not suitable for outdoor or high-moisture environments as it tends to degrade when exposed to heat and water. Lastly, the model's performance is currently limited to the specific waste types included in the training set, and its inability to retrain itself dynamically based on new captures remains a challenge for long-term deployment.

Even with all the aforementioned limitations, our study contributes significantly to the domain of smart waste management by providing a scalable, cost-effective framework for automated sorting. By bridging the gap between high-level AI models and low-cost IoT hardware, the study demonstrates that advanced technology can be made accessible for small-scale and urban applications.

4. Conclusion

Inaccurate waste classification remains a major problem, particularly for complex or mixed materials like plastic packaging, leading to lower recycling efficiency and poor resource recovery. Deploying AI-based waste sorting solutions also comes with technical challenges, including the complexity of waste materials, inconsistent data quality, and the high costs of specialized equipment. These challenges highlight the urgent need for a reliable, scalable, and affordable automated waste sorting system that can adapt to diverse conditions and help improve recycling rates while protecting both public health and the environment.

The successful design and development of this machine learning-driven automated waste sorting system validate the feasibility of using AI and IoT to address the growing global waste crisis. By integrating the ESP32-CAM with a MobileNetV2 CNN, the system provides a reliable, high-precision solution for the classification of biodegradable and non-biodegradable materials. With a validation precision of 93.57%, the prototype

demonstrates that intelligent sorting can be achieved with low-cost components and limited dataset size offering a viable path toward sustainable waste management in both urban and industrial settings.

The implementation of automated sorting systems offers substantial economic advantages. By increasing the accuracy and frequency of sorting, municipalities can reduce the volume of waste sent to landfills, thereby lowering tipping fees and operational costs. From an environmental perspective, the system supports circular economy goals by ensuring that resources are diverted from waste streams back into the production cycle. The reduction in human contact with hazardous materials also represents a significant advancement in occupational health and safety for the waste management sector.

For future work enhancements, several technical improvements are recommended. Implementing edge inference, where the machine learning model is run directly on the ESP32-CAM or a dedicated AI chip would eliminate the dependency on a local web server, further reducing latency and increasing system reliability. Additionally, future works would look into increasing the size of the dataset to include a wider variety of waste materials, and training without the use of transfer learning techniques. This will enable the algorithm to learn from live dataset. The incorporation of different sensor modalities (such as moisture or weight sensors) would also improve the system's robustness in complex real-world environments. The use of more durable materials, such as PVC or stainless steel, is also recommended for future industrial or outdoor versions of the platform.

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