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Design and Implementation of an Organic and Inorganic Waste Detection System Using Capacitive, Inductive, and LDR Sensors with Rule-Based Classification

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Abstract

The continuous increase in daily waste accumulation has become a major issue in many areas, primarily due to the mixing of various waste types and the lack of effective household waste management systems. This complicates waste processing and contributes to environmental degradation. This study aimed to design and implement a practical tool for detecting organic and inorganic waste types, specifically for use by household waste collection personnel. The developed system utilizes three sensors capacitive, inductive, and light-dependent resistors (LDR) to acquire characteristic data from different types of waste. The device is designed in the shape of a pistol to enhance mobility and ease of use by waste collection workers. For the waste-type classification system, several machine learning methods were evaluated, namely Adaptive Boosting (AdaBoost), Support Vector Machine (SVM), and K-Nearest Neighbor (KNN). Based on the experimental results, AdaBoost was selected as the primary model because of its superior cross-validation accuracy and balanced evaluation metrics, such as precision, recall, and F1-score. Consequently, AdaBoost predictions were used to establish a rule-based classification logic by extracting threshold values from the most influential sensor features. This approach ensured that the classification decisions were based on reliable and validated data patterns. Experimental testing demonstrated that the device could classify organic and inorganic waste types with an accuracy of 91.67%. In addition, the system can estimate the composition of mixed waste with a *Mean Absolute Error (MAE)* of 5.61% using white plastic bags and 4.45% using red plastic bags, indicating an average deviation of less than 6% from the ground truth. The presence of this device has been proven to accelerate and simplify the waste sorting process, thereby enhancing the efficiency of household waste management.

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I. Introduction

Waste management has become an increasingly pressing issue, particularly in Indonesia, as the country's population continues to grow rapidly. In West Java Province alone, daily waste generation reached 11,189.3 kg in 2021, with a five-year average of over 40,000 tons per year [1]. The current manual waste sorting process at final disposal sites is time-consuming and inefficient, resulting in the accumulation of unprocessed waste at these sites. Most household waste remains unsorted, despite regulations that require it to be separated at the point of generation [2]. Instead, sorting is often carried out by scavengers, which is a labour-intensive and slow process, contributing to low recycling rates and excessive landfill accumulation [3], [4], [5]. This process is labour-intensive and time-consuming. Sorting household waste into organic and inorganic types is one solution to mitigate this problem. Proper sorting of household waste into organic and inorganic categories is one solution that can facilitate more efficient waste processing [6], [7], [8]. However, in practice, only a small proportion of households separate their waste, despite the fact that such efforts could significantly reduce landfill accumulation, as stated in Law No. 18 of 2008 [9]. If waste is sorted correctly, organic waste can be processed into compost, while inorganic waste can be recycled or further processed at an inorganic waste-processing plant [10], [11], [12]. Legal regulations are crucial in addressing waste management issues, particularly in the area of waste sorting, which is often not strictly enforced. Indonesia's waste management system is inefficient due to the lack of specific regulations [13].

In this context, there is a strong need for practical tools that enable waste collection personnel to process household waste efficiently and effectively. Such tools should be capable of detecting the composition of organic

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and inorganic waste in household bags, thereby reducing the reliance on manual checking and accelerating subsequent processing. By supporting waste collection workers, these tools can help ensure that waste is pre-sorted before reaching disposal sites, leading to more effective downstream treatment [12], [14], [15], [16].

In recent years, various automated waste-sorting technologies have been proposed to overcome these challenges. Sensor-based devices employing colour sensors, metal detectors, or optical sensors have been integrated with microcontrollers such as Arduino Nano, Arduino Mega, and ESP32 [17], [18], [19], [20], [21], [22], [23]. IoT-based approaches using NodeMCU ESP8266 have also enabled remote waste monitoring and management [24], [25]. Recently, computer vision approaches leveraging deep learning models, such as YOLOv8 and YOLOv9, have demonstrated strong performance in classifying visible waste types [26]. These advances highlight the potential of automation to improve waste sorting efficiency.

Despite these developments, several limitations remain to be addressed. Sensor-based devices are typically designed for close-contact operations and struggle to differentiate materials with similar properties [24], [25]. IoT-based solutions depend heavily on stable Internet connectivity, which restricts their deployment in areas with limited infrastructure. Vision-based systems perform well in controlled environments but lose accuracy under suboptimal conditions, such as blur, occlusion, or opaque bags [26]. Moreover, most systems focus solely on binary categorisation, such as organic versus inorganic, without analysing waste composition in greater detail [27].

To overcome these limitations, this study proposes a portable, non-contact device that integrates capacitive, inductive, and light-dependent resistors (LDR) sensors with an Arduino Nano microcontroller. Unlike earlier smart-bin prototypes that require proximity (approximately 3 mm) for classification [24], the handheld design enables users to estimate the percentage composition of organic and inorganic waste more quickly and systematically once the bag is opened, thereby eliminating the need for manual sorting of items. This functionality makes the system more practical for real-world applications.

Previous studies employing multi-sensor fusion without learning algorithms have often relied on fixed threshold values to distinguish between waste types. However, threshold-based classification is insufficient for identifying inorganic waste, as this category encompasses diverse materials, including plastic, glass, and metal, each of which produces overlapping sensor responses. In particular, accurate discrimination requires the simultaneous combination of information from LDR, capacitive, and inductive sensors. To address this challenge, this study applies a lightweight rule-based machine learning approach that derives classification rules from the characteristic patterns of these sensors. This method enables more reliable threshold determination for inorganic waste detection while remaining computationally efficient for deployment on microcontroller platforms, in contrast to more resource-intensive deep learning models.

The primary objective of this study was to develop a portable and accurate tool for detecting and classifying the composition of organic and inorganic waste, thereby supporting more effective waste management and source-level sorting. The key contributions of this study include the following: (1) the development of a novel ergonomic handheld device utilising three types of sensors; (2) the integration of sensor-based detection with machine learning rule-based classification to enhance accuracy; (3) the capability to analyse the proportion of organic and inorganic waste contained within a bag or container, providing percentage-based information rather than simple binary classification.

This study is structured as follows: Section 2 presents the research methods used, including the design of the mechanical and electronic systems. Section 3 presents the experimental results and provides an in-depth discussion of the device's performance. Finally, Section 4 presents the conclusions and recommendations for future development.

II. Materials And Methods

A. Design System

In this study, we employed a combination of capacitive, inductive, and LDR sensors. This selection was based on the physical characteristics of the most commonly encountered household waste, namely organic and inorganic materials. The capacitive sensor is sensitive to differences in dielectric properties, making it effective in distinguishing between organic waste, which generally has a high moisture content, and inorganic waste, which is typically drier. The capacitive sensor operates based on the variation in capacitance between two electrodes separated by a dielectric medium. The capacitance is expressed as Eq. (1):

$$C = \varepsilon_r \varepsilon_0 \frac{A}{d} \tag{1}$$

where C is the capacitance (F), ε_r is the relative permittivity of the dielectric material, ε_0 is the permittivity of free space ($8.854 \times 10^{-12}\ F/m$), A is the electrode area (m^2), and d is the separation distance (m). Differences in dielectric constant allow the sensor to discriminate between organic waste and dry inorganic materials.

Inductive sensors are beneficial for detecting metallic components in inorganic waste, such as cans or aluminium foil, which are difficult to identify using optical or ultrasonic sensors. The inductive sensor detects metallic components by exploiting the principle of electromagnetic induction. Its inductance is given by Eq. (2):

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$$L = \mu \frac{N^2 A}{l} \tag{2}$$

where L is the inductance (H), μ is the magnetic permeability of the core (H/m), N is the number of coil turns, A is the cross-sectional area of the coil (m^2), and l is the length of the magnetic path (m). Meanwhile, the LDR offers a low-power and straightforward approach for measuring surface reflectance, allowing for the differentiation of organic waste, which tends to absorb light, from inorganic materials such as plastics or paper, which generally reflect more light than organic waste. Mathematically, the resistance of an LDR can be modelled as a power-law function of the incident light intensity I(lux), as shown in Eq. (3):

$$R_{LDR} = \frac{K}{I^{\gamma}} \tag{3}$$

where R_{LDR} is resistance of the LDR in (Ω), K is a material dependent constant, and γ is an empirical constant typically in the range of 0.7–1.0. This equation indicates that inorganic waste, which reflects more light, produces a lower resistance value, while organic waste that absorbs more light results in higher resistance. Other alternatives, such as cameras or infrared sensors, require higher computational resources, stable lighting conditions, and higher costs. In contrast, ultrasonic sensors are more suitable for distance or volume measurements than for material composition identification [28].

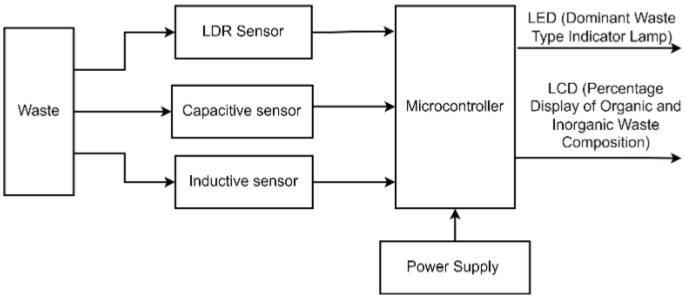

Fig. 1 Block diagram of the system

This study was divided into two main stages: system design and testing. Decision-making for waste categorisation utilises machine learning to provide recommendations for the classification scheme of waste types. As shown in Fig. 1, the system's input is a mixture of organic and inorganic waste. The proposed system detects two main pieces of information: the percentage of each type of waste and an indicator of the kind of waste mixture. A capacitive sensor was selected to detect organic waste because it can detect a wide range of materials, including non-metals. An inductive sensor was used to detect inorganic waste. Furthermore, to provide better evidence, we added an LDR sensor to address situations where capacitive and inductive sensors cannot adequately detect waste. For the power system in this design, we used two CR123 lithium-ion batteries with a nominal voltage of 3.7 V. These batteries are of the lithium-ion type and can be easily recharged. Therefore, a battery charging module is required to replenish the battery's power, along with an adapter that converts the alternating current (AC) power source into direct current (DC) power, enabling battery charging. The details of the component selection are presented in Table 1.

Table 1. Component details

System Component	Type of Component	Selected Component
Waste detector	Casing material	3D filament ABS
	Capacitive sensor	CR18-8DN
	Inductive sensor	PR18-8DN
	LDR sensor	G15516 5 mm
Control unit	Microcontroller	Arduino Nano
Display	OLED Display	SH1106
Light indicator	LED	RGB TI-3/4
Button	Momentary button	Momentary switch 16 mm
Power source	Battery	CR123/LC 16340
Voltage converter	Step-down	Mini360
Charger	Battery charger module	Charger BMS 3S MRB045
Adapter	AC to DC adapter	Baseus QC 3.0

When selecting the waste detector case material, factors such as price, durability, and density were taken into consideration. 3D ABS filament was chosen because it excels in durability and density. It is heat-resistant, non-breakable, and has a density of 1.05 g/cm³, making the device case both lightweight and durable. The criteria for capacitive and inductive sensors included price, sensing range, voltage, and dimensions. The CR18-8DN capacitive sensor was selected for its superior sensing range of 8 mm, use of DC voltage, and affordability. The PR18-8DN inductive sensor was chosen because of its affordable price, low voltage, and 8 mm sensing range.

The Arduino Nano microcontroller was selected for its compact size (43 mm x x 18 mm), which fits the device's dimensions well, and its affordable price. The SH1106 OLED display was chosen because its area of (29.42 × 14.7) mm matched the device dimensions, considered aesthetics, and provided a resolution of (128 × 64) pixels. Red, green, and blue (RGB) T1-3/4 LEDs were used as light indicators due to their low price and small size. The PBS-11A button was chosen to start and stop the detection process because it has a small dimension (12 mm) and is affordable. An RGB LED lamp was used as an indicator to provide information with different light colours. Two CR123 lithium-ion batteries, each with a voltage of 3.7 V, were used to provide the power supply for the system. These are rechargeable lithium-ion batteries. Fig. 4 shows the system flowchart, where the user prepares waste in a single plastic-wrapped container as the system input. Once the user has prepared the waste, the next step is to classify the waste type, which results in a light indicator output showing whether the waste is organic, inorganic, or mixed.

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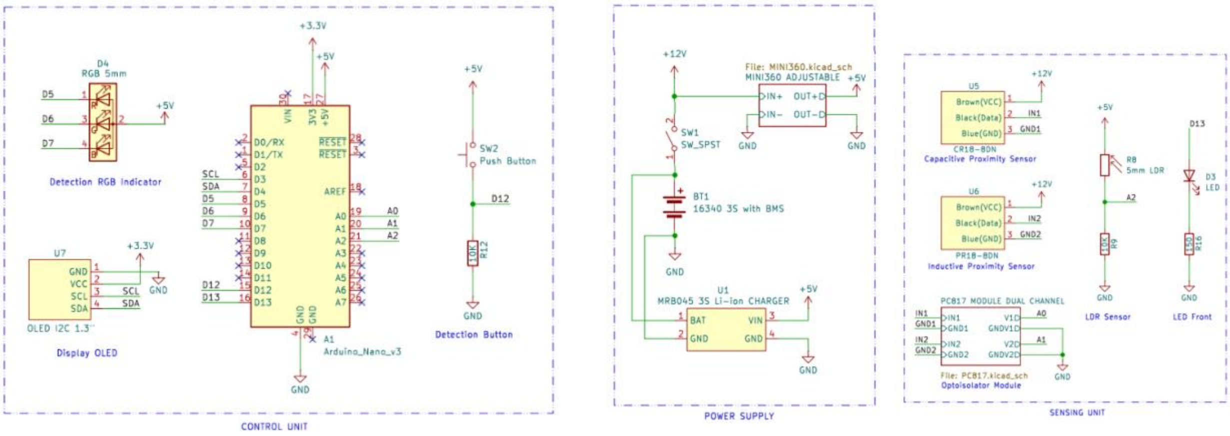
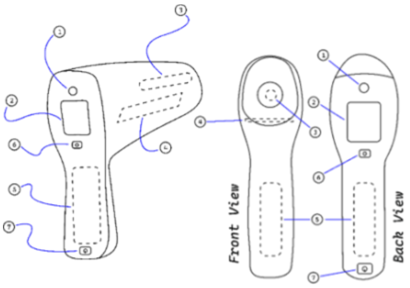


(a) (b)

Fig. 2. Schematic Diagram of the Control Unit Circuit (a) control unit, (b) power supply and sensing unit

B. Hardware Design

This device is designed to be easily held with one hand, having dimensions not exceeding (6×6×16) cm^3 and a weight of less than 800 g, making it convenient for users to detect waste bags. Fig. 3 shows the design of our device. The design is shaped like a pistol, where the device's tip, which contains the sensors, is directed toward the waste bag.



1. Indicator of mixed waste type in the form of light
2. Display of waste type percentage
3. Capacitive or waste type detection sensor
4. Processing unit and controller requirements
5. Battery
6. Detect button
7. Power button

Fig. 3 Design of Waste Detection System

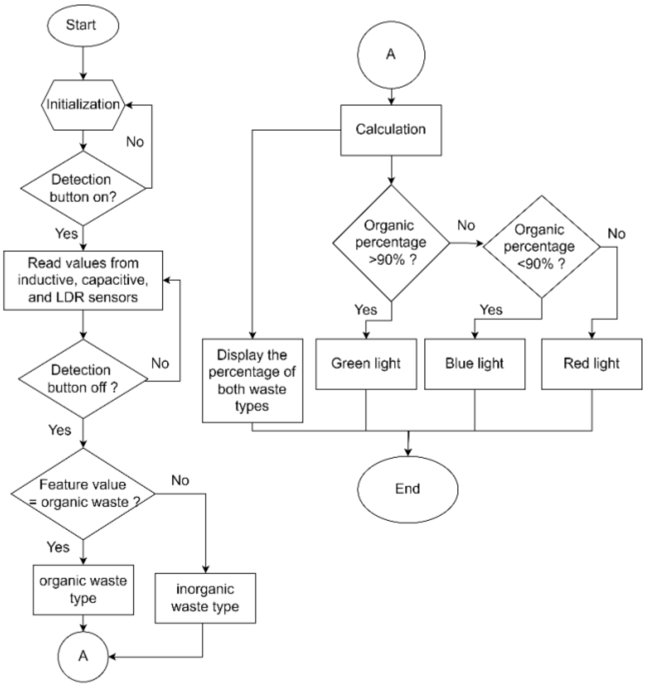


Fig. 4 Flowchart of the System Design

The pistol-like shape provides a comfortable grip, and this design choice is based on the sensor's ability to detect objects at a distance of approximately 15 mm. Therefore, minimising direct contact between the user and the object being detected is recommended. Fig. 2 presents a schematic diagram of the device's control unit. The components included in this unit are as follows: an RGB LED connected to pins D5, D6, and D7; an OLED display connected to pins D3 and D4; and a detection button connected to pin D12. The microcontroller was the Arduino Nano V3, which was powered by a regulated 5V supply from the battery. As shown in Fig. 2, three 16340 lithium-ion batteries are connected in series. These batteries are equipped with a Battery Management System (BMS) MRB045, which manages and protects the batteries from undervoltage (below 2.7 V) and overvoltage (above 4.2 V) in each cell. The total voltage supplied by the batteries with the BMS ranges from 8.1 to 12.6 V. The batteries are then connected to a Mini360 step-down module, which converts the fluctuating battery voltage to a stable 5V output, serving as the power source for the microcontroller.

The sensing unit comprises components used for waste detection. This unit features a PC817 optocoupler module, which connects the CR18-8DN and PR18-8DN sensors to the Arduino Nano. The module isolates the high-voltage side (12 V from the CR18-8DN and PR18-8DN sensors) and low-voltage side (5V from the Arduino Nano). This isolation is essential to protect the Arduino and other low-voltage components from the potentially harmful voltages or noise generated by the sensors. The CR18-8DN sensor was connected to the A0 pin of the Arduino through the optocoupler, while the PR18-8DN sensor was connected to the A1 pin through the optocoupler. Additionally, a 5 mm LDR sensor was connected to the A2 pin of the Arduino, protected by a 73 10 kΩ resistor. An LED connected to the D13 pin of the Arduino is also included in this unit, protected by a 150 Ω resistor.

C. Calibration Sensor

Before implementing the system, calibration was performed on the inductive, capacitive, and LDR sensors,

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as well as on the battery capacity. During the calibration of the capacitive sensor, several organic and inorganic waste samples were tested. As shown in Fig. 5 , a value of 0 indicates that the sensor successfully detected an object, and a value of 1 indicates that no object was detected. The results show that the capacitive sensor can detect organic waste with high water content; however, it also responds to glass, cans, and aluminium-coated plastics, as these materials act as secondary electrodes that alter the capacitance. In contrast, pure plastic cannot be detected because it functions solely as a dielectric, without changing the capacitance. Therefore, additional sensors are required to improve the classification accuracy, which is why an inductive sensor was introduced. As shown in Fig. 6, the inductive sensor was proven to detect only metallic waste (e.g., cans). Other aluminium-coated materials could also be detected, but they did not significantly impact the overall classification results. It can be concluded that the detection data from the inductive sensor complements those of the capacitive sensor, which also detects cans.

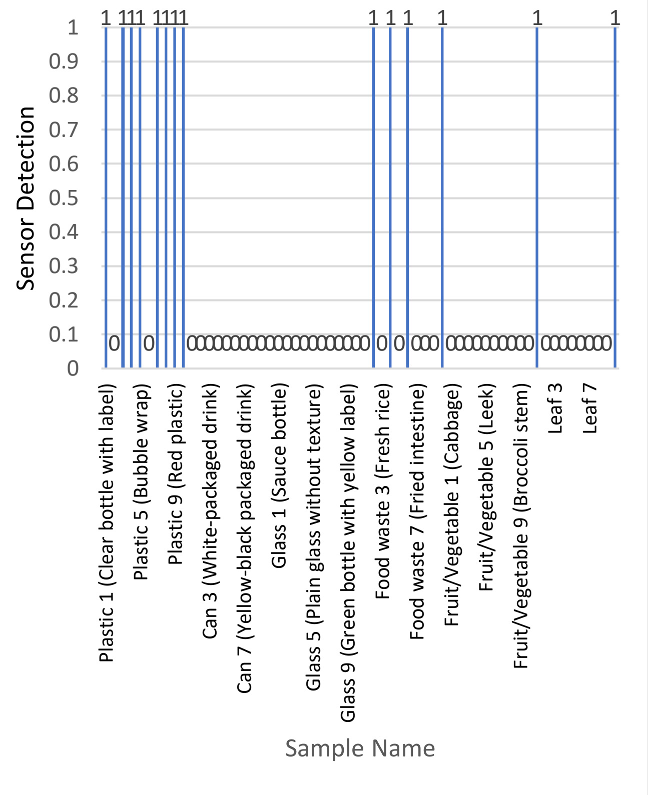

Fig. 5 Capacitive Sensor Calibration Results

An LDR sensor was employed to detect inorganic waste in the form of plastics and glass, which are difficult to distinguish using a capacitive sensor. Its working principle relies on the change in resistance with varying light intensities; the resistance decreases as the light intensity increases and vice versa. With the assistance of an LED directed toward the plastic bag, the sensor can detect material transparency more stably, without being influenced by ambient lighting conditions.

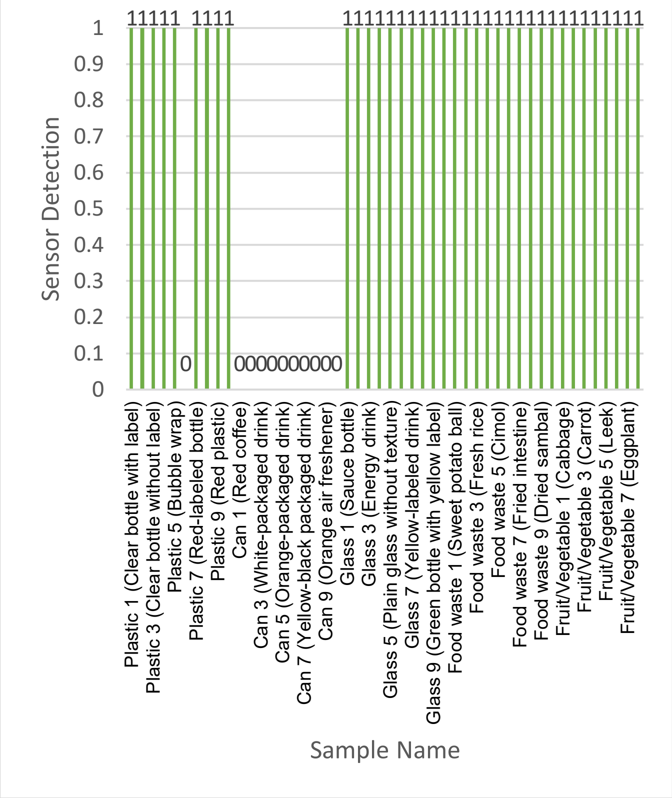

Fig. 6 Inductive Sensor Calibration Results

The LDR sensor was calibrated by comparing its output with that of a standard lux meter under different illumination conditions. The LDR was connected to a microcontroller to record its output in ADC values and voltages, while the lux meter served as a reference in lux units. Measurements were performed by varying the light intensity from bright to dim. For example, at an LDR reading of 623 ADC with an output voltage of 3.04 V, the lux meter recorded 357 lux, whereas at 241 ADC with 1.18 V, the lux meter recorded only 6 lux. These data were then used to establish the relationship between the LDR output and the actual light intensity, resulting in a calibration curve for converting ADC/voltage values into lux units.

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As shown in Fig. 7, the LDR output values were generally higher for inorganic waste than for organic waste. However, the colour and type of plastic and glass significantly influenced the detection results. For darker-

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coloured materials, the LDR values decreased and approached those of organic waste, thereby increasing the risk of misclassification. The colour of the plastic bag also affected the detection performance; white and red plastic bags still allowed differentiation of the contents, whereas black plastic bags yielded no readings (value 0). Therefore, although the LDR is effective in distinguishing plastics and glass from organic waste, it has limitations when applied to dark-colored materials or black plastic bags. This limitation is clearly illustrated in Fig. 7, where black plastic samples consistently yield a sensor reading of 0, indicating that the system currently performs optimally only when the waste is contained in lighter-coloured plastic bags.

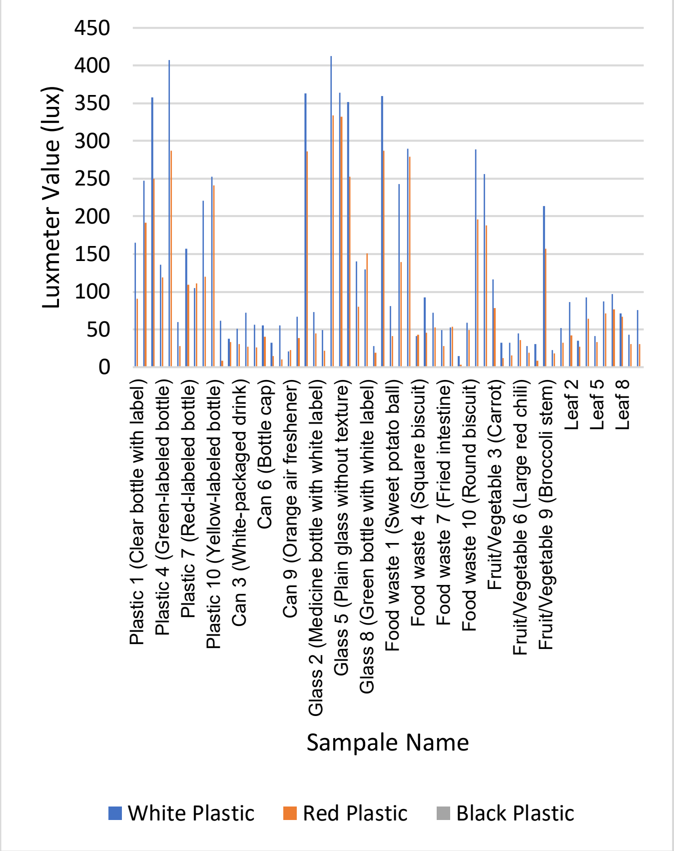

Fig. 7 **LDR Sensor Calibration Results**

D. Waste Classification Method

To determine the waste type classification method, we adopted machine learning technology to guide the development of a rule-based system for waste category determination. This process begins with collecting data from three types of sensors: capacitive, inductive, and LDR. The acquired data were processed using several machine learning algorithms. In this study, we employed a supervised learning approach, in which the model was trained using a dataset containing features as inputs to predict the corresponding output or label. The evaluated supervised learning algorithms included a Support Vector Machine (SVM), a Decision Tree, K-Nearest Neighbours (KNN), and AdaBoost. These four machine learning methods were selected based on their respective abilities to handle the characteristics of sensor data. SVM is effective for classification with nonlinear boundaries, decision trees are easily interpretable and can serve as the foundation for rule-based systems, KNN is simple yet capable of recognising similarity patterns among samples, and AdaBoost enhances the performance of weak learners into a stronger model. Moreover, all four algorithms are relatively lightweight in terms of computational requirements, making them suitable for field implementation without the need for high-capacity hardware, as required in deep learning.

Table 2. **Comparison of Cross-Validation Accuracy and Test Accuracy of Classification Models**

Model	Cross-Validation Accuracy	Test Accuracy	Primary Parameters
AdaBoost	**0.8475**	**0.8082**	**learning_rate=1.0, n_estimators=200**
SVM	0.8371	0.8082	c=1, gamma=1
KNN	0.8266	0.8082	n_neighbors=7, weights='uniform'
Decision tree	0.7852	0.7671	max_depth=none, min_samples_split=10

The dataset consists of two components: input features and output labels. The input features were obtained from three sensor readings: capacitive, inductive, and LDR sensors. The capacitive and inductive sensors produced binary values (0 indicating detection and 1 indicating no detection), whereas the LDR sensor generated an ADC value representing the light intensity. The output label denotes waste classification, specifying whether a given sample is organic or inorganic. The dataset comprised 363 samples, encompassing various combinations of organic and inorganic waste materials.

The dataset was stored in an Excel file and processed using machine learning algorithms in Python on a computer. Before selecting the best model, experiments were conducted to determine which algorithm achieved the highest level of accuracy. Data preprocessing was performed before model training, where features and target labels were extracted and read from an Excel file within the code to process the dataset. The dataset was then divided into a training set (80%) and a testing set (20%) to evaluate the model's performance on unseen data.

During training, 10-fold cross-validation was applied to obtain more stable performance estimates and reduce the risk of overfitting. In this method, the dataset was divided into ten folds, where the model was trained on nine folds and validated on the remaining fold. This process was repeated ten times, so that each fold served as validation data once, and the results were averaged to provide a reliable estimate of the model's performance. Parameter optimisation was conducted using GridSearchCV, with variations adapted to each algorithm: the kernel and C values for SVM, maximum tree depth for

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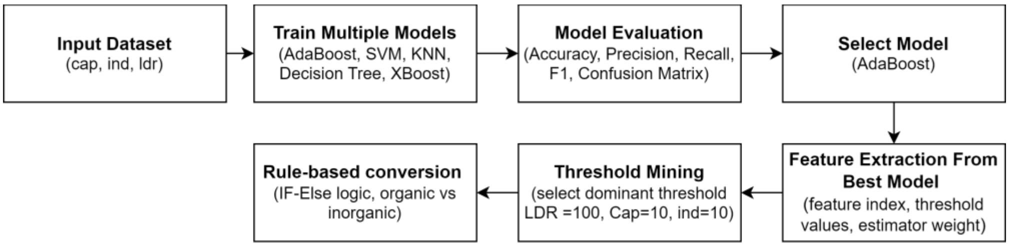


Fig. 8 System flow of model evaluation, threshold extraction, and rule-based classifier implementation

Decision Tree, the number of neighbours (k) for KNN, and the number of estimators and learning rate for AdaBoost. Each model was tested with combinations of two parameters, each with three candidate values. The configuration that achieved the best cross-validation accuracy was then selected for further analysis.

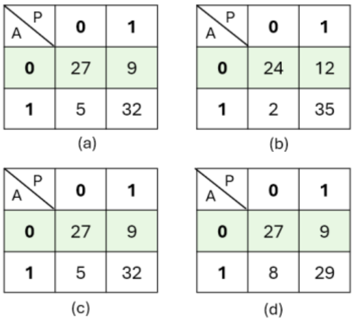
Cross-validation is a model evaluation technique used to accurately measure the performance of machine learning models and prevent overfitting. In this process, the dataset is divided into several subsets or folds. The model is trained on specific subsets and tested on the remaining subsets. This process is repeated several times, with each subgroup used once as the test data. The results from these iterations are combined to provide a more stable estimate of model performance. Table 2 compares the cross-validation and test accuracies of the classification models. Subsequently, the test set was evaluated by presenting the confusion matrix to obtain the accuracy, precision, recall, and F1-score for each model. Fig. 9 shows the confusion matrix results for each model, where A represents the actual value and P represents the predicted value. A confusion matrix is a table that displays the number of correct and incorrect predictions grouped according to the exact and predicted class categories. The confusion matrix consists of four main components. Subsequently, the test set was evaluated by presenting the confusion matrix to obtain the accuracy, precision, recall, and F1-score for each model. The confusion matrix consists of four main components. The true Positive (TP) is the number of correct predictions for the positive class. True Negative (TN) is the number of correct predictions for the negative class. False Positive (FP) is the number of incorrect predictions for the positive class (negative class predicted as positive). False Negative (FN) is the number of incorrect predictions for the negative class (positive class predicted as negative).

Tabel 2 presents a comparison of the cross-validation accuracy and test accuracy results for the four classification models: AdaBoost, SVM, KNN, and Decision Tree. The AdaBoost model achieved the highest cross-validation accuracy of 84.75%, with a test accuracy of 80.82%, indicating strong and stable performance. The SVM and KNN models yielded the same test accuracy as AdaBoost (80.82%) but slightly lower cross-validation accuracies (83.71% and 82.66%, respectively). The Decision Tree model showed the lowest performance in cross-validation (78.52%) and test accuracy (76.71%), indicating a higher risk of overfitting. Tabel 3 presents the evaluation results of the four classification models, based on the confusion matrix and its derived metrics, including accuracy, precision, recall, and F1-score. The results indicated that the SVM and AdaBoost models had the same accuracy of 80.82%. However, upon closer examination, the AdaBoost model demonstrated a more balanced metric, with a precision of 78.05%, a recall of 86.49%, and an F1-score of 82.05%. In contrast, while SVM achieved the highest recall (94.59%), its precision was lower (74.47%), indicating a tendency to produce more false positives.

Table 3. Comparison of Confusion Matrices

Model	Accuracy	Precision	Recall	F1-score
AdaBoost	**0.8082**	**0.7805**	**0.8649**	**0.8205**
SVM	0.8082	0.7447	0.9459	0.8333
KNN	0.8082	0.7805	0.8649	0.8205
Decesion Tree	0.7671	0.7632	0.7838	0.7734

This is further supported by the results in Tabel 2, where AdaBoost achieved the highest cross-validation accuracy of 84.75%, outperforming SVM (83.71%), KNN (82.66%), and Decision Tree (78.52%). This indicates that the AdaBoost model is stable in evaluating the test data and has better generalisation capability across cross-validation folds.



A \ P	0	1
0	27	9
1	5	32

(a)

A \ P	0	1
0	24	12
1	2	35

(b)

A \ P	0	1
0	27	9
1	5	32

(c)

A \ P	0	1
0	27	9
1	8	29

(d)

Fig. 9 Confusion Matrices: (a) AdaBoost, (b) SVM, (c) KNN, and (d) Decision Tree

Based on the results, AdaBoost was selected as the primary model in the waste-type classification system because it provided the best performance in terms of both cross-validation accuracy and balanced evaluation metrics, such as precision, recall, and F1-score. In the classification stage, this system initially employed AdaBoost as the primary learning algorithm. The AdaBoost algorithm combines multiple weak classifiers

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into a single strong classifier. The training dataset is formally defined in Eq. (4).

$$D = \{(x_i, y_i)\}_{i=1}^{N}, x_i = [x_{LDR}, x_C, x_I],\ \ y_i \epsilon \{0,1\} \tag{4}$$

where x_i represents the sensor feature vector (LDR, capacitive, inductive) and $y_i > \in \{0,1\}$ is the class label, with 0 for inorganic and 1 for organic waste. The index $(i = 1,2,\ldots,N)$ indicates each sample, and N is the total number of samples. The initial sample weights are assigned equally, as shown in Eq. (5) :

$$w_i^{(1)} = \frac{1}{N},\quad i = 1,\ldots.,N \tag{5}$$

where $w_i^{(1)}$ is the initial weight of the sample i. At iteration m, the weighted classification error is computed as in Eq. (6):

$$\varepsilon_m = \sum_{i=1}^{N} w_i{}^{(m)}, (y_i \neq K_m(x_i)), \tag{6}$$

where ε_m represents the proportion of misclassified samples with respect to their weights, and K_m is the weak classifier (decision stump) at iteration m. The weight of classifier mmm is defined in Eq. (7):

$$\alpha_m = \frac{1}{2} ln\left(\frac{1-\varepsilon_m}{\varepsilon_m}\right) \tag{7}$$

where α_m reflects the importance of the classifier, with higher values for more accurate weak classifiers. Sample weights are updated according to Eq. (8):

$$w_i^{(m+1)} = \frac{w_i^{(m)}.\exp\left(-\alpha_t y_i K_m(x_i)\right)}{\sum_{i=1}^{m} w_i^{(m)}.\exp\left(-\alpha_t y_i K_m(x_i)\right)} \tag{8}$$

This update increases the weights of misclassified samples so that subsequent iterations focus more on them. The final AdaBoost prediction is given in Eq. (9):

$$F(x) = \sum_{m=1}^{M} \alpha_m K_m(x) \tag{9}$$

The M is the total number of weak classifiers, $F(x)$ is the margin score. However, owing to hardware constraints, such as the limited computational capacity of the Arduino Nano, the complex AdaBoost model could not be implemented directly. To address this, the predictions from AdaBoost were analysed to extract the most influential thresholds from the training data distribution of the three sensor features (LDR, capacitive, and inductive), and then translated into a lightweight, logic-based rule system. Due to the limited computational capacity of the Arduino Nano, the complete AdaBoost ensemble could not be directly implemented. To overcome this, the trained model was analysed to extract simplified rules. As shown in Fig. 8, AdaBoost consists of decision stumps that split the data using a single sensor feature and a threshold, each weighted by αm. Two outputs were examined: predictions, representing binary labels (0 = inorganic, 1 = organic), and decision scores, representing the margin function $F(x)$ in Eq. (9). These results were stored in a tabular form and analysed to identify the consistent decision boundaries. From this analysis, clear patterns emerged: when the capacitive and inductive sensor values were below 10, the system struggled to distinguish between organic and inorganic waste, even when combined with LDR readings.

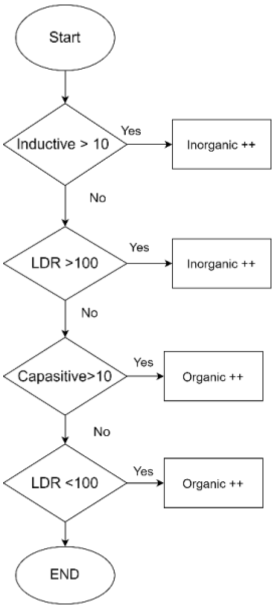

Fig. 10 **Flowchart of the Rule-Based System**

In contrast, when the capacitive and inductive values exceeded 10, the classification became much more reliable. Similarly, the LDR sensor showed a consistent trend, with values above 100 generally indicating inorganic waste and values below 100 corresponding to organic waste. Based on these observations, the dominant thresholds were set to 10 for both the capacitive and inductive sensors and 100 for the LDR.

These thresholds were distilled into a lightweight, rule-based classifier implemented using IF–ELSE statements, as illustrated in the flowchart in Fig. 10. The classification process followed a sequential evaluation of the sensor readings: if the inductive sensor value exceeded 10, the waste was classified as inorganic. If this condition was not met, the LDR value was checked, and readings above 100 also indicated the presence of inorganic waste. When neither of these conditions is satisfied, the capacitive sensor is examined, where values greater than 10 correspond to the presence of organic waste. Finally, if the LDR value was below 100, the sample was classified as organic. This systematic yet lightweight approach demonstrates how AdaBoost's decision boundaries can be transformed into human-readable rules, preserving classification consistency while enabling efficient real-time implementation on low-power microcontrollers, such as Arduino.

III. Results

After conducting tests for each sensor and designing the circuit, the next stage is integrating all system components into a single automatic waste classification

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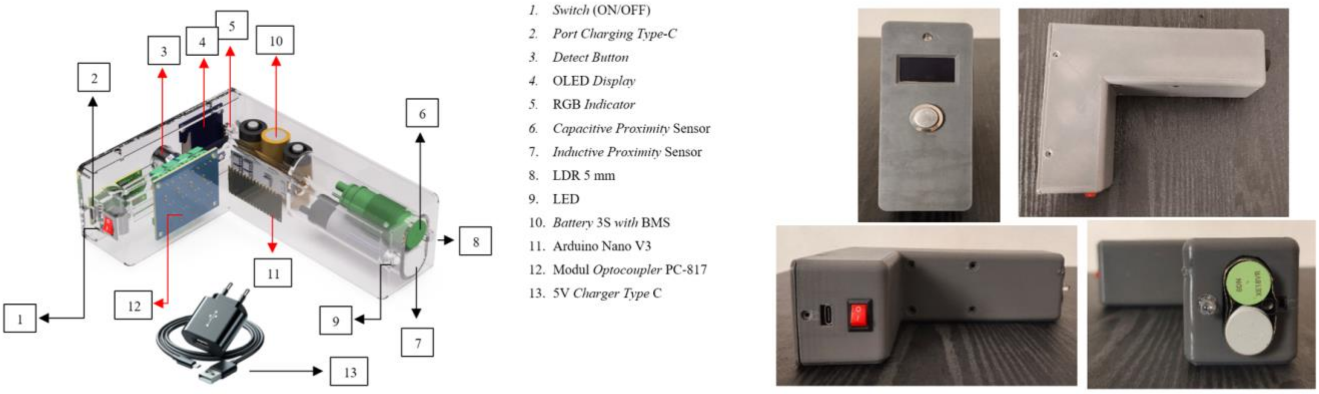

(a) (b)

Fig. 11. Implementation of an organic and inorganic waste detection system (a) shows the internal view of the implemented system, while (b) presents the final result of the integrated system

prototype. This system consists of three main sensors: an LDR sensor, a capacitive sensor, and an inductive sensor, each used to detect the physical characteristics of waste, such as the light/reflectance level, dielectric properties, and the presence of metal. These sensors were connected to an Arduino Nano as the central controller, and the detection output was displayed on the LCD and LED indicators. The Arduino receives analogue signals from the sensors and processes them using the rule-based classification logic extracted from the AdaBoost model. Arduino Nano was chosen due to its small size and its ability to support the designed system.

Fig. 11 shows the final design of our prototype, which is shaped like a pistol and portable, making it easier for users to detect the amount of waste in the provided container. Fig.11 (a) illustrates the placement of the sensors, microcontroller, Li-ion battery, LDR sensor, capacitive and inductive proximity sensors, PC817 optocoupler module, LED, and LCD. The designed device was rechargeable using a 5V adapter with a USB Type-C cable. Fig 11 (b) shows the final implementation results of the designed device. The system operation begins by pressing the power button (1). The front part of the device (6, 7, and 8) was positioned near the surface of the waste bag. By pressing and holding the detection button (2), the device starts scanning, and the process stops once the button is released. The system automatically classifies the waste type and displays the composition percentage on a screen (3). The dominant waste type is indicated by the LED indicator (4): blue for inorganic, green for organic, and red for mixed waste

A. Waste Detection System Testing

System testing began by preparing three types of organic wastes (food scraps, vegetables, fruits, and leaves) and three types of inorganic wastes (plastic, cans, and glass). Each waste type consisted of ten samples, resulting in a total of 60 test samples. Details of the waste types are shown in Fig.12 and Fig.14, the orange labels indicate the waste category that should be detected, whereas the green labels represent the detection results from the designed device. The detection code '0' represents organic waste, whereas code '1' corresponds to inorganic waste. The test results showed that four inorganic samples were not detected correctly: plastic water bottles, black food containers, black glass shards, and dark glass bottles. Meanwhile, among the organic waste types, only one sample was misclassified: rice, as indicated in Fig. 14 with a blue label (detected as inorganic). The accuracy calculation was performed using Eq.(10), which is the number of correct detections divided by the total number of samples, and then multiplied by 100%.

$$Accuracy(\%) = \frac{Number\ of\ correct\ detections}{Total\ number\ of\ samples} \times 100\% \quad (10)$$

Table 4 presents the accuracy calculation results of the designed detection system. Based on the test data, five detection errors were observed out of 60 tested samples. Consequently, the system achieved an accuracy of 91.67%, indicating that the device performed well in distinguishing between organic and inorganic waste. From these observations, it was found that detection errors generally occurred in dark-colored (black) inorganic waste, which was misidentified as organic waste. Conversely, some organic waste with light or white colours was detected as inorganic. This phenomenon was due to the system's tendency to classify waste based on the resistance values from the LDR sensor. Dark-colored waste tends to produce lower LDR values and is classified as organic, whereas lighter-colored waste yields higher LDR values and is classified as inorganic.

Table 4. Overall test results

Waste Type	Number of Samples	Correct Detections	Incorrect Detections	Accuracy (%)
Inorganic	30	26	4	86.67
Organic	30	29	1	96.67
Average				91.67

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Fig. 12 **Result of inorganic waste samples**

(a) (b) (c)

Fig. 13 **(a) Blue LED for Inorganic Waste, (b) Red LED for Mixed Waste, (c) Green LED for Organic Waste**

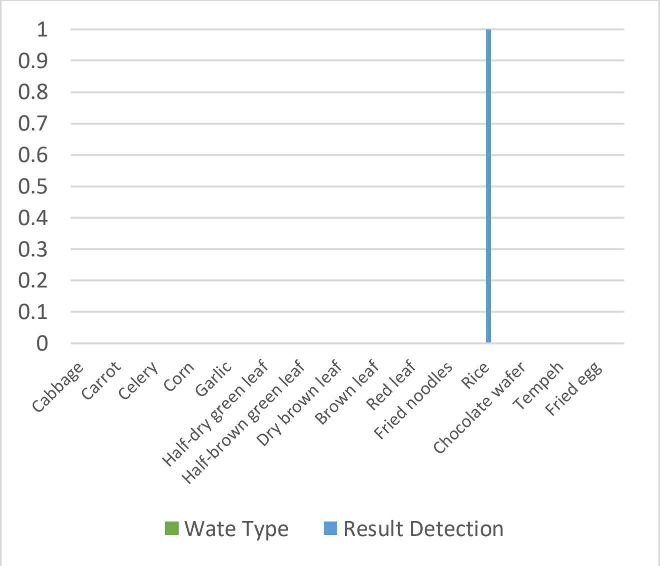

Fig. 14 **Result of inorganic waste samples**

B. Mixed Waste Detection System Testing

The test was conducted by preparing 11 mixed waste samples with varying proportions of organic and inorganic materials, including those with 100%, 90%, 80%, 70%, 60%, and 50% organic content. Each mixture was placed in two types of household plastic bags, red and white, with standard dimensions of approximately 20–25 cm in width and 30–35 cm in height. As noted earlier, black plastic obstructs the sensors and prevents effective detection; therefore, only red and white plastic bags were used in this study. All experiments were conducted under standard indoor lighting conditions, with illumination levels of approximately 300–500 lux, to ensure consistent illumination. Data collection was performed by positioning the device sensors at a maximum distance of 15 mm from the surface of the plastic bags, in accordance with the sensing limitations of the capacitive and inductive sensors used. Each sample was measured three times to ensure consistency, and the sensor readings were recorded for further analysis.

Table 5. **Results of Mixed Waste Testing**

Samples of Mixed Waste	White Plastic (%)		Red Plastic (%)		Colour Indicator LED Display
	Inorganic value	Organic Value	Inorganic Value	Organic Value	
Inorganic 100%	100	0	93	7	Blue
	100	0	98	2	Blue
	100	0	97	3	Blue
Inorganic 90%	93	7	85	15	Blue
	92	8	84	16	Blue
	90	10	87	13	Blue
Inorganic 80%	74	26	73	27	Red
	77	23	89	11	Red
	88	12	73	27	Red
Inorganic 70%	80	20	78	22	Red
	76	24	64	36	Red
	74	26	88	12	Red
Inorganic 60%	72	28	65	35	Red
	64	36	59	41	Red
	67	33	63	37	Red
Inorganic 50% / Organic 50%	55	45	53	47	Red
	63	37	46	54	Red
	57	43	52	48	Red
Organic 60%	35	65	38	62	Red
	44	56	37	63	Red
	36	64	43	57	Red
Organic 70%	29	71	28	72	Red
	38	62	27	73	Red
	27	73	33	67	Red
Organic 80%	21	79	17	83	Red
	29	71	28	74	Red
	20	80	21	79	Red
Organic 90%	21	79	7	93	Red
	23	77	14	86	Red
	17	83	12	88	Red
Organic 100%	6	94	4	96	Green
	11	89	0	100	Red
	12	88	9	91	Red

Tabel 5 shows the test results for displaying waste percentage information. In this study, we employed the error measurement matrix *Mean Absolute Error* (MAE), which is defined in Eq. (11). Here, y_i represents the actual composition of the waste (either organic or inorganic,

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expressed in %), x_i denotes the detected composition (organic or inorganic, expressed in %), and N is the total number of measurements.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}| y_i - x_i| \qquad (11)$$

Table 5 presents the results for a sample containing 80% inorganic waste (i.e., 20% organic waste in the ground truth), where the error values varied across repetitions. For white plastic, the detected organic compositions were 26%, 23%, and 12%, resulting in absolute errors of 6%, 3%, and 8%, respectively. For red plastic, the detected organic compositions were 27%, 11%, and 27%, corresponding to absolute errors of 7%, 9%, and 7%, respectively, which are considered acceptable. These results indicate that both white and red plastics exhibit deviations from the actual values, with white plastic generally showing more balanced error levels than red plastic.

A similar calculation was performed for all sample compositions, and the results were averaged to obtain the overall MAE of the system. The white plastic achieved an MAE of 5.61%, and the red plastic achieved an MAE of 4.45%. These findings demonstrate that the system exhibits an average deviation of less than 6% from the ground truth. Although the red plastic produced a slightly lower MAE, the white plastic exhibited more consistent performance across various waste composition scenarios.

In this scheme, the LED output was categorised based on the dominant type of waste in the bag. The LED lights up blue when the percentage of inorganic waste exceeds 90%, green when the rate of organic waste exceeds 90%, and red when neither organic nor inorganic waste reaches 90%. The test results showed that the LED consistently produced the correct colour output corresponding to the detected waste composition.

Table 6. Comparison of Waste Detection Studies

No	Authors	Sensor/ Method	Result/Accuracy
1	Vesga et al., [29]	Capacitive sensor + Random Forest	~94 %
2	Akbar et al.,[30]	Inductive + Capacitive + Infrared Proximity + Ultrasonic (IoT, NodeMCU ESP8266)	Not specified (successful distinction; optimal distance: 3 mm)
3	Arifin et al., [31]	Capacitive Proximity + Inductive Proximity + Photodiode + ANN	100 % (training & test, lab environment)
4	Dewa et al., [32]	Inductive + Capacitive Proximity + Ultrasonic	95 %
3	**Our Works**	**Inductive + Capacitive + LDR+ AdaBoost**	**91.67%**

Furthermore, the system was equipped with a visualization interface to enhance its usability. The calculated waste percentages were clearly displayed on the screen, accompanied by a battery status indicator located in the upper-right corner, as shown in Fig. 13. In addition, three LED indicators were implemented to represent the classification results: blue for mixtures containing more than 90% inorganic waste, green for mixtures with more than 90% organic waste, and red for mixed compositions without a dominant type. Testing confirmed that both the textual display and LED indicators functioned correctly and conveyed the information in a transparent and interpretable manner, as illustrated in Fig.13.

We compared the results of this study with those of previous studies, as shown in Tabel 6 Vesga et al. [29] utilised a capacitive sensor in conjunction with the Random Forest algorithm, achieving an accuracy of approximately 94%. Although this is higher than our result, relying solely on a capacitive sensor can be less effective when the materials have similar dielectric properties. Akbar et al. [30] combined inductive, capacitive, infrared, and ultrasonic sensors with an IoT-based NodeMCU ESP8266 platform. Their system successfully distinguished waste types at an optimal detection distance of 3 mm. However, they did not report the overall accuracy, and their design had higher complexity and maintenance requirements. Arifin et al.[31] proposed a system that integrates capacitive, inductive, and photodiode sensors with an artificial neural network (ANN), achieving 100% accuracy in training and testing. However, these results were obtained under controlled laboratory conditions, raising questions about the system's robustness in real-world scenarios with variable waste characteristics. Dewa et al.[32] designed a device using inductive and capacitive proximity sensors combined with ultrasonic sensing and reported 95% accuracy across 20 waste samples. However, their prototype required dry waste of specific dimensions to avoid sensor interference, which limited its applicability in diverse field conditions.

In contrast, our research integrates inductive, capacitive, and LDR sensors with the AdaBoost algorithm, achieving 91.67% accuracy while maintaining a more straightforward, low-cost, and portable design. Unlike previous studies that focused mainly on the binary classification of organic versus inorganic waste, our device also estimates the percentage composition of waste inside plastic bags. We achieved an MAE of 5.61% for white plastic and 4.45% for red plastic, demonstrating that the percentage estimation deviated by less than 6% from the ground truth. This provides richer information for waste management operations, supporting more effective recycling strategies and reduced landfill usage. Furthermore, the pistol-type handheld design renders the

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system portable and practical for deployment in multiple locations without requiring permanent installation.

Although the device achieved good classification accuracy, several limitations must be considered. Detection remains limited by the type of plastic used, as black plastic can obstruct sensor performance. Additionally, environmental factors, such as changes in lighting and movement during waste mixing, can also reduce accuracy. The use of LEDs helps to stabilise the readings under varying illumination, but it does not eliminate the effect. Another environmental aspect that may influence performance is temperature and humidity levels. According to the specifications, inductive and capacitive sensors can operate reliably within a temperature range of –25 to 70 ℃ (general use) or –30 to 80 ℃ (indoor use) and under relative humidity levels of 35–95% RH. In this study, all experiments were conducted indoors at an average temperature of 25–30 °C and humidity of 40–60% RH, which fell well within the operational range of the sensors. Therefore, under these controlled conditions, neither temperature nor humidity significantly affected the accuracy of detection. However, in real-world applications, sensors may be exposed to more extreme conditions. High humidity, for instance, can alter the dielectric properties of organic materials, whereas temperature fluctuations may cause drift in sensor readings. Furthermore, vibrations or irregular handling of waste bags during collection may affect the consistency of classification.

Therefore, future work will focus on systematic testing under diverse environmental conditions, including different lighting intensities (low light, direct sunlight, and nighttime), wider temperature variations, and controlled humidity levels. Additionally, implementing signal compensation mechanisms or adopting sensor fusion strategies should be considered to enhance system robustness. These steps will enable more comprehensive validation and optimisation of the system for large-scale real-world waste management applications.

IV. Conclusion

The developed organic and inorganic waste detection device can classify waste types and calculate the composition of mixtures of organic and inorganic wastes. Based on testing with predetermined samples, the device achieved a classification accuracy of 91.67%. For composition detection, the system achieved an MAE of 5.61% using white plastic bags and 4.45% using red plastic bags, demonstrating an average deviation of less than 6% from the ground truth. This development contributes positively to more efficient waste management, mainly by providing convenience and accelerating the sorting process compared to manual methods. Therefore, the device has the potential to improve efficiency while reducing the workload of household waste disposal. However, this device has several limitations. The types of waste that can be detected are still restricted, and the performance may be affected by varying environmental conditions. Although the use of LEDs helps reduce the effects of lighting variations, it does not eliminate their impact. Additionally, sample movement during the detection process can decrease classification accuracy. Therefore, future work should focus on enhancing the device's stability under various environmental conditions, refining the detection method for mixed waste, and expanding the sensing range and types of waste that can be detected.

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