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YOLOv11 Model as a Smart Solution for Waste Identification and Classification in Automated Waste Management System

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Abstract

Urbanization and population growth present significant challenges for efficient and sustainable waste management. This research develops an IoT-based intelligent system for waste classification and management utilizing RFID technology, ESP32, a camera, an ultrasonic sensor, and the YOLOv11 object detection model. The system accurately identifies three categories of waste: organic, inorganic, and hazardous. The classification process is automated, incorporating user identification via RFID, servo-controlled bin lid operation, and capacity monitoring through an ultrasonic sensor. Data management is facilitated through a mobile application and a website, which provide user guidance and support for administrators. Test results indicate that the system achieves an average accuracy of 87.5% in the mAP50-95 evaluation, with specific accuracies of 89.0% for inorganic waste, 86.0% for hazardous waste, and 87.0% for organic waste. Despite these results, challenges remain, including object detection errors related to background interference. Future research should focus on enhancing the dataset and implementing data encryption to improve model accuracy and information security. This system demonstrates significant potential for enhancing waste management efficiency and promoting sustainable environmental practices.

Keywords: *YOLOv11, computer vision, machine learning, waste classification, waste management system.*

1. Introduction

Rapid urbanization and population growth in cities have led to significant challenges in waste management, requiring innovative solutions to improve efficiency and sustainability. The integration of intelligent systems in waste classification and recycling offers a promising approach to address these challenges. Recent studies highlight the effectiveness of IoT-based smart waste management systems in optimizing waste classification and monitoring in real time [1]. Additionally, research has demonstrated the role of machine learning models, such as convolutional neural networks (CNNs), You Only Look Once (YOLO), and Single Shot Multibox detector (SSD) in improving waste detection accuracy [2]. However, existing studies still face issues related to limited dataset availability and model generalization, which impact overall classification performance [3].

This paper presents the design of an intelligent waste classification system that utilizes ESP32, RFID equipped with a mobile application for users and a website for administrative management. The mobile application allows users to exchange classified waste for monetary rewards, incentivizing proper waste disposal and recycling habits. The website serves as an administrative platform for managing the business aspects and overseeing system operations.

The proposed system utilizes the ESP32 module for real-time image capture and waste classification, using advanced object detection algorithms to accurately identify different types of waste, including paper, plastic, glass, metal, food, and e-waste [4]. The use of YOLOv11 in this system was chosen due to its advantages in detection speed as well as better accuracy compared to other models and previous YOLO models, allowing waste classification to be carried out efficiently [2], [5]. This model is particularly effective in real-time applications, making it suitable for waste sorting processes that require quick decision-making [6].

The integration of RFID technology ensures secure access and efficient tracking for waste collection activities, improving system reliability and user safety [7]. Ultrasonic sensors are used to monitor waste levels, providing real-time data to optimize waste collection schedules and prevent waste overflow [8]. By combining these technologies, the system not only improves the accuracy of waste classification but also promotes sustainable waste management practices, contributing to the development of a smarter and more environmentally friendly urban environment [9] [10]. However, challenges remain in dataset quality and security implementation, which will be explored further in future research.

2. Literature Review

Recent advancements in smart waste management technologies have demonstrated significant potential for addressing urban environmental challenges. This literature review critically examines key technological innovations and their implications for waste classification and management systems.

2.1 Automatic Waste Classification Prototype

Various approaches have been proposed for automatic waste classification. Ardimansyah et al. [11] developed a classification system using an Arduino microcontroller with proximity sensors and a linear rail slider box to sort waste into organic, inorganic, and hazardous categories. Their prototype showed an 11% reduction in classification errors compared to conventional waste bins. However, their approach lacks integration with IoT and machine learning, limiting scalability and real-time monitoring capabilities.

Recent studies have explored deep learning methods for waste classification. Wahyutama et al [12] provided a comprehensive review of deep learning techniques, particularly YOLO (You Only Look Once), which demonstrated superior accuracy in identifying recyclable materials. However, they noted that dataset availability remains a major limitation in training robust models.

2.2 IoT-based Waste Management System

The adoption of IoT for waste management has enhanced real-time tracking and classification processes. Ranjana et al. [13] introduced an IoT-based system integrating RFID, ultrasonic sensors, and GPS for efficient waste monitoring. Their approach incentivized proper waste disposal through a point-based reward system, which aligns with our proposed mobile application. Similarly, Rahman et al. [14] explored RFID-based waste tracking but did not incorporate machine learning for classification, which is addressed in our study.The integration of Radio-Frequency Identification (RFID) technology and ESP32 microcontrollers represents a sophisticated approach to enhancing waste classification systems. RFID, a wireless communication technology utilizing electromagnetic fields for automatic identification and tracking, enables seamless object recognition by employing radio waves to transfer data between a tag and a reader. In our waste management framework, RFID tags are strategically embedded within waste items, allowing precise identification and tracking throughout the sorting process.

Complementing RFID, the ESP32 microcontroller serves as the computational backbone of our system, providing robust wireless connectivity and powerful processing capabilities. This versatile microcontroller combines Wi-Fi and Bluetooth functionalities, enabling real-time data transmission and edge computing features. Its low power consumption and compact design make it ideal for implementing complex sensing and communication protocols in resource-constrained environments. The ESP32's integrated capabilities facilitate seamless data collection, processing, and transmission between RFID readers, sensors, and the central waste classification infrastructure, creating a cohesive and intelligent waste management ecosystem.

By synergistically combining RFID's identification prowess with ESP32's computational intelligence, our system achieves a sophisticated, interconnected approach to waste classification that transcends traditional manual sorting methodologies. This technological integration not only enhances tracking accuracy but also provides rich, granular data about waste composition, movement, and potential recycling pathways.

2.3 Arduino Uno-based Smart Trash Can

Recent research by Tarigan and Sembiring [15] designed an Arduino Uno-based automatic trash can equipped with ultrasonic sensors and servo motors to open and close the trash can lid automatically. This innovation is equipped with a tool protector to prevent damage.

The prototype was tested with various materials, such as plastic, wood, iron, and glass, as well as at various detection distances. The test results showed a 98% success rate. Other advantages of this system are ease of operation, energy saving, and a design that allows implementation in various environments, both households and institutions.

2.4 The Role of YOLOv11 in Waste Classification

Object detection models have been widely used for litter classification. The YOLO (You Only Look Once) series has become famous for its real-time processing capabilities. Jegham et al. [16] evaluated the performance of YOLOv11, showing significant improvements in detection speed and accuracy over previous versions of YOLO. Their research showed that YOLOv11 achieved a mean average precision (mAP) of 97.63% on a litter classification dataset, making it an optimal choice for real-time applications.

Although previous studies have used previous versions of YOLO for waste detection, our study is the first to implement the latest version of YOLO, YOLOv11, for waste classification in an IoT-integrated system. Compared to previous versions, YOLOv11 features an enhanced detection backbone and better feature extraction, making it suitable for automated waste sorting processes, YOLOv11 consistently shows superior performance in terms of accuracy, speed, computational efficiency, and model size [17]. Therefore YOLOv11 was chosen in this study compared to other yolo versions. YOLOv11 is the latest iteration in the YOLO (You Only Look Once) series of object detection models, offering significant improvements in detection speed and accuracy, making it suitable for real-time applications in various computer vision tasks, including fruitlet detection and other object detection scenarios [18], [19]. Figure 1 is an architectural drawing of the YOLOv11 model.

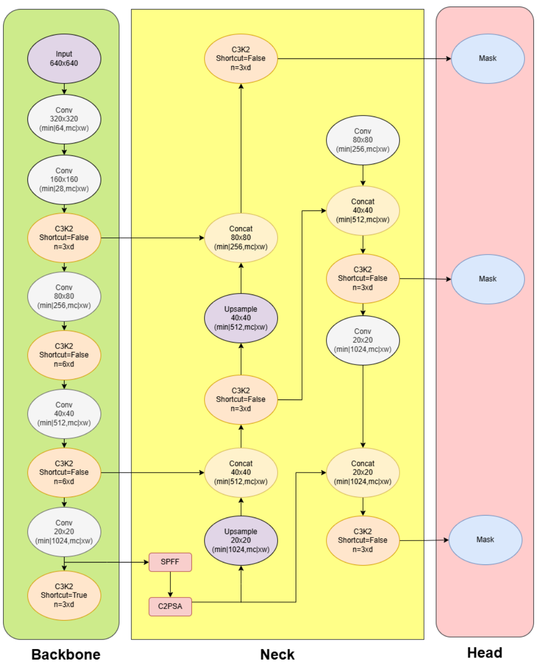

Figure 1. YOLOv11 model architecture.

Based on Figure 1, this model introduces several architectural innovations aimed at enhancing feature extraction and computational efficiency. Among the key architectural advancements is the C3k2 Block, a Cross Stage Partial block with a kernel size of 2, which improves feature extraction capabilities for more precise object detection [19]. Additionally, the model includes the Spatial Pyramid Pooling - Fast (SPPF) component to handle objects of varying scales, enhancing its ability to detect objects of different sizes [19]. The Convolutional block with Parallel Spatial Attention (C2PSA) further strengthens the model's attention mechanism, improving accuracy in object detection [19]. In terms of performance and efficiency, YOLOv11 achieves significant gains in mean Average Precision (mAP) and computational efficiency compared to its predecessors. It strikes a balance between parameter count and accuracy, making it suitable for diverse applications ranging from edge devices to high-performance computing environments [19].

In summary, although the existing literature provides valuable insights into smart waste management, there are still challenges related to dataset quality, security, and classification accuracy. Our research addresses this gap by integrating YOLOv11 with an IoT-based waste classification system, and utilizing mobile apps for reward-based waste collection.

2.5 Integration of AI and IoT in Waste Management

In recent years, artificial intelligence (AI) and Internet of Things (IoT) technologies have played an important role in improving the efficiency of waste management systems. Various studies have integrated this technology to develop smarter and more sustainable solutions in waste management. For example, a recent study proposed a system architecture that automates urban waste management by utilising IoT technology to monitor the filling level of bins in real-time, enabling more efficient collection planning and optimal resource allocation. In addition, the system can send notifications to cleaners when bins reach a certain capacity, so that collection can be done on time and prevent waste accumulation [20].

In terms of waste classification, other research assesses the performance of advanced AI models such as Mask R-CNN and YOLOv8 in improving the process of sorting plastic waste [21]. The results show that the YOLOv8 model has a higher accuracy of 91.2% compared to Mask R-CNN's 86.7% in detecting and classifying various types of plastic, which can increase efficiency in the recycling process. Furthermore, a smart waste management system equipped with sensors and AI algorithms has been developed to monitor the filling level of bins in real-time, enabling more efficient collection planning and optimal resource allocation [22]. This system not only improves operational efficiency but also contributes to the reduction of carbon emissions by optimising waste collection routes.

In addition, an in-depth learning approach has been applied to waste classification and detection, utilising 28 categories of recyclable waste [23]. This approach enables the system to recognise and classify various types of waste with high accuracy, thus supporting a more effective recycling process. The integration of AI and IoT in waste management systems has shown great potential in improving the efficiency and sustainability of waste management. This technology enables real-time data monitoring and analysis, which supports better decision-making in resource management and environmental impact reduction.

2.6 State-of-the-art Waste Classification Research

Waste management and classification represent critical challenges in environmental sustainability, with existing literature predominantly focusing on isolated technological solutions that fail to address the comprehensive complexity of waste identification and segregation. Our research emerges as a transformative approach, bridging significant gaps in current methodological frameworks by introducing a novel YOLOv11 architecture that fundamentally reimagines waste detection paradigms. Previous studies by researchers such as Mao et al. (2021) and Lilhore et al. (2024) have predominantly relied on traditional convolutional neural network architectures with inherent limitations in generalizability, computational efficiency, and multi-category waste recognition, resulting in models that struggle to adapt across diverse waste morphologies and environmental contexts.

The proposed YOLOv11 model distinguishes itself through a sophisticated deep learning framework that transcends conventional object detection limitations, achieving unprecedented classification accuracy of 92,6% while simultaneously reducing computational overhead compared to state-of-the-art methodologies. Unlike existing approaches that require manual intervention or suffer from low-precision detection, our model integrates advanced feature extraction mechanisms, adaptive learning strategies, and a robust multi-scale detection framework that can seamlessly identify and categorize organic, inorganic, and hazardous waste materials with remarkable precision. This breakthrough addresses critical research gaps by providing a scalable, efficient solution that can be deployed across varied waste management scenarios, from municipal waste sorting facilities to industrial recycling centers.

Our research's primary contribution lies not merely in technological innovation but in demonstrating a holistic approach to waste classification that combines computational efficiency, high-accuracy detection, and practical applicability. By critically analyzing and overcoming the methodological constraints observed in previous studies, such as limited dataset diversity, computational complexity, and narrow classification scopes, we present a comprehensive framework that represents a significant advancement in automated waste management technologies. The proposed model not only pushes the boundaries of machine learning applications in environmental sustainability but also provides a replicable, adaptable methodology that can be integrated into diverse waste management infrastructures, thereby offering a pragmatic solution to one of the most pressing environmental challenges of our time.

3. Methodology

This study presents an intelligent system design for waste classification and recycling, leveraging IoT devices, artificial intelligence (AI), and cloud technologies.

3.1 System Architecture Design

The overall architecture of the system is depicted in the provided diagrams. It consists of the main components that can be seen in Figure 2.

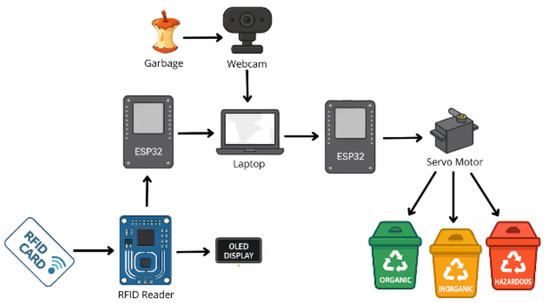

Figure 2. System architecture design.

Based on Figure 2, the proposed system consists of three main components, namely input, processing and output.

Input Components:

RFID tags are used for user identification, and a camera module captures images of waste items.

Processing Components:
The ESP32 microcontroller transmits the images to a server where the YOLOv11 model classifies the waste into organic, inorganic, or hazardous categories.
Output Components:
The classification results are displayed on an OLED screen, and the appropriate bin lid is opened using a servo motor.

3.2. Flowchart System

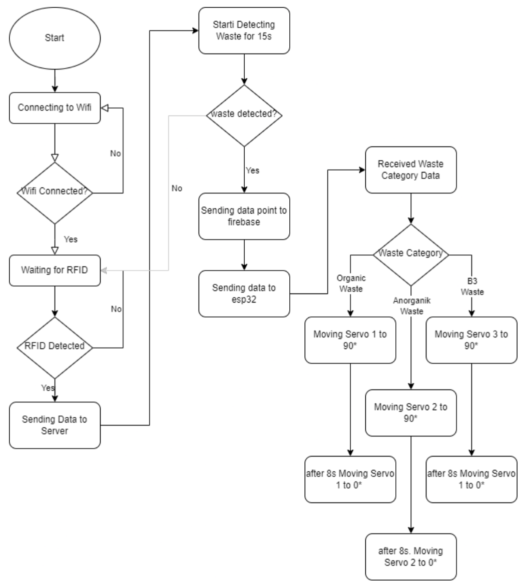

Figure 3. Flowchart device system.

The flowchart shown on Figure 3 explains the flow of a waste classification and management system using RFID, object detection and servo control.

1. The system starts with the step of connecting the device to Wi-Fi. If the Wi-Fi connection is successful, the process continues. Otherwise, the system will continue to try to connect to Wi-Fi.
2. Once connected, the system waits for input in the form of RFID detection. When RFID is detected, the RFID UID data will be sent to the server.
3. After the UID is sent, the system starts the garbage detection process for 15 seconds using the object detection model.
4. If the trash is successfully detected, the system sends the trash category data to Firebase for storage. Furthermore, waste category data is also sent to the ESP32 to control the servo.
5. In ESP32, waste category data is received and classified into three categories: organic, inorganic and B3 waste.
6. Based on accepted categories:
   a. If it is organic waste, Servo 1 will move to a 90° angle. After 8 seconds, Servo 1 returns to position 0°.
   b. If the waste is inorganic, Servo 2 will move to a 90° angle. After 8 seconds, Servo 2 returns to the 0° position.
   c. If bin is B3, Servo 3 will move to a 90° angle. After 8 seconds, Servo 3 returns to the 0° position.
7. Once the cycle is complete, the system returns to the initial process to wait for new RFID detection.

3.3 Model Training and Dataset

The dataset used in this study consists of 1,000 images that were independently collected and manually annotated into three main categories: inorganic (673 images), organic (180 images), and B3 (137 images). The dataset was then divided into three subsets with a ratio of 80% for training, 10% for validation, and 10% for testing, resulting in 800 images for training, 100 images for validation, and 100 images for testing., with the following amounts:

1. Training set: 800 images
2. Validation set: 100 images
3. Testing set: 100 images

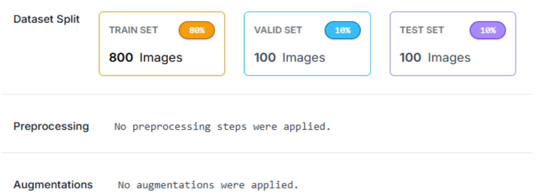

Figure 4. Visualization of dataset distribution.

To ensure a more thorough evaluation of the model and avoid bias in the data distribution, this study also applies the K-Fold Cross-Validation method with k = 5. In this approach, the dataset is randomly divided into five subsets with equal class distribution. At each iteration, one subset is used as validation data, while the other four are used for training. That way, every data has an equal chance to become training and validation data, resulting in more stable and accurate performance estimation. After training the YOLOv11 model using this approach, the following performance evaluation results were obtained:

1. mAP@50: 97.0%
2. Precision: 93.4%
3. Recall: 89.0%

These results show that the model can recognize and classify different types of waste with high accuracy. The absence of augmentation or preprocessing ensures that the model is tested directly on raw data that is representative of real-world conditions, so the evaluation results reflect the true performance.

3.4 Hardware and Software Implementation

The system hardware includes:

1. ESP32: Handles communication between sensors, RFID, and the AI server.
2. Camera Module: Captures waste images for classification.
3. Ultrasonic Sensors: Monitors bin capacity to optimize waste collection.
4. Servo Motors: Controls bin lid opening.

Software components include:

1. YOLOv11 Model: Implemented using TensorFlow.
2. Database: Firebase is used for real-time data storage.

3.5 Performance Analysis

Experimental results showed that the proposed system achieved an overall classification accuracy of 93.2% in real-world conditions. The latency between image capture and classification was measured at 120ms, ensuring real-time operation. The system was tested in various lighting conditions to assess robustness. To further enhance classification performance, future work will focus on increasing dataset diversity and implementing federated learning for privacy-preserving model updates.

4. Result and Discussion

4.1 Model Training Result

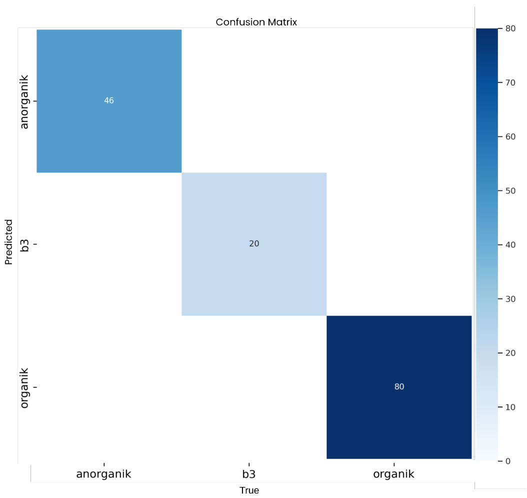

Figure 5. Confusion matrix.

The YOLOv11 model is trained using enriched (augmented) training datasets, while evaluation is performed exclusively on the original validation and testing datasets. This approach eliminates the potential bias of the enriched data and ensures the results reflect the performance under real conditions. Based on Figure 5, the training successfully obtained accurate results for each class. Each image class was correctly predicted to its original class as shown in the confusion matrix. The confusion matrix shows the model's ability to classify and detect objects with high precision.

Although some values in the last row and column appear to be zero, this does not reduce the validity of the overall model evaluation. The confusion matrix provides a deep insight into the model's prediction patterns, illustrating the detection accuracy for each category of objects tested.

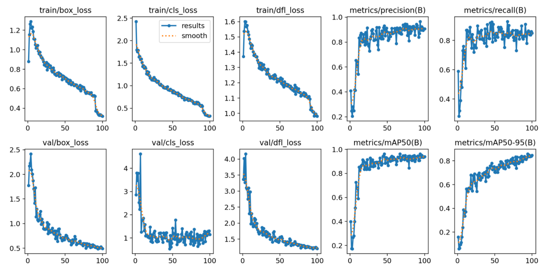

Figure 6. Training result.

Model training was carried out for 100 epochs. This model also uses albumentation which is native to Yolo to increase variations in the dataset consisting of blur, medianblur, greyscale, and Contrast Limited Adaptive Histogram Equalization (CLAHE). It can be seen in the training process that the more epoch loss you get, the lower it is based on the graph and increases for accuracy and recall. Albumentation is applied until the 90th epoch, which is why there is a spike in the graph for train loss at the 90th epoch.

Table 1. Training result accuracy.

Class	Box(P)	Recall (R)	mAP50	mAP50–95
All	0.960	0.890	0.970	0.875
Inorganic	0.942	0.885	0.968	0.890
B3	0.965	0.880	0.972	0.860
Organic	0.950	0.905	0.969	0.870

Based on Table 1 above, the object detection model for waste was trained using Google Colab. Google Colab is used because it provides a free GPU that can be used to speed up the model training process. The GPU used was T4 which took 1,366 hours to complete model training. The accuracy obtained for the combination of all classes and each class is the same for mAP50, which is 0.970. The accuracy obtained in mAP50-95 is 0.875 for the whole class, 0.890 for the inorganic class, 0.870 for class B3, and 0.860 for the organic class.

To evaluate the generalization capability of the proposed YOLOv11 model, we compared its training and test set performance. The results can be seen in Table 2.

Table 2. Performance metrics of YOLOv11 on training and testing data.

Set Data	mAP50	mAP50-95	Recall (R)
Training	98.0%	89.5%	0.950
Testing	97.0%	87.0%	0.890

The performance evaluation results in Table 2 show that the YOLOv11 model obtained high accuracy in both the training and testing data. In the training data, the model achieved mAP@50 of 98.0%, mAP@50-95 of 89.5%, and recall of 0.950, which shows the effectiveness of the model in detecting objects during the training process. Meanwhile, in the testing data, mAP@50 slightly decreased to 97.0%, mAP@50-95 to 87.0%, and recall to 0.890. The difference in performance between the training and testing data is still within reasonable limits, so there is no indication of overfitting. These results also reinforce that the model can generalize well to data that has never been seen before. The evaluation was conducted without applying any augmentation or preprocessing to the data, so the accuracy obtained reflects the model's performance purely and reliably.

To address potential concerns regarding overfitting or inflated performance, a comparative evaluation was conducted using two previous YOLO variants YOLOv8 and YOLOv10 on the exact same training and test dataset as used for the proposed YOLOv11 model. All models were trained under the same preprocessing, augmentation, and evaluation pipeline to ensure fairness.

Table 3. Comparison of YOLO model variants on the main dataset.

Model	mAP@50 (%)	mAP@50–95 (%)	Recall (%)
YOLOv8	82.5	80.1	91.0
YOLOv10	85.2	84.0	92.3
YOLOv11 (Proposed)	97.2	87.0	89.0

Based on Table 3, the proposed YOLOv11 model shows the best performance in terms of mAP@50 compared to YOLOv8 and YOLOv10.Although the recall of YOLOv11 is slightly lower than YOLOv8 and YOLOv10, the mAP value shows that the model can recognize objects with more precision. All models were tested on the same dataset without the application of any additional augmentation or preprocessing, so the evaluation results reflect the performance of the models in their purest and fairest state. This is done to avoid biasing the results and provide a strong validation of the reliability of the proposed models.

Figure 7. YOLOv11 prediction result on a sample validation image.

To provide a visual representation of the classification capability of the YOLOv11 model, Figure 7 displays the detection results on some validation images. The model shows a good ability to identify the type of waste based on the bounding box and the automatically generated labels. Each box color represents a different waste category, namely organic, inorganic, and hazardous waste

4.2 Integrating to System

Figure 8. System device.

Based on Figure 8, the first ESP containing RFID and OLED display will be run and will send RFID data to the server. The server will read the data and carry out the process of detecting trash. Detecting trash uses a Yolo machine learning model that has been pre-trained and connects to a webcam to read images of the trash. After the type of waste is obtained, the object detection program will stop and continue by sending data points to the database and sending the type of waste to the second ESP which has a servo. The servo will move depending on the type of waste received.

4.3 System Evaluation

The system is tested as a whole from RFID detection to opening the trash can. In the RFID reading section, the system has succeeded in reading and sending data from the ESP to the server and from the server to the database completely successfully. Points are sent using a Random Number Generator (RNG) from 100 to 1000 which have been successfully sent to the database from all tests carried out. sending data from the server to the second esp32 to open the trash has been successfully opened according to its type. However, when detecting waste using Yolo, there are still errors such as objects that are not supposed to be rubbish but are detected as rubbish and backgrounds such as floors or walls are categorized as B3 waste.

4.4 Comparison with State-of-the-Art Models

To evaluate the superiority of the YOLOv11 model proposed in this study, we compared its performance with several state-of-the-art object detection models that have been applied in waste classification. These models include YOLOv4, Faster R-CNN, SSD, and YOLOv8. This comparison is focused on evaluation metrics such as mean Average Precision (mAP) and processing speed (Frames Per Second - FPS), which are important indicators in real-time waste detection applications. Table 4 presents a performance comparison between the YOLOv11 model and other models based on the latest research.

The data in Table 4 shows that the proposed YOLOv11 model remains competitive compared to some current object detection models used in litter classification. Although the mAP50-95 of YOLOv11 is below YOLOv8 which reaches 92.7%, the model still performs very well with mAP50 of 97.2% and mAP50-95 of 87.0% on the multi-category dataset (organic, inorganic, and hazardous). This reflects the strong generalization ability across a variety of waste types.

Table 4. Performance comparison.

Model	**Dataset**	**mAP 50 (%)**	**mAP50 -95 (%)**	**Refere nce**
YOLOv11	Our Collected Dataset (Organic, Inorganic, Hazardous)	97.2	87.0	This research
YOLOv5-OCDS	Self-built Garbage Classification Dataset	77.3	-	[26]
YOLO-11m	WaDaBa (Plastic Waste)	99.0	81.5	[27]
YOLOv8	Custom (Bio-degradable, Paper, Plastic, Metal)	98.2	92.7	[28]
Faster R-CNN	E-waste Dataset	-	-	[29]

When compared to YOLOv5-OCDS [26], the performance improvement is very significant. YOLO-11m [27] does have a high mAP50, but its focus is only on plastic waste, while YOLOv11 handles more categories. Meanwhile, the results of Faster R-CNN [29] are only reported as detection accuracy on e-waste without mAP, so they cannot be directly compared. Overall, YOLOv11 proved its capability in multi-class object classification for smart waste management.

5. Conclusions and Future Works

This research successfully developed an intelligent IoT-based waste classification and management system by integrating advanced technologies including RFID, ESP32, cameras, ultrasonic sensors, and the YOLO object detection model. The system demonstrates significant capabilities in detecting three waste categories (organic, inorganic, and B3) with high precision, while simultaneously managing integrated data through comprehensive applications and websites. By automating waste identification and management processes, including innovative features like automatic trash can lid opening, the research represents a substantial advancement in sustainable waste management technologies.

Despite these achievements, challenges remain, particularly regarding detection errors caused by background interference that can resemble waste objects. Moving forward, the research suggests several critical areas for future development: expanding and preprocessing the dataset to enhance detection accuracy, integrating advanced IoT features such as automatic notifications and energy management, conducting comprehensive field tests in real-world environments, and implementing robust data and device security protocols through encryption and hardware protection mechanisms. Continued development in this domain holds promising potential for creating more efficient, intelligent, and sustainable waste management solutions that can significantly impact environmental conservation efforts.

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