KOMPUTASI: JURNAL ILMIAH ILMU KOMPUTER DAN MATEMATIKA
VOL. 22 (2) (2025), 99-107, p-ISSN: 693-7554, e-ISSN:2654-3990

Smart Waste Management System Using Computer Vision

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Abstract

Waste management in a university setting is a complex task that involves handling diverse waste streams in classrooms, laboratories, and canteen areas, proper segregation of wastes, and disposal while ensuring compliance with environmental regulations and sustainability goals. In response to the inefficiencies in handling adequate waste segregation at Guimaras State University (GSU), this study presents the development of a Smart Waste Management System using Computer Vision. The system aims to develop a model to classify waste according to waste type, handle automatic segregation, and provide stakeholders with real-time updates. Adopting the Cross Industry Standard Process for Data Mining (CRISP-DM) is part of the approach, including business understanding, data understanding, data preparation, modeling, evaluation, and deployment phases. The complications of waste management processes have been identified through interviews with utility personnel at Guimaras State Unversity – Mosqueda Campus. A prototype bin was developed using hardware electronic technologies and third-party platforms such as Edge Impulse and Blynk to handle waste identification for proper disposal and segregation. The study's primary results include a substantial decrease in the complexity of the waste management process, as well as promoting adequate waste segregation. By utilizing hardware technologies and training a machine learning model, the system was able to manage waste identification, automated waste disposal operations, and offer real-time updates to the stakeholders. Overall, the Smart Waste Management System using Computer Vision offers efficiency and sustainability in the waste management process at GSU.

Keywords: *smart waste management; computer vision; arduino; esp32 camera; esp32*

1. Introduction

Waste management is an essential issue for the university and globally. Poor waste disposal causes environmental pollution, health risks, and ineffective recycling processes [1]. Conventional waste segregation techniques are typically labor-intensive, time-consuming, and error prone. In response to these issues, improvements in artificial intelligence (AI) and computer vision have opened doors to Smart Waste Management Systems [2] [3], which facilitate effective, automated waste sorting and disposal [4].

This study focuses on using computer vision and machine learning techniques to create a smart trash management system [5] that can automatically classify waste into three categories: biodegradable, non-biodegradable, and recyclable. The system uses image processing and deep learning models to properly detect various types of waste items [6], eliminating human interaction and enhancing waste segregation at the source [7].

Collecting waste from the smaller surroundings of the university is challenging and costly [8]. Guimaras State University is the only state university and college in the Province of Guimaras, like many educational institutions are affected by the negative impacts of improper waste management on the study and work environment of its students, instructors, and staff.

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Received: 24 May 2025, Accepted: 31 July 2025 and available online 31 July 2025
DOI: https://doi.org/10.33751/komputasi.v22i2.44

Many issues have been investigated that signify a direct connection with the increase in waste material generation and related difficulties in handling it. The problems encountered where garbage is not segregated well at source and sanctions are not properly imposed are the most encountered, and lack of information/education among stakeholders is the least encountered [9], which makes it difficult to recycle or reuse some waste and may cause being dug up by animals as resulted to scattered garbage everywhere.

These issues are the results of an improper collection disposal mechanism used for waste material [10], the increase in moving trends of people toward universities and colleges, and the lack of intelligent technology used to support solid waste management systems [11].

Consequently, the management of waste material has become a challenge due to a large amount of waste littered everywhere [12]. Furthermore, various problems also occur due to the existing systems that are not only inadequate and inefficient but also their non-scientific procedures involved in solid waste management [13].

Generally, this study is to develop and visualize a smart waste management system using computer vision to identify wastes and trigger automated segregation also it uses an ultrasonic sensor, providing a comprehensive solution to measure the fill level of the containers and provide updated information at any time and notify waste management services to empty them when they are full or almost full. It can also alert the waste management services including the university utility of Guimaras State University if an undesirable incident happens such as disposal of garbage. The overall output of the proposed study, Smart Waste Management System Using Computer Vision, is to address the problem of improper waste segregation in the University and promote an environment-friendly Guimaras State University.

The main objective of this study is to develop, identify, and visualize a centralized Smart Waste Management System using Computer Vision that is specifically adapt to the needs of Guimaras State University. The goal is to develop a waste management platform that can sort different types of waste to simplify the waste management process. It includes improving waste segregation accuracy, optimizing resource utilization, reducing environmental pollution, and integrating smart technology for sustainable waste management solutions. Furthermore, the system can send an email request to the utilities for waste disposal and grant access to Guimaras State University. Moreover, this study is limited and will take place at Guimaras State University - Mosqueda Campus, Alaguisoc, Jordan, Guimaras, Philippines. Likewise, further data on sorting waste is not included in the system.

2. Methods

This study used a CRISP-DM (Cross Industry Standard Process for Data Mining) Methodology Approach [14][15] for the development of a Smart Waste Management System using Computer Vision aiming for higher accuracy and lower error rate in waste classifications. The Neural Network-based approach [16] primarily performs the waste classification of collected waste samples.

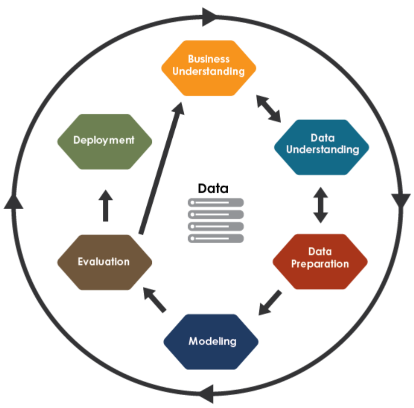

Figure 1. Process Model of the System

Figure 1 represents the Process Model consisting of six (6) major phases stating the different phases/stages of the CRISP-DM Model used in the study.

2.1 System Architecture

A System Architecture [17] is the conceptual model that defines a system's structure, behavior, and views.

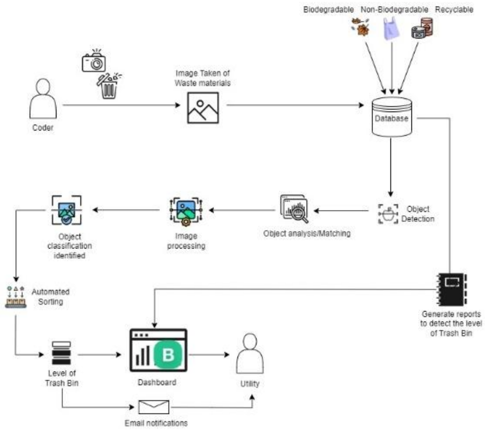

Figure 2. System Architecture

Figure 2 illustrates how images of waste materials are captured, processed for object detection, and classified into biodegradable, non-biodegradable, and recyclable categories then stored in a database for automated sorting. The system also generates reports, monitors trash bin levels, and sends email notifications to utility personnel if the smart bin is full.

2.2 Schematic Diagram

A Schematic Diagram is a picture that represents the components of a process, device, or other object using abstract, often standardized symbols and lines.

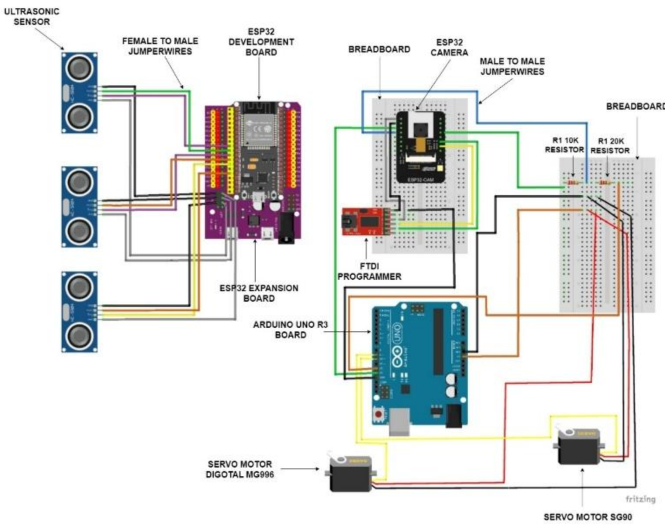

Figure 3. Schematic Diagram

Figure 3 shows the schematic diagram of the System's hardware components. It illustrates the connections between components such as an ESP32 development board, Arduino Uno, ultrasonic sensors, an ESP32 camera, servo motors, jumper wires, resistors, and a breadboard, highlighting how they interact to enable waste detection, classification, and sorting.

2.3 Building the Machine Learning Model

The researchers built the machine learning model, a Neural Network Architecture, using the Edge Impulse. After labeling and creating the impulse of the images on the dataset, the researchers trained the data collected on Edge Impulse using FOMO (Faster Objects, More Objects) MobileNetV2 0.1, a machine learning algorithm that brings object detection to highly constrained devices.

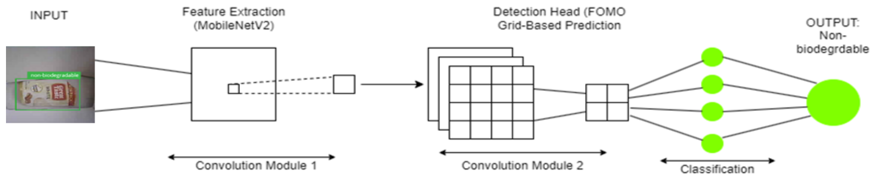

Figure 4. Architecture of FOMO (Faster Objects, More Objects) MobileNetV2 0.1 Model

Figure 4 shows the Object Detection Model Architecture using MobileNetV2 and FOMO (Faster Objects, More Objects) grid-based prediction, illustrating the input image, feature extraction, detection head, and final classification output as non-biodegradable.

2.4 Creating Prototype Bin

The researchers developed the Prototype Bin using cardboard and PVC tubes. For the camera placement, the researchers improvised and used a selfie stick. The prototype bin dimensions are shown in Figure 9. After creating the prototype bin, the researchers devised microcontrollers to create an intelligent machine. An Arduino Uno R3 microcontroller with connected components such as MG996R servo motors and an ESP32 cam board with an FTDI programmer to create the prototype bin was used in this process. The MG996R servo motors were the ones responsible for the automated sorting.

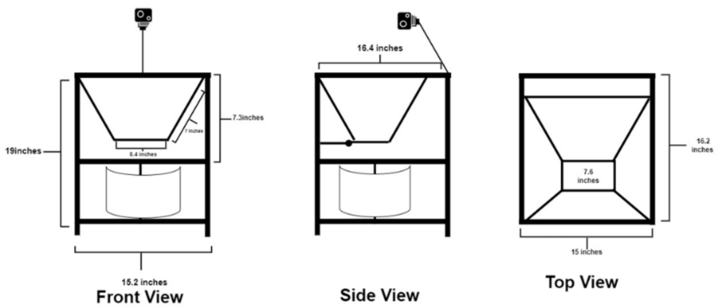

Figure 5. Dimensions of the Prototype Bin

Figure 5 shows the Structural design of the waste classification bin with camera placement, showing front, side, and top views along with dimensions for the container and funnel components.

3. Result and Discussion

The results obtained are data or facts obtained from research. Important data or facts that cannot be clearly narrated can be displayed in the form of tables or pictures or other illustrations.If the results are presented in the form of tables or figures, they do not need to be described at length. The discussion is a review of the results, explaining the meaning of the research results, conformity with the results or previous research, the role of the results in solving the problems mentioned in the introduction, and the possibility.

This section is the most important part of your article. The following are things that you must pay attention to in writing the results and the research results must be clear and concise, the datapresented has been processed (not raw data), set forth in the form of narratives, tables or pictures, and given easy-to-understand explanations. It is important to highlight differences between your results or findings and those of previous publications by other researchers. It is important to be compared with related references.

3.1. Model Testing

The researchers evaluated the model performance using metrics such as F1 Score, Precision, Recall, and Accuracy to determine how well it classifies waste into categories like biodegradable, non-biodegradable, and recyclable. This process was done using the Edge Impulse. The F1 score of the design model is expressed as:

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \qquad (1)$$

Where:

Precision = TP/(TP + FP) (2)

Recall = TP/(TP + FN) (3)

TP is True Positive, FP is False Positive, and FN is False Negative.

Table 2. Confusion Matrix

Actual/Predicted	Background	Biodegradable	Non-biodegradable	Recyclable
(Class 0) Background	TP (BG)	FP	FP	FP
(Class 1) Biodegradable	FN	TP (Bio)	FP	FP
(Class 2) Non-biodegradable	FN	FP	TP (Non-bio)	FP
(Class 3) Recyclable	FN	FP	FP	TP (Rec)

Table 2 presents a confusion matrix that categorizes predictions into classes: Background, Biodegradable, Non-biodegradable, and Recyclable, showing true positives, false positives, and false negatives for each class.

Table 3. Computed Confusion Matrix

	Background	Biodegradable	Non-biodegradable	Recyclable
Background	19563	2	1	6
Biodegradable	7	36	0	0
Non-biodegradable	0	0	69	0
Recyclable	0	0	0	44
F1 Score		0.88	0.99	0.93

Table 3 displays the computed confusion matrix with actual numerical values for each classification and their corresponding F1 scores, indicating the model's performance in accurately classifying different types of waste.

3.2. Precision

Precision shows how the predicted positives were correct as in equation 2

Biodegradable (Class 1)
(36)/(36 + 2) = 36/38 = 0.9474 **(97.74 %)**
Non-biodegradable (Class 2)
(69)/(69 + 1) = 69/70 = 0.9857 **(98.57 %)**
Recyclable (Class 0)
(44)/(44 + 6) = 44/50 = 0.8800 **(88.00 %)**

3.3. Recall

Recall refers to how many actual positives were correctly identified as in equation 3

Biodegradable (Class 1)
(36)/(36 + 7) = 36/38 = 0.8372 **(83.72 %)**
Non-biodegradable (Class 2)
(69)/(69 + 0) = 69/69 = 1.000 **(100 %)**
Recyclable (Class 0)
(44)/(44 + 0) = 44/44 = 1.000 **(100 %)**

3.4. F1 Score

F1 score is a metric used to evaluate the performance of a classification model by combining precision and recall into a single value as in equation 1

F1 Score of Class 1, Class 2, and Class 3.
Biodegradable (Class 1)
2 * (0.9474 * 0.8372) / 2 * (0.9474 + 0.8372) = 0.8889 **(88.89 %)**
Non-biodegradable (Class 2)
2 * (0.9857 * 1.000) / 2 * (0.9857 + 1.000) = 0.9928 **(99.28 %)**
Recyclable (Class 0)
2 * (0.8800 * 1.000) / 2 * (0.8800 + 1.000) = 0.9362 **(93.62 %)**

3.5. Accuracy

Accuracy refers to a metric that measures how well a model performs by calculating the proportion of correct predictions it makes compared to the total number of predictions.

Formula: Accuracy = Total Correct Predictions / Total Samples (4)

Background (Class 0) = 19572, Correct Predictions = 19563
Biodegradable (Class 1) = 43, Correct Predictions = 36
Non-biodegradable (Class 2) = 69, Correct Predictions = 69
Recyclable (Class 3) = 44, Correct Predictions = 44

TOTAL SAMPLES = 19728, TOTAL CORRECT PREDICTIONS = 19712

19712 / 19728 = 0.9991 **(99.91 %)**

3.6. Prototype Testing

The researchers tested the performance of the Smart Waste Management Bin prototype by manually recording the accuracy and the time it takes to trigger automated sorting after detection on different time frames to ensure its efficiency in identifying waste. The Prototype bin was tested every hour from 7 a.m. until 12 p.m. for the Morning until noon and 12 p.m. until 5 p.m. for the afternoon.

Figure 6. Prototype of the Smart Waste Management System

Figure 6 shows the prototype of the Smart Waste Management System. It highlights the testing process, where researchers assessed the prototype bin's ability to identify and sort waste accurately.

Table 4. Accuracy of Waste Detection and Triggering Segregation Duration during (Morning to Noontime)

Table 4 presents the accuracy of waste detection and the corresponding triggering segregation duration

Waste Samples	Accuracy (%) and Triggering Segregation Duration (m/s) during (AFTERNOON)									
	TIME									
	1 PM		2 PM		3 PM		4 PM		5 PM	
BIODEGRADABLE	%	s	%	s	%	s	%	s	%	s
Crumpled Paper	99.6%	4.9s	99.6%	7.1s	97.7%	20.6s	94.1%	37.4s	94.9%	33.7s
Dried Leaves	98.8%	5.7s	99.6%	8.2s	97.6%	12.4s	97.5%	6.3s	94.5%	20.3s
Siomai Plate	98.4%	28.2s	98.4%	37s	94.4%	30.8s	87.5%	43.6s	85.4%	35.5s
Tape	0%	0s	0%	0s	0%	0s	90.8%	48.8s	92.2%	55.2s
NON-BIODEGRADABLE	%	s	%	s	%	s	%	s	%	s
Juicebox	85.9%	15.5s	83.9%	24.5s	85.9%	29.2s	89.6%	8.3s	89.9%	22.4s
Biscuit Wrapper	95.8%	30.9s	95.3%	1:03s	95.3%	35.1s	96.4%	49.6s	94.7%	38.3s
Yakult	89.7%	30.2s	87.7%	20.8s	86.2%	28.5s	85.7%	25.6s	84.7%	28s
Coffee Wrapper	93.7%	15.7s	91.4%	2.8s	93.8%	12.7s	91.4%	5.63s	93.4%	10.7s
RECYCLABLE	%	s	%	s	%	s	%	s	%	s
Coke Swakto	87.9%	14.1s	87.5%	2.5s	89.5%	20.7s	81.6%	16.2s	83.8%	22.7s
Royal Swakto	88.2%	10.6s	87.4%	2.3s	87%	15.8s	81.7%	4.6s	83.7%	12.5s
Sprite Swakto	85.9%	12.5s	85.4%	13.2s	87.4%	18.1s	90.8%	12.2s	92.5%	18.1s
Mountain Dew Plastic bottle	81.9%	10.7s	81.6%	4.6s	83.7%	12.7s	85.2%	2.6s	84.8%	15.9s

for different waste samples categorized as biodegradable, non-biodegradable, and recyclable.

Table 5. Accuracy of Waste Detection and Triggering Segregation Duration during the (Afternoon)

Table 5 presents the accuracy of waste detection and the corresponding triggering segregation duration for different waste samples categorized as biodegradable, non-biodegradable, and recyclable.

Waste Samples	Accuracy (%) and Triggering Segregation Duration (m/s) during (MORNING – NOONTIME)											
	TIME											
	7 AM		8 AM		9 AM		10 AM		11 AM		12 PM	
BIODEGRADABLE	%	s	%	s	%	s	%	s	%	s	%	s
Crumpled Paper	99.6%	5.6s	97.6%	10.7s	97.3%	18.9s	99.1%	15.9s	99.6%	12.5s	96.5%	18.3s
Dried Leaves	99.6%	10.7s	97.6%	15.3s	96.6%	20.2s	98.3%	22.7s	99.6%	8.2s	97.3%	11.8s
Siomai Plate	91.5%	8.9s	87.5%	22.6s	89.5%	28.6s	89.5%	33.8s	87.5%	14.6s	88.2%	22.8s
Tape	92.1%	18.9s	92.8%	24.4s	90.1%	37.7s	94.8%	44.7s	99.1%	37.6s	92.5%	50.2s
NON-BIODEGRADABLE	%	s	%	s	%	s	%	s	%	s	%	s
Juicebox	96.8%	12.6s	97. 2%	15.3s	96.4%	22.4s	96.8%	20.8s	96.8%	6.9s	95.3%	12.5s
Biscuit Wrapper	94.5%	21.7s	94.5%	17.7s	96.5%	18.9s	95.5%	18.9s	94.5%	34.6s	93.5%	28.2s
Yakult	95.2%	25.3s	94.5%	27.9s	93.2%	28.3s	96.0%	35.7s	99.2%	20.3s	93.8%	30.7s
Coffee Wrapper	96.9%	13.6s	97.9%	12.9s	96.9%	23.7s	97.1%	22.1s	96.9%	2.6s	98.4%	10.6s
RECYCLABLE	%	s	%	s	%	s	%	s	%	s	%	s
Coke Swakto	94.6%	8.9s	93.6%	12.9s	94.8%	18.9s	91.2%	23.5s	90.6%	2.5s	94.7%	18.8s
Royal Swakto	96.5%	12.5s	93.5%	10.8s	94.7%	12.9s	94.9%	18.8s	93.5%	3.4s	95.3%	12.3s
Sprite Swakto	97.2%	10.6s	95.6%	15.2s	96.2%	18.8s	97.0%	17.5s	97.2%	5.1s	95.6%	10.5s
Mountain Dew Plastic bottle	90.0%	17.3s	93.0%	22.6s	92.2%	25.6s	90.9%	28.4s	90.0%	11.9s	92.5%	15.9s

4. Conclusion

The findings of this study affirm that the implementation of the Smart Waste Management System utilizing computer vision technology presents a viable and innovative solution to the inefficiencies associated with manual waste management processes observed at Guimaras State University–Mosqueda Campus. The system effectively addresses prevalent issues such as inadequate waste segregation at the source, inconsistent enforcement of waste-related sanctions, and limited awareness among stakeholders. Through the integration of image processing and real-time monitoring capabilities, the system enhances operational efficiency, reduces reliance on manual labor, and fosters environmentally responsible behavior within the academic community. Its implementation not only enhances operational efficiency and sustainability but also serves as an educational tool for promoting environmental responsibility within the academic setting. To strengthen its applicability, future improvements should include the expansion of image datasets, algorithm optimization, and collaboration with local waste management authorities to ensure policy alignment and long-term impact. This research highlights the potential of smart technologies in transforming waste management systems and contributing to broader sustainability goals.

5. Acknowledgement

The researchers express their sincere gratitude to everyone who contributed to the completion of their capstone project. They acknowledge Almighty God for His guidance and strength. Special thanks go to their Research Coordinator for invaluable support, as well as the panelists for their insightful feedback. They deeply appreciate their Capstone Adviser and College Dean for their mentorship. Their mentor is recognized for technical expertise and dedication to refining their work. Finally, they extend their heartfelt appreciation to their families and friends, especially their parents, for their unwavering love and support throughout their academic journey.

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