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Improving Real-Time IoT-based Waste Segregation leveraging YOLOV8 and DeepSORT for Davao Material Recovery Facilities

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APPROVAL SHEET

The thesis, entitled **"Improving Real-Time IOT based Waste Segregation leveraging Yolov8 and DeepSort for Davao Material Recovery Facilities"** prepared and submitted by Group 24-CS-009 consisted of **Charles John Brynt A. Mata, Primes Bryan S. Villa, Dyxter R. Tomas** in partial fulfillment of the requirements for the degree of **Bachelor of Science in Computer Science** is hereby accepted.

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Finally, the researchers dedicate this work to the Lord Jesus Christ, whose unwavering guidance, wisdom, and strength empowered them to persevere and accomplish this endeavor.

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LIST OF ABBREVIATIONS

Yolo	You Only Look Once
MRF	Material Recovery Facility
CENRO	Community Environment and Natural Office
PWS	Prime Integrated Waste Solutions

ARTICLE 1

Improving Real-Time IOT based Waste Segregation leveraging Yolov8 and DeepSort for Davao Material Recovery Facilities

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Abstract

In response to the increasing waste management challenges in Davao City, where Material Recovery Facilities (MRFs) significantly fall behind both national and international waste management standards, this study presents a cost-effective, real-time IoT-based waste segregation system that leverages You Only Look Once (YOLOv8) and DeepSORT algorithms. Existing MRFs in the city primarily rely on manual labor, leading to misclassification, inefficiencies, and environmental threats, ultimately pushing our landfills to their breaking point. The proposed system automates the classification and segregation of waste using a curated, locally relevant dataset, integrating object detection with mechanical actuation through IoT components. The system was trained and fine-tuned to identify multiple waste types, including biodegradable, recyclable, and special waste, under various lighting conditions. Performance testing demonstrated that the system functions reliably in real-world settings, although challenges persist with specific waste classes such as black-colored batteries. Usability feedback from City Environment and Nature Resources Office (CENRO) personnel indicated strong satisfaction with the system's speed and sorting accuracy. The project aligns with Sustainable Development Goals related to public health and sustainable cities, and it offers a scalable solution that could enhance waste management practices across local MRFs. Future improvements may involve expanding the dataset, enhancing camera resolution, and refining detection for visually ambiguous waste. This research contributes a novel integration of AI and IoT for practical, real-time waste segregation within a Philippine urban context.

Keywords: YOLOv8, DeepSort, IoT, Waste Segregation, Waste Management, Object Detection

SDGs: Goal 3 (Good Health and Well Being) and Goal 11 (Sustainable Cities and Communities)

1. Introduction

In Davao City, waste management is a pressing concern, like many other cities worldwide. United Nations Environment Programme (UNEP) stated that the increasing volume and complexity of waste, estimated at around 11.2 billion tons of solid waste collected worldwide, poses a serious risk to ecosystems and human health. Despite the city's beautiful scenery and warm atmosphere, dealing with all the waste is a growing problem. According to SunStar, since the COVID-19 pandemic started in March 2020, the amount of waste being collected in Davao City has increased to a staggering 600-650 tons per day. However, in a recent interview with Mr. Orly from City Environment and Natural Resources Office (CENRO), researchers found that the situation has deteriorated even further, with 800-850 tons being collected daily. This increase is due to several factors, including population growth and changes in consumption patterns. Additionally, the city's waste landfill at New Carmen has already exceeded its capacity, worsening the waste management crisis.

The researchers also found that although Section 32 of RA 9003 mandates that each barangay should have a Material Recovery Facility (MRF), only 33 out of 182 barangays practice solid waste management and have material recovery facilities. According to SunStar (2023) only five are functioning, namely those Barangay Hizon, Gumalang, Tacunan, Mintal, and Catalunan Grande. This highlights serious issues with how waste management challenges are being handled.

To manage this challenge, countries worldwide have developed a variety of automated Material Recovery Facilities (MRFs) by integrating advanced technologies, aiming to improve recycling rates and overall operations for a more sustainable future. For instance, nations like Australia are utilizing highly advanced automated sorting technologies. Australia's Cleanaway's Eastern Creek MRF in Sydney employs high-speed, sensor-based material recovery systems with advanced optical sorters integrated with near-infrared (NIR) spectroscopy and RGB color sensors, which identify and classify each container in real-time. Crucially, this detection is processed by an AI-driven control system that precisely tracks items, triggering air jets for automated segregation. In contrast, the Philippines currently has only two fully automated MRFs, operated by Prime Integrated Waste Solutions Inc., located in Cebu and Porac, Pampanga. While these facilities are advanced and use machinery, they do not incorporate AI-integrated or vision-based object identification systems for real-time waste sorting. Their sorting process primarily relies on components such as vibrating sieves for size separation, magnetic separators for metals, and air-density separators for lighter materials. This highlights a significant difference in technological advancement between existing Philippine MRFs and more advanced overseas facilities like those in Australia.

Currently, waste segregation in Davao City's MRFs is a tedious and labor-intensive process that begins with waste being gathered from each purok (sub-village) and transported to the facilities, where significant human effort is then required to manually sort it one by one. This manual process is prone to human error and improper segregation practices, leading to inefficiencies and increasing the risk of landfill overflows. Recognizing the urgent need to address this problem, the researchers aim to tackle Davao City's waste segregation challenges. This study aims to implement a system that uses cutting-edge technologies to reduce the human workload and make the process more efficient. By understanding the difficulties faced by the dedicated workers in the MRFs, they envision a shift in waste management practices that will help streamline operations and mitigate environmental hazards. The goal is to empower Davao's MRFs, making waste segregation faster, more precise, and reducing the need for manual labor.

This study proposes a novel and cost-effective IoT-based approach to waste segregation in Davao City's MRFs by leveraging innovative technologies like the YOLOv8 and DeepSORT algorithms for real-time waste classification and segregation. YOLOv8 (You Only Look Once version 8) is a state-of-the-art object detection algorithm renowned for its exceptional speed and accuracy in identifying various objects within images and video streams. Its efficiency makes it ideal for real-time applications where rapid processing is crucial. Complementing YOLOv8, DeepSORT is an advanced tracking algorithm that excels at maintaining the identity of detected objects across multiple frames, even when they are moving quickly. This combination is particularly advantageous for waste segregation on a conveyor belt, as YOLOv8 swiftly identifies waste items, and DeepSORT ensures continuous and accurate tracking, enabling precise mechanical sorting.

Unlike existing local MRFs that rely on manual sorting or older mechanical methods without AI integration, this project introduces an unprecedented level of real-time object detection and automated control for Davao City, designed to be economically viable for local implementation. By integrating IoT devices like the Arduino, the project aims to automate and control the sorting process, significantly reducing the need for manual labor while maximizing efficiency and accuracy. In addition to traditional waste classes, the system will also classify and segregate special wastes into different bins. There are existing studies that show prominent results on this topic such as the study of Rishabh Jain et al. (2019) where they leveraged IoT-based smart solutions in operating and addressing the waste management challenges. There's also a study by Kavya Balakrishan et al. (2019) where they used unique ways on segregating materials such as a magnet for metallic items, blower for lightweight plastics, etc. This unique blend of advanced technology and practical application positions the project as a beacon of innovation in waste management, offering a comprehensive solution that respects human effort and promotes a more sustainable future.

Davao City faces a significant challenge in proper waste segregation of recyclable materials from non-recyclables. Without effective segregation practices, the city's landfills are at risk of overflowing, leading to environmental hazards. Material Recovery Facilities (MRFs) currently rely on manual sorting of waste, which is labor-intensive and prone to human errors, resulting in suboptimal waste segregation. According to Sujan et al. (2022), manually separating waste is hazardous for human health, time-consuming and haphazard. This inefficiency burdens both the workers and the facilities, contributing to the accumulation of unsorted waste being sent to the landfills. Furthermore, the lack of infrastructure improvements and automation means there is no consistent dataset of different waste classes, which hinders effective waste management. Addressing these challenges through the development of an automated waste segregation system is critical for promoting environmental sustainability and enhancing the efficiency of MRFs in Davao City.

The general objective is to develop waste segregation system with YOLOv8-DeepSORT for real-world applications, particularly in Materials Recovery Facilities (MRFs) in Davao City along with its sub-objectives:

1.) Curate a comprehensive, locally relevant dataset with diverse waste classes for object detection that shows Davao City's variety of waste types.

2.) Train the YOLOv8 model with the custom dataset and evaluate its performance.

3.) Integrate real-time YOLOv8-DeepSORT detection with different IoT components.

This study holds significant importance in addressing the waste management challenges faced by Davao City, which generates around 800-850 tons of waste daily. The implementation of an advanced waste segregation system aims to improve the efficiency of Material Recovery Facilities (MRFs), reducing the labor-intensive burden on workers and reducing the volume of waste directed to landfills. This will enhance environmental sustainability by promoting the processing of recyclable materials and minimizing pollution.

Furthermore, the study aligns with Sustainable Development Goals (SDGs) 3 and 11. By improving waste segregation processes, it contributes to SDG 3 (Good Health and Well-being) by reducing exposure to hazardous waste and sources of diseases, in doing so improving public health. It also supports SDG 11 (Sustainable Cities and Communities) by enhancing the waste management infrastructure, making urban living more sustainable, and reducing environmental impacts.

In addition to local benefits, this research sets an inspiration for other urban areas with similar challenges, encouraging global collaboration and innovation in waste management practices. By sharing knowledge and methodologies, the project aims to pave the way for more efficient and sustainable waste management solutions locally and beyond.

2. Related Studies

This chapter reviews existing works that support the development of an IoT-based AI waste segregation system. It covers how waste is processed in MRFs locally and internationally, explores how IoT components are used in smart segregation systems, and highlights object detection algorithms that enable real-time classification of waste. These studies help identify the strengths and limitations of current approaches and provide a foundation for the proposed system.

2.1 Segregation Process with MRF Facilities

Table 1. Comparative Matrix: Proposed System vs. Local (PWS) and International (Eastern Creek)

Feature / Aspect	Proposed Study (YOLOv8 + DeepSORT IoT System)	PWS MRF (Philippines)	Eastern Creek MRF (Australia)
Type of System	AI-driven prototype with real-time classification	Fully mechanized, non-AI	Fully automated with AI-based control
Object Detection	YOLOv8 (custom-trained for local waste)	Not Implemented	Optical + NIR sensors
Tracking	DeepSORT for moving object tracking	Not Implemented	AI-based item tracking
Segregation Method	Servo motors via Arduino control	Mechanized Trommel, magnets, air classifier	air-jet system
Handled Waste	12 classes (included local waste eg. Durian peel)	General waste	Standard recyclables

Feature / Aspect	Proposed Study (YOLOv8 + DeepSORT IoT System)	PWS MRF (Philippines)	Eastern Creek MRF (Australia)
AI Integration	Full (YOLOv8 + DeepSORT)	Not Implemented	Factory controlled
Cost	low-cost prototype	Multi-million peso setup	Factory controlled
Deployment	Barangay / LGU-ready, scalable	Centralized facilities	Industrial scale only

This section explores how waste is sorted and processed in Material Recovery Facilities (MRFs), both in local and international contexts. It highlights the differences in automation, object detection, and scalability between traditional systems and modern AI-integrated solutions. The comparison establishes the technological gap and shows how the proposed system addresses current limitations using an AI-IoT approach.

To provide a clear overview, Table 1 presents a comparative matrix between the proposed waste segregation system, the local MRFs operated by Prime Integrated Waste Solutions (PWS) in the Philippines, and the internationally renowned Eastern Creek MRF in Australia. This comparison emphasizes the novelty, flexibility, and cost-effectiveness of the proposed system, especially for community-level deployment.

2.1.1 Segregation Process of MRF in Philippines.

There are currently only two fully automated Material Recovery Facilities (MRFs) in the Philippines—one located in Cebu and the other in Porac, Pampanga. Both facilities are operated by Prime Integrated Waste Solutions Inc. (PWS), the waste management arm of Prime Infra. These two MRFs utilize the same modern mechanized process, but they differ in capacity. The Pampanga facility is the largest, with a capacity of up to 5,000 tons per day, while the Cebu facility can process around 1,000 tons per day. Each facility is composed of four fully automated processing lines, and each line consists of several components that work together to sort different types of waste materials.

The sorting process begins when waste is dumped into a hopper, which feeds the materials onto a main conveyor belt. At the start of the line, manual pre-sorting may occur to remove large or hazardous materials before the waste proceeds to the automated stages. The first mechanical component is the vibrating sieve (or trommel/shaker screen), which separates materials by size. Smaller particles, such as soil or food scraps, fall through the screen, while larger items like plastic bottles or cardboard continue along the line. Next, a magnetic separator removes ferrous metals (such as iron and steel cans), which are collected into a dedicated bin for baling. After that, an air-density separator (also known as an air classifier) uses airflow to separate lighter materials like plastic and paper from heavier materials such as glass and organic waste. These materials are then directed into separate bins. Finally, each stream is sent to a baling station, where materials such as metals, plastics, and fibers are compressed into bales for recycling, and residual or non-recyclable waste is wrapped into landfill-ready blocks for proper disposal or storage.

As of today, there are no AI-integrated or vision-based object detection systems incorporated into these fully mechanized facilities. While PWS MRFs are advanced in terms of mechanical sorting, they do not use artificial intelligence for real-time detection and classification of waste. In contrast, the research prototype presented in this study introduces an AI-based waste detection system integrated with IoT components, capable of identifying and automatically sorting waste in real time—something currently not implemented in existing MRFs in the Philippines.

2.1.2 Process of MRF Internationally.

How recycling is sorted in Australia specifically Perth, Melbourne and Sydney. First, there are 193 material recovery facilities in the whole of Australia. Most are hand-sorted; nine are semi-automated, and nine are fully automated. The automated ones are operated by large companies. The sorting process begins with recyclables being placed on a conveyor belt and transported to a sorting line. Contaminants like non-recyclable plastics and small foreign objects are removed manually. Steel cans are extracted using a magnet, and glass is conveyed to a recovery bin. Most materials are then compressed and baled for efficient transport to the department that processes the recycling.

Cleanaway’s Eastern Creek Material Recovery Facility (MRF), located in Sydney, Australia, is one of the country’s most advanced fully automated recycling centers, designed specifically to support the New South Wales “Return and Earn” container deposit program. Collected containers from the program are delivered in bulk by trucks to the facility, which processes over five million units per day using a high-speed, sensor-based material recovery system.

The process begins with the receiving and hopper feeding stage, where the delivered containers are tipped into a large receiving hopper. A conveyor system then transports the mixed materials to an initial inspection zone, where workers manually remove oversized or problematic contaminants such as plastic films, hazardous waste, or bulky items that could obstruct the automated line. From there, the materials pass through a rotating trommel screen—a large cylindrical sieve—that separates items based on physical size. Smaller debris such as broken glass, caps, or residual organics fall through perforations in the screen, while larger containers advance to the optical sorting stage. At this critical stage, advanced optical sorters integrated with near-infrared (NIR) spectroscopy and RGB color sensors identify and classify each container in real time. These sensors analyze the spectral and visual properties of passing items to detect specific material types (e.g., PET, HDPE, aluminum, steel, glass, and Tetra Pak). Each detection is processed by an AI-driven control system, which precisely tracks the location and timing of each item as it moves along the conveyor. Once a container is identified, a corresponding air jet—acting as the mechanical segregator—is triggered to blow the item into its designated chute or drop zone. Segregated materials are then directed through dedicated conveyor streams into material-specific hoppers or silos, maintaining high levels of purity and minimizing cross-contamination. Throughout the sorting lines, optional manual operators may be positioned at critical points to monitor the output and remove any incorrectly sorted items. Once a sufficient quantity of a particular material accumulates in its storage unit, the material is automatically funneled into a horizontal baling machine. This baler compresses the recyclables into dense, uniform rectangular bales, which are then securely strapped, labeled, and discharged onto pallets for temporary storage or direct transportation to domestic and international recycling markets.

At the Materials Recovery Facility (MRF) in Hampshire, UK, collected materials are tipped into the loading area and moved onto conveyors by a mechanical shovel to ensure a controlled, constant flow. The elevating conveyor runs at a faster speed to thin out the material before it reaches the pre-sort area, where non-recyclable items are manually removed and discharged into storage bays below. The mixed materials then enter a sorting area, where they are separated into three components: containers and fine materials, newspapers and magazines, and card and some papers. Manual checks are performed to remove any remaining non-recyclables. The MRF is equipped with advanced automatic recognition and sorting systems, which use optical identification and air jets at three separate locations within the facility.

According to Ioannis Antonopoulos et al. (2021), achieving high recovery rates and effective segregation of plastic waste in Europe is challenging. Waste is collected through national Extended Producer Responsibility (EPR) programs or Deposit Refund Schemes (DRS) and delivered to Material Recovery Facilities (MRFs), where it is inspected for non-recyclable items or hazardous materials. Larger items and contaminants are manually removed or mechanically separated during pre-sorting. The waste then undergoes various sorting processes, is compressed into bales, and divided into specific streams like PET bottles, HDPE containers, mixed plastics, films, and metals. The aim is to produce high-purity fractions for efficient processing into secondary raw materials at recycling plants.

2.2 IOT Components

As IoT serves as the backbone of this research, a specific study by Cherry Agarwal et al. (2020) emphasizes that using a conveyor belt significantly eases waste segregation, reducing human effort. In their design, waste passes through multiple sensors, including capacitive proximity sensors for dry waste, inductive proximity sensors for metallic waste, and moisture sensors for wet waste. One strength of their research is the ability to detect both wet and dry waste. However, a gap exists in that the presence of even a small amount of water on the conveyor belt can cause dry waste to be incorrectly identified as wet waste, this usually happens when wet waste was the first to pass through in conveyor belt.

Rishabh Jain et al. (2019) emphasizes the efficacy of leveraging IoT-based smart solutions, operating within a cloud-based framework, to address waste management challenges. By integrating sensors into containers deployed within waste bins, they establish a data-driven approach to waste segregation. When waste levels surpass predetermined thresholds, the system triggers automated email alerts, facilitating real-time notifications to users regarding bin capacity. Although their trash bin can maximally handle only 10 items.

According to Kavya Balakrishnan et al. (2019), as the popularity increases, waste also increases, and in the meantime, as waste accumulates, so do diseases. They developed a segregator to address this issue. Their innovative solution categorizes waste into metallic, organic, and plastic components. To separate lightweight plastics, they incorporate a blower, while a magnet is utilized for metallic items. Each bin is equipped with sensors that trigger SMS alerts to garbage collectors when waste reaches sensor level, ensuring timely collection and efficient management of waste disposal.

S.A.A.Jude et al. (2019) they proposed an automatic waste segregator (AWS) which are low cost and a easy solution mainly for households. The waste segregator mainly categorize mettalic, organic, and plastic making the waste management simplier and efficient. Each of the categories have its own bin and each bin have its own micro sensor. When the waste are at the level of the sensor it will send SMS to the truck so the bin will be pick up using the gsm technology

Suriyaa Kumari et al. (2018) implemented a system which notify the user and other authorities when the waste bins are near to be fully filled at the same time there is a also a condition where if inside the bins are in high temperature or in high humidity also alerts the user within the system as this is their main objective was to inform the householders. The IoT components they used include Arduino for control and GSM modules for sending

SMS notifications to household users, along with a dashboard for real-time monitoring and visual display of alerts.

2.3 Algorithms and frameworks

Songzhe Pan et al. (2024) advocate for the utilization of the YOLOV8 algorithm and CNN in waste segregation due to their complementary strengths. YOLOV8 excels in object detection, offering rapid and accurate identification of various waste items. Meanwhile, CNN, renowned for its prowess in deep learning, processes the data gleaned from YOLOV8, enabling nuanced classification of waste types. This synergistic approach harnesses the efficiency of YOLOV8's object detection alongside the robust analytical capabilities of CNN, culminating in a comprehensive and effective solution for waste segregation.

Michel Mudemfu's (2023) study presents a compelling argument for the integration of intelligent solid waste sorting using deep learning techniques, particularly emphasizing the efficacy of the YOLOv8 algorithm. While YOLOv8 demonstrates commendable performance, the success of the algorithm hinges not only on its inherent capabilities but also on the quality of the dataset used for training. In their research, Mudemfu advocate for the enhancement of model performance through the augmentation of the TrashNetV2 dataset. Techniques such as random rotation, random blur, random cropping and many more. Through these augmentation methods, their aim is to fortify the dataset and, consequently, improve the effectiveness of the trained model.

According to Sujan Poudel et al.(2022) Waste Management is important for humans as well as nature for healthy life and a clean environment. The major step for effective waste management is the segregation of waste according to its types. Manually, the separation of waste is hazardous for human health as well as time-consuming and haphazard. Therefore, the involvement of technology such as the Internet of Things (IoT) and Artificial Intelligence (AI) can address this problem. Specifically, Convolutional Neural Networks (CNNs) are employed in their research to classify images of waste materials accurately into distinct categories. Which produce a promising result.

In their 2023 study, Shiwansh Bhargav et al. propose a method using the same algorithm and object detection framework as our waste segregation system, specifically the DeepSORT algorithm and YOLOv8 object detection. While their study primarily focuses on tracking everyday common objects, their main objective is to achieve high-speed detection, even for objects at the frame's edge. They aim for high accuracy in the final frame from the sensor, which is crucial for our project that involves classifying waste moving rapidly on a conveyor belt. They highly recommend these tools because DeepSORT can effectively detect and classify fast-moving objects.

Dorothy Hua et al. (2020) propose that waste disposal has long been a problem in developing countries, particularly because hazardous waste poses significant risks for manual segregation by humans. To mitigate these risks, they suggest implementing Artificial Intelligence (AI) with deep learning algorithms to classify the hazardous level of waste, thereby minimizing the potential for human harm. In their project, they use OpenCV for object detection and a Convolutional Neural Network (CNN) trained on the TrashNet dataset for classification.

According to Siddhi S. Mhadlekar, their project began with the YOLO model to detect plastic materials, but it couldn't classify plastic types. For classification, the VGG16 model was used. Initial results with 120x120 images showed that 4 epochs achieved 77%

accuracy, which is considered good. However, with 256x256 images, although the accuracy reached 91.72%, the calculation time doubled, making it impractical for real-world systems. This summary highlights the progression from detection to classification, the effectiveness of the VGG16 model, and the trade-offs between image size and processing time.

The project created by Nandhini Murugan started by capturing camera feeds from individual Pi cameras. Frames were then fed into a convolutional neural network (CNN) model trained to recognize features like color and shape to identify biodegradable, combustible, or non-combustible waste. Waste was categorized based on training with predetermined images. The system checked and signaled waste availability, potentially using a conveyor for efficient processing. The input signals categorized waste types, and the system sent ON/OFF signals to actuators for waste segregation into separate bins. This process continued until objects were identified or no further interruptions occurred. The workflow process in their research article greatly enhances our implementation of IoT concepts as the systematic process aligns well with our own project.

3. Methods

3.1 Localized Dataset Curation

The dataset used in this study was carefully curated to reflect the waste types observed during our initial data gathering phase in our interview with Sir. Orly Limpangog conducted in City Environment and Natural Resources Office (CENRO) Davao City. It includes twelve waste classes: plastic bottle, paper, cardboard, can, durian peel, rambutan peel, banana peel, lanzones peel, 9v battery, cylindrical battery, laptop battery, and phone battery. Images for each class were sourced from Roboflow Universe, Kaggle, and photographs captured locally by the research team using a custom-built conveyor belt system. All classes included their own set of locally captured images, which formed the foundation of the dataset. Roboflow provided pre-annotated datasets, while Kaggle contributed a range of unannotated but diverse image sets. Roboflow was also used as the main platform for organizing, annotating, and managing these datasets.

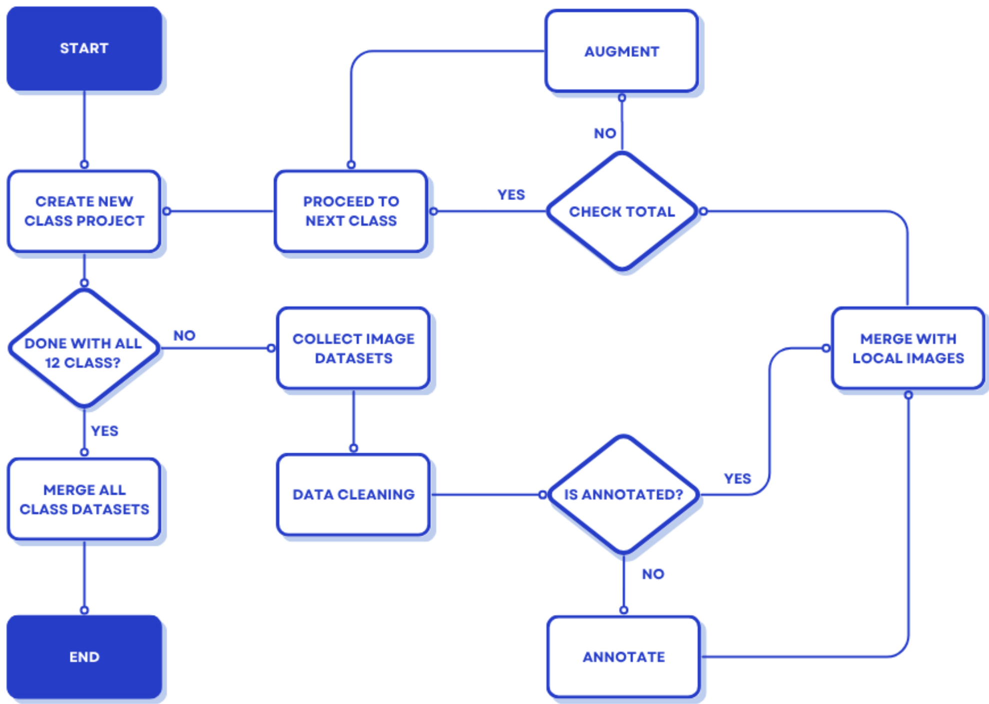

Fig. 1. Dataset Curation Process

Illustrated in Figure 1, outlines the step-by-step flow of dataset curation used in this study. The process began by initiating a new Roboflow project for each of the 12 waste classes. This strategy was adopted to work around the image upload limits imposed by Roboflow's free plan, allowing better organization and scalability. Once a class-specific project was created, the team gathered relevant images from multiple sources, local images captured using the conveyor belt system, annotated and unannotated datasets from Roboflow Universe, and unannotated datasets from Kaggle. After gathering the images, the team proceeded with data cleaning. This involved manually inspecting each image to remove those that were blurry, duplicated, or irrelevant to the target class, ensuring only high-quality and class-appropriate images remained.

Following the cleaning stage, the images were checked for existing annotations. If the images were already annotated (typically from Roboflow Universe), they were moved forward in the process. However, unannotated images commonly from Kaggle or local captures underwent manual annotation using Roboflow's labeling tools. Each waste object in an image was enclosed in a bounding box and labeled according to its class (e.g., banana peel, cardboard, 9V battery, etc.), maintaining consistency throughout the dataset. Once annotation was complete, these images were merged with their corresponding locally captured images, forming a more diverse and realistic dataset for each class.

The next step was to check whether each class had reached the target size either 1,000 images or more than 1,000 total annotations. In cases where the dataset for a class was below the threshold, image augmentation was performed. Augmentation techniques such as flipping, rotation, blurring, cropping, and hue adjustments were applied to increase dataset size and variability. This ensured the model would be exposed to diverse scenarios and lighting conditions, improving generalization during training.

After completing the dataset for a class, the researchers proceeded to the next waste class, repeating the same process until all 12 classes were curated. Once every class-specific dataset had been finalized, they were merged into one unified dataset, consisting of 9,729 images and 17,787 total annotations. This combined dataset was then split into training, validation, and testing sets using a 70-20-10 ratio, preparing it for the YOLOv8 training process.

3.2 Model Training and Evaluation

This section outlines the training and evaluation methodology used to develop the object detection and tracking components of the IoT-based waste segregation system. It includes the training process for the YOLOv8 model, evaluation metrics, fine-tuning procedures, and integration of the DeepSORT tracking algorithm.

3.2.1 Training Process

This study utilized the YOLOv8 model to detect and segregate waste items on a conveyor into their respective bins. YOLOv8 is a deep learning-based object detection framework that integrates a convolutional neural network (CNN) architecture optimized for real-time applications. The network combines convolutional, pooling, and fully connected layers, enhanced by activation functions such as ReLU and techniques like batch normalization to improve training stability. Optimization methods, including gradient descent, momentum, and adaptive learning rates, are applied to accelerate convergence and improve accuracy (Pan et al., 2024).

The dataset was split into training, validation and testing with Roboflow train/test split feature, allocating 70% of the dataset to training allows the YOLOv8 model to learn effectively from a substantial portion of the data. The 20% of the dataset allocated to validation provides a reliable basis for evaluating the model's performance The remaining 10% could be used for testing which plays a critical role for further fine-tuning if necessary. The researchers decided to use a 70-20-10 split for the dataset in our training process is grounded in achieving an optimal balance between model training, validation, and testing, which ensures both robust learning and reliable evaluation. The YOLOv8 model was trained using the training set, with the default hyperparameters provided by the YOLOv8 framework such as learning rate, batch size, and epochs carefully adjusted based on feedback from the validation set.

3.2.2 Evaluation Metrics

Throughout the training process, TensorBoard was utilized to visualize and monitor key metrics such as loss, precision, recall, and F1-score. These metrics provided insights into the model's performance and guided adjustments to hyperparameters to optimize performance. After training, the model was evaluated using the test set to assess its performance on unseen data.

3.2.3 Fine Tuning

Following the initial training and evaluation, the model's hyperparameters were fine-tuned based on the evaluation results to maximize performance. This iterative process of training, evaluation, and adjustment was repeated until satisfactory performance was achieved. The model underwent three training stages as part of the fine-tuning process. The first was a 20-epoch run to observe initial model behavior and identify early issues in detection and class performance. The second stage involved 50 epochs to adjust hyperparameters, including learning rate and batch size, and to test early stopping. The final stage was a 300-epoch training with early stopping enabled. Training stopped at epoch 228 when the model's validation performance plateaued for 10 consecutive epochs. These stages helped refine the model before arriving at the final version used in testing.

3.2.4 DeepSORT Algorithm

Deep learning-based object detection, Kalman filtering, and data association techniques are combined by the DeepSORT (Deep Simple Online and Realtime Tracking) algorithm to provide reliable multi-object tracking. Deep neural networks are integrated to improve on traditional SORT, allowing accurate tracking even in difficult situations with occlusions or crowded scenes. Given that it can track multiple waste items in real-time, ensuring accurate monitoring and effective sorting, DeepSORT is especially helpful for waste segregation on conveyor belts. Higher recycling rates and less manual intervention are achieved in material recovery facilities by integrating DeepSORT with YOLOv8 to enhance the automation and accuracy of waste segregation processes.

3.3 IoT Integration

In the experimental setup of the study, there are several IoT devices that are integrated to enable real-time waste segregation based on the predictions of the YOLOv8-DeepSORT model. These devices include the Below is an enumeration of the key IoT devices used in our system and their specific roles:

Arduino Uno: The Arduino Uno served as the primary microcontroller for controlling the system. It was responsible for managing inputs and outputs, including motor control and communication with other components. The Arduino Uno was programmed and debugged via a USB connection.

Gsou 1080p T16s Camera: The Gsou 1080p T16s Camera was used to capture real-time, high-resolution images of waste items moving along the conveyor belt. The camera's clarity allowed for accurate waste classification, and it was integrated into the system for image processing and analysis.

DC Motor: A DC motor was used to drive the conveyor belt, offering consistent and reliable control of its movement.

Servo Motor with Plastic Arm: A servo motor equipped with a plastic arm was used for waste segregation, precisely directing waste into the appropriate bins.

Power Distribution: A 5V 3A and 12V external power supply was used to provide stable power to the servo motors and DC motos.

Prototyping and Connections: Breadboard and jumper wires facilitated the prototyping and connections of components. Miscellaneous components like connectors were used to stabilize and secure the connections.

The figure below summarizes the components used in the system, their quantities, and approximate costs:

Table 2. IoT Components and Costs

Components	Quantity	Approximate Cost
Arduino Uno R3 (Compatible) CH340G USB-serial (blue, with cable)	1	₱ 550.00
Type 37 High Torque DC motor 12V 70RPM speed reduction gear box	1	₱ 575.00
MG995 High Torque Servo Motor Metal Gear (180° / 360° rotation)	3	₱ 1170
12V External Power Supply AC/DC adapter	1	₱ 231.00
5V AC/DC adapter	1	₱ 160.00
Breadboard and Jumper Wires	1 set	₱ 500.00
MB102 Breadboard Power Supply Module 3.3V 5V For Arduino Solderless	1	₱175.00
Conveyor DIY Flat Belt	8ft	₱400.00
Miscellaneous	-	₱ 3000.00
Total Estimated Cost		**₱ 6,761.00**

3.4 Architectural Design

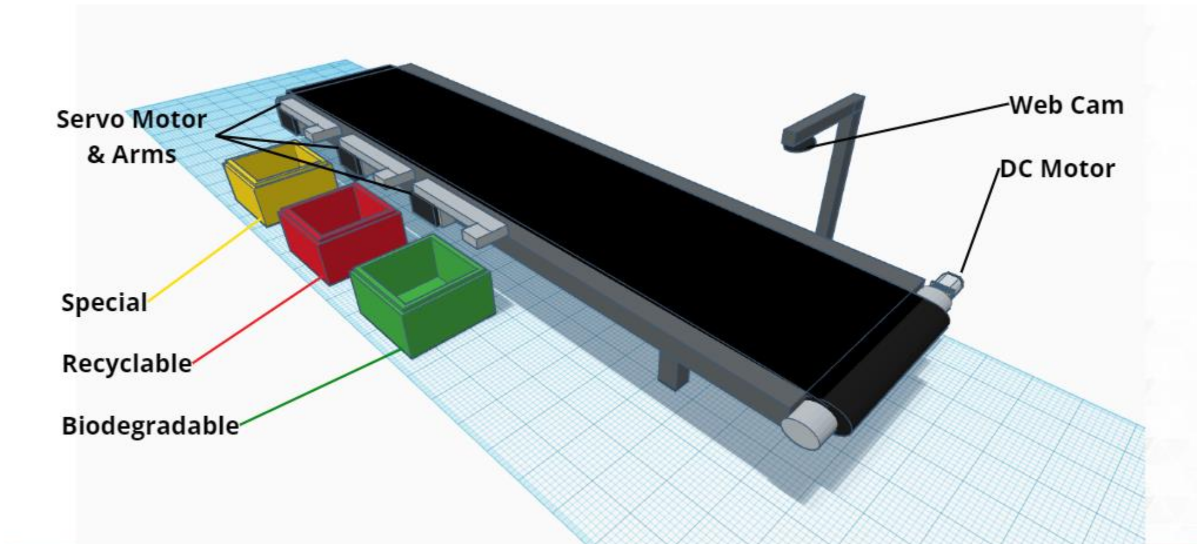

Fig. 2. Architectural Design of Waste Segregation

The architectural design of the IoT-based Waste Segregation system implemented in our study integrates several key components to facilitate efficient waste sorting. Central to this system is a motorized conveyor belt, which consists of 2 rollers and a wooden frame with a black DIY flat belt as the primary mechanism for transporting waste items through the sorting process. Positioned alongside the conveyor are three distinct bins, yellow for one special, red for recyclable, and green for biodegradable materials, each designed to collect different waste categories. Above the bins, a mechanism with servo motor arms is positioned to effectively push or drop sorted waste into the corresponding bins. Additionally, a camera mounted on a mic stand at one end of the conveyor captures images of the passing waste items to assist in identifying and sorting materials based on visual characteristics

3.5 Conceptual Framework

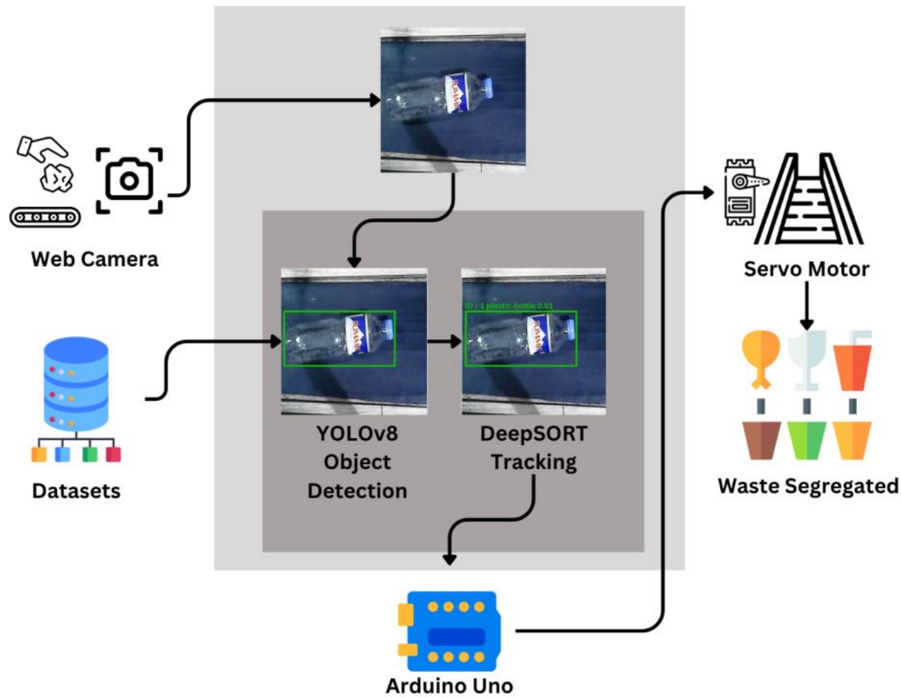

Fig. 3. Conceptual Framework of Waste Segregation System

The conceptual framework of the waste segregation system begins with waste items placed on a conveyor belt, which then pass through the web camera equipped with a YOLOv8 model for object detection. As the waste moves along the conveyor belt, the camera identifies and classifies each item into one of the 12 classes trained using our curated dataset. Based on the classification results. When a waste item is classified, the the arduino controls the servo motor and then the linear actuator arm pushes the waste into its bin category, directing the item to the appropriate bin or collection area. The system integrates IoT devices such as Arduino Uno, and Servo Motors for sorting and control, automating the operation of the arm and facilitating timely segregation based on the classification results.

3.6 **Usability Evaluation**

To ensure the robustness and clarity of the feedback questionnaire, it underwent an initial evaluation by Professional Mechanical Engineers from Mapúa Malayan Colleges Mindanao. This evaluation aimed to assess the questionnaire's suitability and effectiveness in gathering relevant data for the system's usability assessment. The questionnaire was rated on a scale of 1 to 5, where 5 signifies Excellent, 4 Very Good, 3 Good, 2 Fair, and 1 Need Improvement. The evaluation yielded an average rating of 4.67, signifying that the questionnaire was considered "Very Good" to "Excellent" and deemed suitable for deployment. This high rating confirms the questionnaire's quality in effectively capturing user satisfaction and system usability. The Professional Mechanical Engineers who evaluated the questionnaire were Engr. Lee Ceasar L. Catarman, Engr. Ace Vann Cardiff T. Aleria, and Engr. Liregine S. Cayme.

Following this evaluation, to measure the usability of our IoT-based waste segregation system, the researchers will evaluate its effectiveness and efficiency through accuracy and error rates while conducting a feedback questionnaire to measure user satisfaction. Accuracy rate will be calculated by the proportion of correctly sorted waste items out of the total processed, while the error rate will track the misclassified items.

Accuracy Rate = (Number of Correctly Sorted Items / Total Number of Items) × 100

Error Rate = (Number of Incorrectly Sorted Items / Total Number of Items) × 100

Additionally, Technical staff from CENRO will complete the questionnaire, which provides a quantitative score based on questions assessing the ease of use and integration of the system. The survey results, alongside accuracy and error rates, will offer comprehensive insights into the system's performance, ensuring a balanced evaluation of both technical effectiveness and user acceptance.

4. **Result and Discussions**

This chapter presents and discusses the key findings from our study. It begins by detailing the performance of the waste segregation system through real-world tests under various lighting conditions. This is followed by an in-depth analysis of the deep learning model's performance metrics, including training results, precision, recall, and F1 score. Finally, the chapter concludes with the results of the system's usability evaluation. Each section interprets the significance of these findings, highlighting the system's strengths, identifying current limitations, and discussing their implications for waste segregation at Material Recovery Facilities in Davao City.

4.1 **Results of the Locally Relevant Curated Dataset**

Table 3. Curated Dataset

ID	Class	Train	Valid	Test	Annotation	Images
0	9v battery	700	200	100	1,253	1,000
1	Banana peel	700	200	100	1,147	1,000
2	Can	700	200	100	1,044	1,000
3	Cardboard	700	200	100	2,346	1,000
4	Cylindrical battery	300	78	42	1,693	450
5	Durian peel	700	200	100	1,852	1,000
6	Langsat peel	140	40	20	1,901	200
7	Laptop battery	642	184	91	974	917
8	Paper	700	200	100	1,685	1,000
9	Phone battery	700	200	100	1,481	1,000
10	Plastic bottle	700	200	100	1,257	1,000
11	Rambutan peel	113	33	16	1,154	162
Total		3,295	1,935	969	17,787	9,729

The distribution of waste images among various classes and stages for our waste classification system is shown in the dataset matrix found in Table 1. This consists of 12 distinct classes, each representing a specific type of waste material, ranging from biodegradeable wastes like "Banana peel" to recyclable materials such as "Plastic bottle" and "Cardboard." The dataset is structured into three subsets: training, validation, and testing, with a total of 3,295 training images, 1,935 validation images, and 969 testing images. This distribution ensures that the model is well-equipped to learn and generalize across various waste types. Furthermore, the dataset contains a total of 17,787 annotations, providing the necessary information for accurate object detection and classification.

4.2 **Deep learning Model Performance Analysis**

This section closely examines the deep learning model's performance through its training results, confusion matrix, precision analysis, recall analysis, and F1 score analysis. These metrics offer insight into what the model can ideally achieve when classifying waste. By comparing these internal performance measures with the system's actual performance in real-world scenarios, as detailed in Section 4.1, we aim to pinpoint the strengths and limitations that emerge when the model is put into practice at Material Recovery Facilities in Davao City.

4.2.1 Model Training Result

The model was trained over a total of 300 epochs with a patience parameter set to 10, meaning that training would halt if there was no improvement with the model's performance for 10 consecutive epochs.

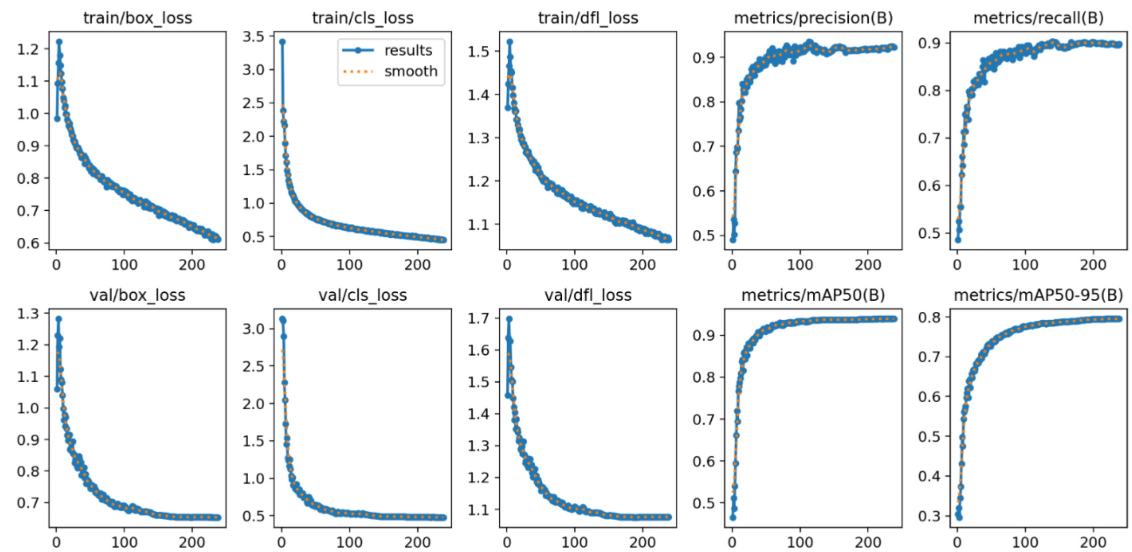

Fig. 4. Models Performance per Epoch

Throughout the training phase, the model demonstrated steady improvement, reaching its peak performance at epoch 228. Training was subsequently halted at epoch 238 due to a lack of significant improvement in validation metrics, thus preventing overfitting.

The model's performance was assessed based on metrics such as mean Average Precision (mAP) and loss values, with the best results recorded during epoch 228.

Comparison to Real-World Performance: While Figure 6 illustrates a strong and improving performance of the model during its training phase, achieving optimal metrics at epoch 228, the real-world tests presented in Section 4.3 reveal that this high theoretical performance does not always translate directly to equally robust real-world system performance. Factors such as varied lighting conditions and the physical characteristics of waste items (e.g., color blending with the conveyor belt) introduced challenges not fully captured during the controlled training environment, leading to discrepancies between the trained model's ideal performance and the system's practical efficacy.

4.2.2 Confusion Matrix

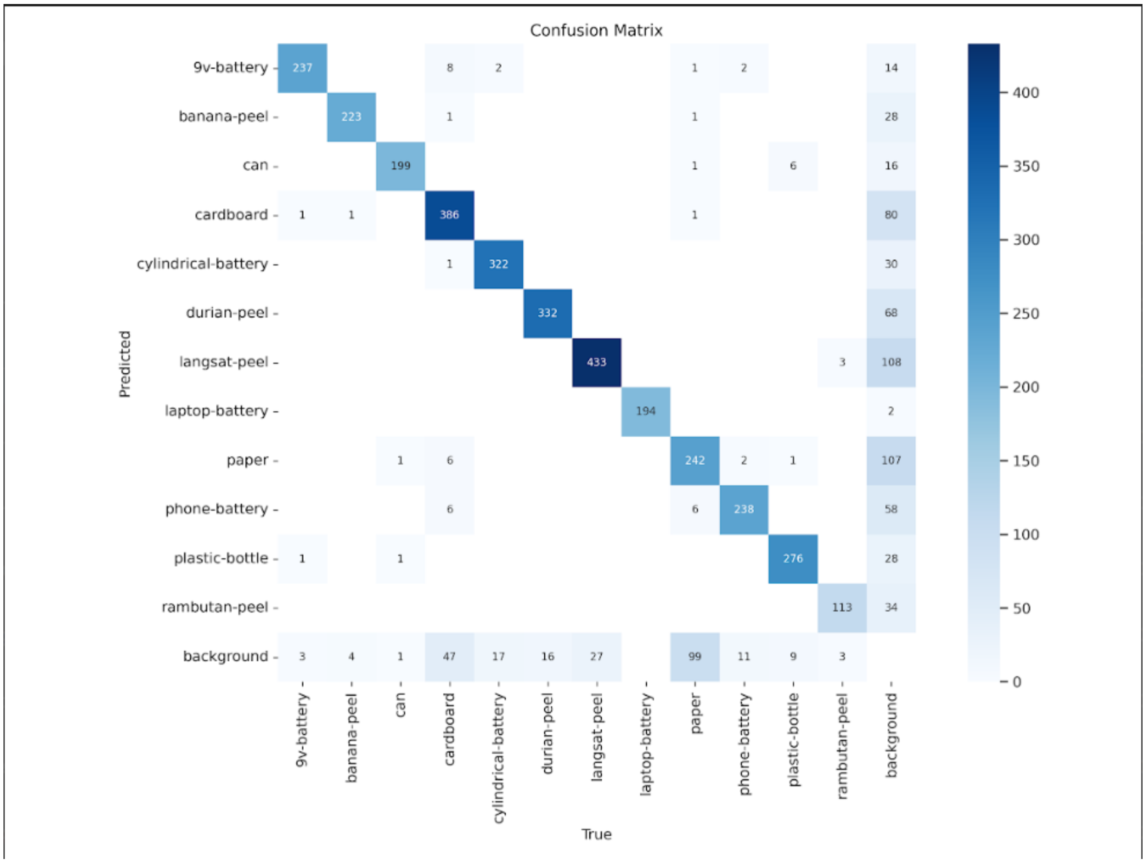

Fig. 5. Confusion Matrix.

In analyzing the performance of our waste classification model, distinct patterns of both correct predictions and misclassifications became evident. As highlighted in Figure 7, the langsat-peel and cardboard classes exhibited the highest prediction accuracy. Specifically, the model correctly identified 433 instances of langsat-peel and 386 instances of cardboard. However, despite langsat-peel leading in accurate predictions, it also accounted for the most background detection errors, misclassifying the background as langsat-peel 108 times. Paper followed closely behind in background misclassifications, with 107 incorrect detections, indicating a similar challenge in distinguishing these materials from the background. This aligns with observations in real-world tests (Section

4.3.4), where Lanzones Peel (a common term for langsat peel in the Philippines) showed a significant drop in correct classification under flashlight conditions, potentially due to lighting making it blend or appear similar to other items.

When it comes to battery waste types, the model encountered more frequent misclassifications. The 9V battery class, in particular, struggled with confusion among other categories. It was misclassified a total of 13 times, detecting cardboard incorrectly 8 times, cylindrical battery twice, paper once, and even confusing itself with a phone battery on 2 occasions. Similarly, the phone battery class showed considerable confusion, misclassifying cardboard 6 times and paper an additional 6 times. These results reveal that the model had difficulty differentiating between the various battery types and certain other classes, particularly cardboard and paper, which may share visual similarities. These internal confusions directly explain the real-world struggles detailed in Section 4.3, where "Phone Battery" and "Cylindrical Battery" were consistently detected but frequently misclassified during actual tests, leading to poor segregation outcomes (Tables 4, 5, 6). The real-world issue of the conveyor belt itself being misclassified as a phone battery under flashlight conditions (Section 4.3.4) further exemplifies these background misclassification challenges in practical settings.

These patterns of errors, especially the high rate of background misclassification for langsat-peel and the frequent confusion between battery types, indicate specific areas where the model’s performance could benefit from further refinement. Improving the model's ability to differentiate between visually similar classes, as well as enhancing its capability to recognize background versus foreground objects, will be critical for increasing overall accuracy and reliability. This evaluation serves as a valuable insight for future iterations of the model, highlighting both its strengths and the areas in need of optimization.

4.2.3 Precision Analysis

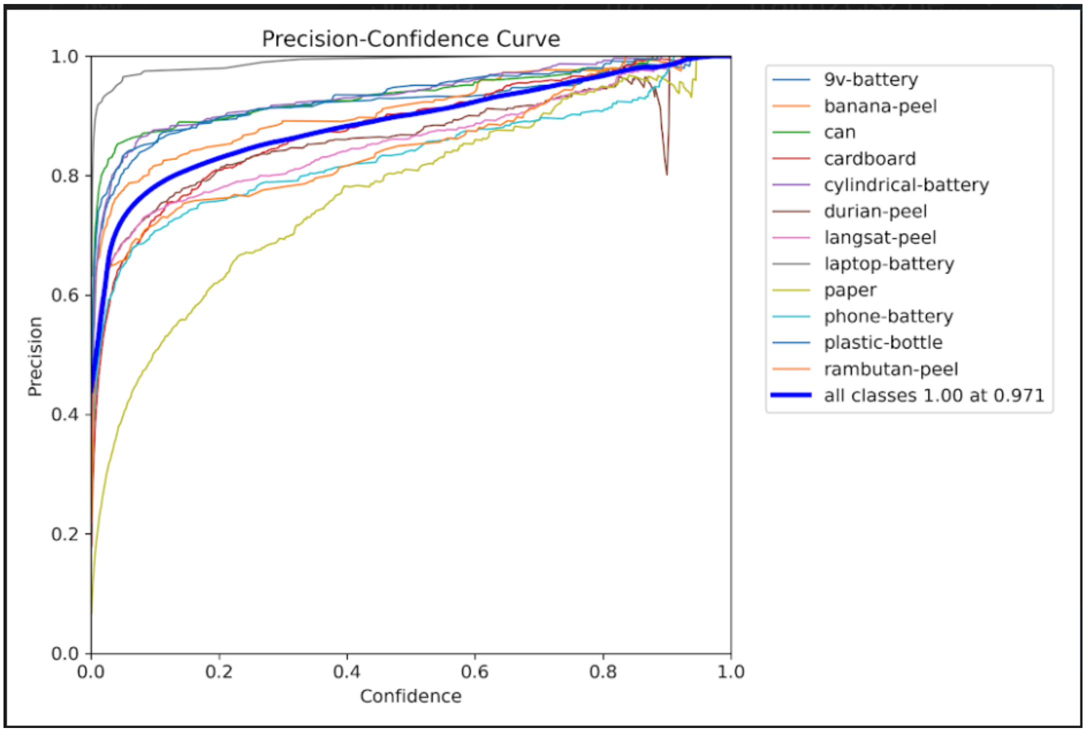

Fig. 6. Precision Confidence Curve

As represented in Figure 8, the precision-confidence curve highlights notable trends in the model's performance for various waste classes. The laptop battery class stands out significantly, achieving the highest precision and confidence, effectively placing it "at the top of the ceiling." This indicates that the model is not only highly confident in its predictions for laptop batteries but also very accurate, with a high percentage of correct predictions. However, this high precision in a controlled environment stands in stark contrast to the 0% detection and segregation of "Laptop Battery" observed in all real-world lighting conditions (Section 4.3.2, 4.3.3, 4.3.4), suggesting that while the model can accurately classify it if detected, the primary challenge is the system's inability to initially detect it due to factors like visual blending with the conveyor belt (Section 4.3.4).

In contrast, the paper class demonstrates very low performance at low confidence levels, sitting at "rock bottom" in the curve. This suggests that when the model has low confidence in its predictions for paper, it struggles significantly with accuracy, resulting in a higher rate of incorrect predictions. However, as confidence increases, so does its precision.

Most of the other waste classes follow a relatively stable trend, with slight improvements in precision as confidence increases. However, an interesting exception is observed in the durian peel class, where the model exhibits a significant drop in precision despite high confidence. This suggests that the model becomes overly cautious when predicting durian peel, leading to more misclassifications for this class. This internal precision challenge for durian peel aligns with its real-world performance, where it was detected but consistently misclassified under Natural Light (Table 4.3.2), demonstrating that even with detection, accurate identification remains an issue for this specific item.

Overall, the precision-confidence curve emphasizes that while some classes, like laptop batteries, are predicted with high confidence and accuracy, other classes, like paper and durian peel, face challenges, particularly at low confidence levels or under certain condition, which are then exacerbated in the dynamic real-world scenarios. These insights can guide further model optimization to improve performance across all classes.

4.2.4 Recall Analysis

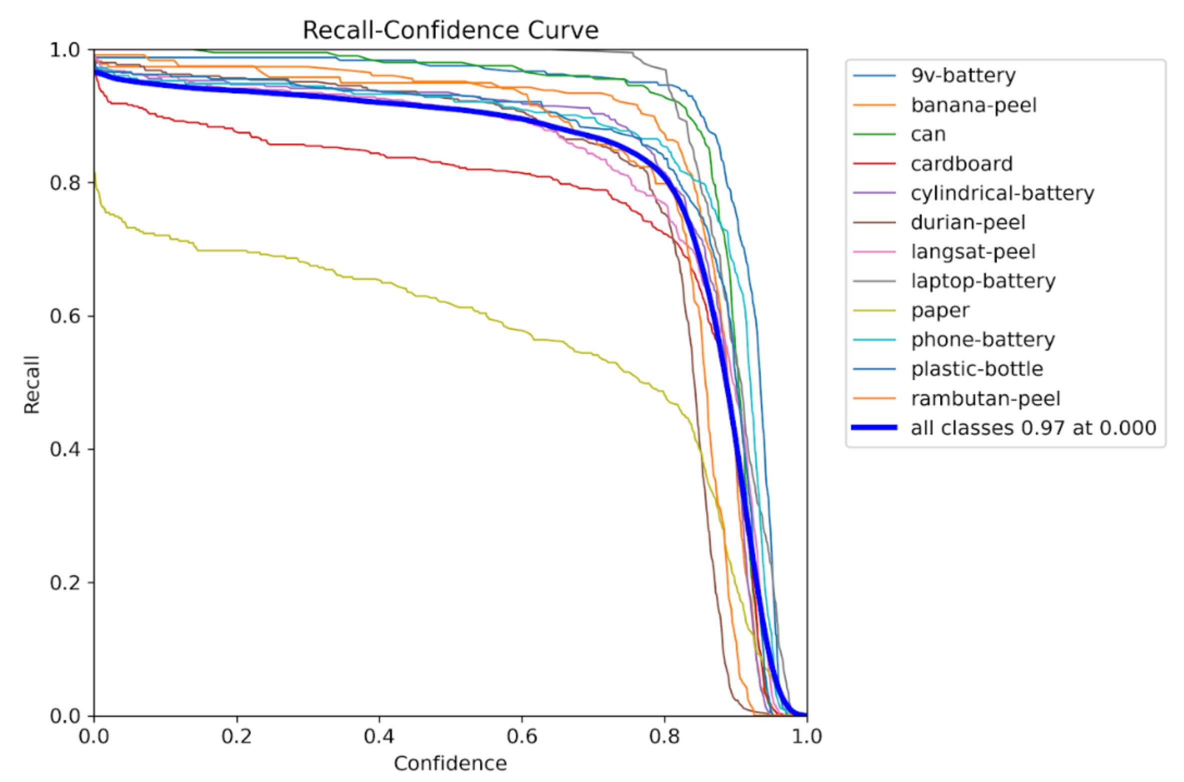

Fig. 7. Recall Confidence Curve

Recall: The Recall Metric reveals considerable visibility across different waste classes, offering insight to model's ability to detect accurately. The Recall Metric reveals considerable visibility across different waste classes, offering insight into the model's ability to detect accurately. As shown in the figure, each waste class has its own recall-confidence curve, which demonstrates how recall decreases as the confidence threshold increases.

The lowest recall value is the paper class, at 0.581 indicating that the model is struggling with detection. The precision for paper is also relatively low compared to other classes at 0.853, with a mean Average Precision of 0.540. This shows the challenges of the model in both accuracy and quality of predictions for this particular class. A possible reason for this difficulty is due to the visual similarities of paper and other waste or paper having the same background color. The internal recall challenges for paper and cardboard are reflected in the inconsistent real-world performance of Cardboard (Section 4.3.4), highlighting that while Paper generally performed well in good light, cardboard in particular posed real detection difficulties for the system.

On the other hand, the highest recall value is laptop battery where it scored a perfect score of 1.0, this shows that the model correctly identifies all instances of laptop batteries. The precision of laptop battery also shows promising result at 0.999 with a mean Average Precision of 0.945. This indicates that the model shows a incredible performance on detecting and classifying this class. Crucially, this perfect theoretical recall of laptop battery is directly contradicted by the 0% detection accuracy in all real-world tests (Tables 4, 5, 6), underscoring that the system's practical limitation lies in object acquisition in challenging environments, not the model's internal classification ability once an item is "seen."

The overall recall of the model for all the waste classes was 0.899 which indicates it's generally strong and consistent where most instances were correctly identified. However, when compared to overall precision value at 0.919, there's a slight gap that indicates that the model might be accurate, there are still instances for a missed detection, especially on difficult classes like paper and cardboard. While the overall model recall is high, the real-world overall detection rates were slightly lower (e.g., 83.33% in "Lights On", 80.55% in "Natural Light"), suggesting that environmental variables can still lead to missed detections in practice, even for a model with strong theoretical recall.

For cardboard, the recall value stood at 0.816, which is lower compared to its precision of 0.923. This shows that although the model can accurately classify cardboard, there are still times where it fails to detect. The relationship between recall and precision was noteworthy. For classes such as can and plastic where it has a precision value of 0.951 and 0.961 and a recall value of 0.975 and 0.921. In contrast, the durian-peel class gives a recall value of 0.911 but has a lower precision value at 0.897, suggesting that even though the model can detect durian peels, it sometimes wrongly classifies other materials as durian peels. This characteristic of high recall but lower precision for durian-peel accurately reflects its real-world performance, where it was detected, but often misclassified (e.g., as a banana peel under natural light, Table 4.3.2).

This analysis provides insights into the model's capabilities. These findings highlight the needs of further refinement and augmentation of the dataset, especially on the classes with a low recall such as paper, to further enhance the overall detection accuracy of the model.

4.2.5 F1 Score Analysis

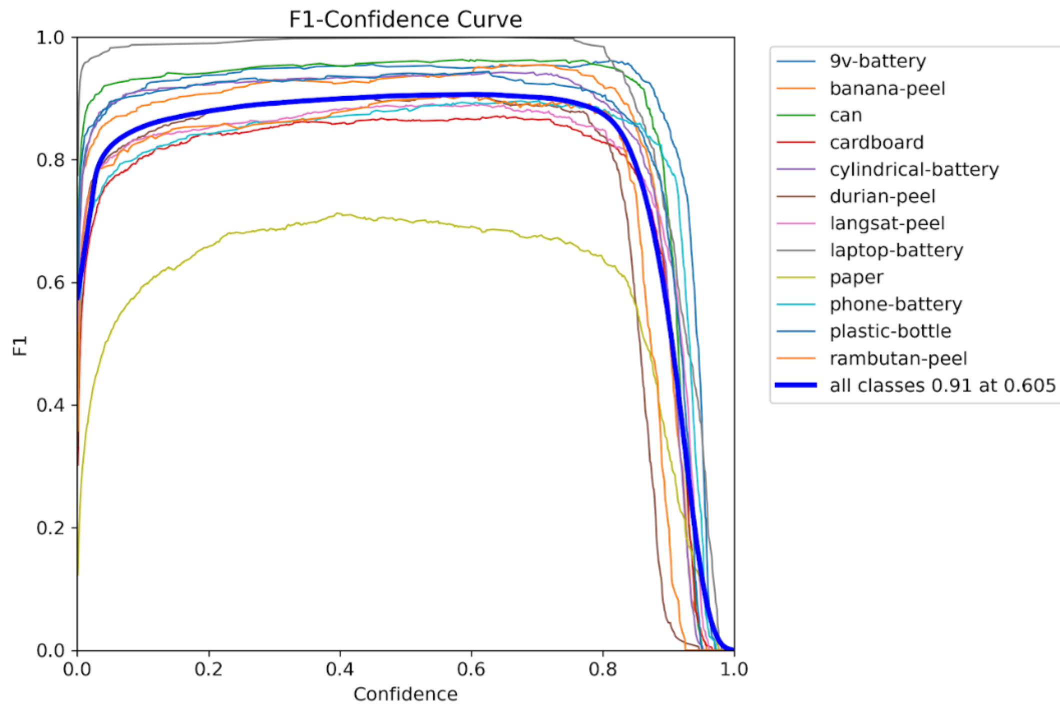

Fig. 8. F1 Confidence Curve

The F1 score is a crucial metric in evaluating the performance of the model. It provides a balance between recall and precision, making it particularly useful when both false positives and false negatives are costly. As shown in the figure, the F1 score for most waste classes remains high across a broad range of confidence values, indicating strong overall performance.

The highest F1 score of 0.999 is laptop battery which shows the effectiveness of the model's detection and classifying. On the other hand, paper still faces challenge with an F1 score of 0.690. This suggests that although the model can detect wastes classes, there are still inconsistencies on certain wastes that are facing issues due to various possible reasons. The near-perfect F1 score for laptop battery is a prime example of the divergence between theoretical model performance and real-world system efficacy, given its 0%

detection and segregation in all practical tests (Section 4.3). This indicates that the system's inability to "see" the object nullifies the model's excellent classification capabilities.

The overall F1 score for all waste classes is relatively high; it was calculated to be 0.909, which indicates a strong performance. This analysis highlights the need for further refinement and augmenting of the dataset to further improve the model and to help the classes with lower F1 scores to increase such as paper and even cardboard. Addressing these issues could enhance the overall accuracy of the model and improve the ability to differentiate between similar waste classes. Despite this high overall model F1 score, the system's correct segregation rate in real-world scenarios was considerably lower (e.g., 63.88% across all tests in Section 4.3), indicating that challenges beyond the model's internal classification, such as inconsistent object presentation and background interference, significantly impact the overall practical performance of the waste segregation system.

4.3 System Performance in Real-World Scenarios (Test Results)

This section presents the practical performance of our waste segregation system through real-world tests. Following the methodology outlined in Chapter 3, particularly the three distinct lighting test cases, we evaluated how well the system detected, classified, and segregated various waste items under different lighting conditions. While generally robust in good lighting, our tests revealed specific challenges and variations in performance under natural and low-light environments, especially for certain waste types and in distinguishing items from the background. The detailed results for each lighting scenario are provided in the following subsections.

4.3.1 Performance under Controlled Lighting (Lights On)

Under optimal "Lights On" conditions, the waste segregation system generally performed well. The overall detection accuracy was 83.33%, meaning most items placed on the conveyor were identified. The system also showed a proper segregation rate of 77.77%, indicating that items frequently ended up in the correct type of bin, even if misclassified. However, the stricter correct segregation rate, where items were both accurately classified and segregated, was lower at 63.88%.

A detailed breakdown of the system's performance metrics for each waste class and category under "Lights On" conditions is presented in Table 4.

Table 4. System Performance Metrics under Controlled Lighting (Lights On)

Waste Class	Detection Accuracy	Classification Accuracy	Properly Segregated (S+SC)	Correctly Segregated (S Only)
Durian	66.6%	50%	66.66%	33.33%
Rambutan Peel	100%	100%	100%	100%
Lanzones Peel	66.66%	50%	66.66%	33.33%
Banana Peel	100%	100%	100%	100%
Laptop Battery	0%	0%	0%	0%
Phone Battery	66.66%	0%	0%	0%
9V Battery	100%	100%	100%	100%
Cylindrical Battery	100%	33.33%	100%	33.33%
Can	100%	100%	100%	100%
Paper	100%	100%	100%	100%
Cardboard	100%	66.66%	100%	66.66%
Plastic Bottle	100%	100%	100%	100%
Bio-degradable	83.33%	75%	83.33%	66.67%
Special Waste	66.67%	33.33%	50%	33.33%
Recyclable	100%	91.67%	100%	91.67%
Overall Percentage	**83.33%**	**76.66%**	**77.77%**	**63.88%**

As presented in Table 3, several waste classes demonstrated excellent performance under ideal lighting conditions, achieving perfect 100% scores across all metrics. These included Rambutan Peel, Banana Peel, 9V Battery, Can, Paper, and Plastic Bottle, indicating the system's strong capability to accurately identify and segregate these common waste types. The "Recyclable" waste category, comprising Can, Paper, Cardboard, and Plastic Bottle, also showed robust performance with 100% detection and proper segregation, alongside over 91% accuracy in both classification and correct segregation.

However, the system encountered notable challenges with specific items. The "Laptop Battery" registered 0% across all performance metrics, suggesting a complete failure in its detection or classification under these conditions. Researchers theorize that the laptop battery's entirely black color, similar to the black conveyor belt, may have caused it to blend in, making it exceptionally difficult for the system to detect. Similarly, while the "Phone Battery" was detected at 66.66%, its classification accuracy and subsequent segregation rates were 0%, indicating consistent misclassification (e.g., being identified as a can in initial tests) despite its presence being noted. Biodegradable items like "Durian Peel" and "Lanzones Peel" also showed lower classification (50%) and correct segregation (33.33%) rates, despite being detected more often. This highlights instances where these fruit peels were misidentified (e.g., Durian being misclassified as Banana), even if they sometimes ended up in the correct general bin type. The "Special Waste" category, encompassing various batteries, exhibited the lowest overall performance, particularly in classification and correct segregation accuracy.

This section shows that our system works well in good light. However, it also highlights areas where the model needs improvement and more training data, especially for difficult waste types. For example, Figure # clearly shows how effectively the system detected and correctly sorted a 'Banana Peel' under 'Lights On' conditions, demonstrating its capability in ideal situations.

Fig. 9. System Performance Metrics under Controlled Lighting (Lights On)

4.3.2 Performance under Natural Light

Under natural light, our system performed quite well overall, detecting most items (80.55% accuracy) and often putting them in the right general bin (83.33% proper segregation). However, the stricter correct segregation rate (where items were perfectly identified and sorted) was a bit lower at 63.88%. Table 5 shows the full results for each item and category under natural light.

Table 5. System Performance Metrics under Natural Light

Waste Class	Detection Accuracy	Classification Accuracy	Properly Segregated (S+SC)	Correctly Segregated (S Only)
Durian	100%	0%	100%	0%
Rambutan Peel	100%	100%	100%	100%
Lanzones Peel	66.66%	100%	66.66%	66.66%
Banana Peel	100%	100%	100%	100%
Laptop Battery	0%	0%	0%	0%
Phone Battery	100%	0%	100%	0%
9V Battery	100%	100%	100%	100%
Cylindrical Battery	100%	100%	100%	100%
Can	100%	100%	100%	100%
Paper	100%	100%	100%	100%
Cardboard	100%	0%	33.33%	0%
Plastic Bottle	100%	100%	100%	100%
Bio-degradable	91.67%	75%	91.66%	66.66%
Special Waste	75%	50%	75%	50%
Recyclable	100%	75%	83.33%	75%
Overall Percentage	80.55%	79.31%	83.33%	63.88%

Many items, like Rambutan Peel, Banana Peel, 9V Battery, and Plastic Bottle, continued to perform perfectly in natural light. Both "Biodegradable" and "Recyclable" categories generally showed strong detection and proper sorting. This means natural light usually didn't stop the system from finding and sorting most items correctly.

However, some challenges remained or appeared. The "Laptop Battery" was still undetectable (0% on all counts). The "Phone Battery" was always detected but never correctly classified or sorted. New issues arose with "Durian," which was detected and properly sorted but never correctly classified, meaning it was consistently misidentified.

"Cardboard" also saw a big drop in its classification accuracy, leading to poor segregation results. The "Special Waste" category, overall, continued to struggle with accurate classification.

These results show that our system can handle natural light well for many types of waste. But, it still faces ongoing or new difficulties with certain items, like batteries and some biodegradable or recyclable materials, when only natural light is available. For example, Figure 4 clearly shows the system successfully sorting a 'Plastic Bottle' in natural light, proving its strength in typical daytime settings.

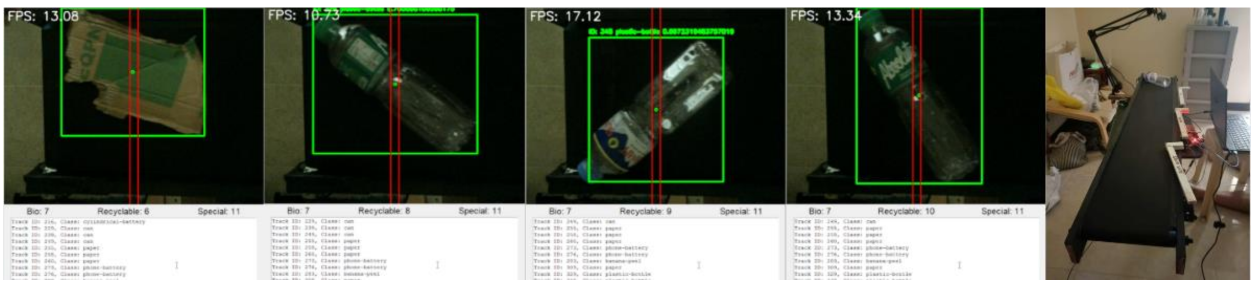

Fig. 10. System Performance Metrics under Natural Light

4.3.3 Performance under Low Light (Flashlight only)

Under "Flashlight Only" conditions, the waste segregation system showed mixed results. It detected items well overall (86.11% accuracy) and often placed them in the right general bin (80.55% proper segregation). However, correctly classifying and segregating items was harder, with a lower rate of 63.88%. This challenge was sometimes made worse because the black conveyor belt itself was mistakenly detected as a phone battery. Table 6 details the system's performance for each waste type under these conditions.

Table 6. System Performance under "Flashlight Only" Conditions

Waste Class	Detection Accuracy	Classification Accuracy	Properly Segregated (S+SC)	Correctly Segregated (S Only)
Durian	100%	100%	100%	100%
Rambutan Peel	100%	100%	100%	100%
Lanzones Peel	66.66%	0%	66.66%	0%
Banana Peel	100%	100%	100%	100%
Laptop Battery	0%	0%	0%	0%
Phone Battery	100%	33.33%	33.33%	33.33%
9V Battery	100%	100%	100%	100%
Cylindrical Battery	100%	0%	100%	0%
Can	100%	100%	100%	100%
Paper	100%	100%	100%	100%
Cardboard	66.6%	50%	66.66%	33.33%
Plastic Bottle	100%	100%	100%	100%
Bio-degradable	91.67%	75%	91.67%	75%
Special Waste	75%	33.33%	58.33%	33.33%
Recyclable	91.66%	87.5%	91.67%	83.33%
Overall Percentage	**86.11%**	**74.19%**	**80.55%**	**63.88%**

As shown in Table 5, even with just flashlight illumination, many items performed perfectly (100% across all metrics). These included Durian, Rambutan Peel, Banana Peel, 9V Battery, Can, Paper, and Plastic Bottle. This shows the system's strong ability to identify and sort these common waste types even in low light. The "Bio-degradable" and "Recyclable" categories also performed well overall.

Some items were still difficult for the system to handle during the flashlight-only test. The laptop battery was not detected at all, possibly because its black color blended in with the black conveyor belt. The phone battery was always detected, but it was often misclassified as a can, leading to low classification and segregation accuracy (33.33%). Adding to that, the conveyor belt itself was sometimes detected and misclassified as a phone battery, which may have affected the system's accuracy. The lanzones peel was also misclassified as a banana, likely because the flashlight made it look more yellow, resulting in 0% correct classification. The cylindrical battery was detected every time but was often confused with the phone battery, so its classification and segregation were also poor. Cardboard had lower performance than in better lighting, with only 66.6% detection and 50% correct classification. Overall, the special waste category (batteries) had the weakest results, especially in correctly identifying and sorting the items.

This section shows that while the system works well for many waste types in low light, challenging items, particularly "Special Waste" and some fruit peels, still pose significant classification problems. This highlights a need to improve the model's ability to recognize objects under various lighting conditions and for items that blend with their background. For instance, Figure 5 could show the system's failure to detect a 'Laptop Battery' under 'Flashlight Only' conditions.

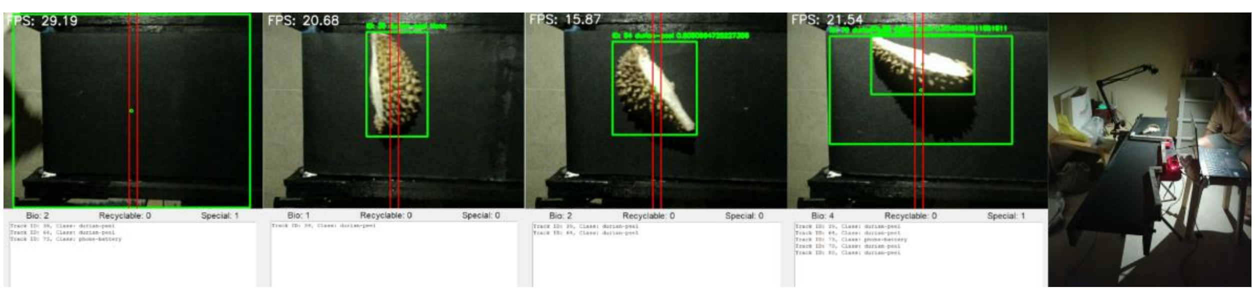

Fig. 11. System Performance under "Flashlight Only" Conditions

4.3.4 **Overall Discussion of Real-world Test Results**

Our waste segregation system was tested in real-world settings under three different lights: regular "Lights On," “Natural Light”, and "Flashlight Only." We found some clear strengths but also consistent challenges.

What Worked Well:

The system was generally good at spotting waste items no matter the light, with high overall detection rates. It also often put items into the right general type of bin. Several items, like Rambutan Peel, Banana Peel, 9V Battery, Cans, Paper, and Plastic Bottles, were perfectly identified and sorted in all light conditions. The Bio-degradable and Recyclable waste categories also performed very well.

Where It Struggled:

The biggest challenge was correctly identifying and sorting items into their exact categories, which was consistently lower across all tests. Specific problems included:

1. Black Objects: The Laptop Battery was never detected or sorted. Researchers believe its black color blended with the black conveyor belt, making it invisible. This issue was made worse because the conveyor belt itself was sometimes detected as a phone battery under flashlight, confusing the system.
2. Similar-Looking Items: The Phone Battery and Cylindrical Battery were often spotted but frequently misclassified (e.g., Phone Battery as a can, Cylindrical Battery as a phone battery or 9V battery). This shows difficulty telling apart similar small items.
3. Changing Looks in Different Lights: The Lanzones Peel was often misclassified as a banana peel, especially with a flashlight, which researchers think made it

look more yellowish. This highlights how different lighting can trick the system.

4. Inconsistent Items: Cardboard performed differently across tests, showing it was sensitive to light changes.
5. "Special Waste": This category, including various batteries, consistently had the lowest overall performance, especially in correct identification and sorting.

What This Means for the Future:

These tests show that while our system works well for many common wastes, we need to improve its ability to:

1. See objects that blend into the background.
2. Tell apart very similar items.
3. Work consistently well under different types of light.
4. Ignore the conveyor belt and focus only on waste.

By fixing these issues, our YOLOv8-DeepSORT system can become much more reliable for waste sorting in Material Recovery Facilities of Davao City.

4.4 Stakeholder Engagement and Usability Evaluation

Fig. 12. Cenro Evaluation Test Survey

This section presents the usability evaluation of the proposed IoT-based AI waste segregation system through real-world testing and survey feedback from personnel at the City Environment and Natural Resources Office (CENRO) in Davao City. The evaluation aimed to determine the system's effectiveness, reliability, and acceptance by intended end-users in a realistic setting.

To gather meaningful feedback, a structured questionnaire was developed based on insights from an interview with a CENRO officer and the guidance of the project's research adviser. The survey consisted of 13 items rated on a 5-point Likert scale, focusing on various aspects such as system accuracy, consistency, ease of use, and perceived impact on waste management. The results of the system testing and the corresponding survey responses are presented and analyzed in this section.

4.4.1 Coordination, Interview, and Survey Design

Prior to testing, the researchers formally submitted a request letter to **Ms. Marivic L. Reyes**, Acting Department Head of CENRO Davao, seeking approval to conduct an interview and system evaluation at their facility. Once the request was approved, an interview was conducted with **Mr. Orly Limpangog**, a Barangay Monitoring Assistant, who provided an overview of CENRO's existing waste segregation process and offered operational insights relevant to system development.

These insights helped the researchers better align the system with real-world practices and also guided the formulation of a usability questionnaire. The survey instrument was further refined with input from the research adviser, **Mr. Patrick Cerna**, to ensure clarity, relevance, and appropriateness. The final questionnaire consisted of **13 items**, using a **5-point Likert scale** ranging from “Strongly Disagree (1)” to “Strongly Agree (5),” and aimed to evaluate system performance, reliability, transparency, error handling, and overall utility in the context of local waste management.

4.4.2 On-site Testing and System Evaluation

Following system integration, the team returned to the CENRO office for real-world testing. The system was deployed in Mr. Limpangog’s office, where five available personnel participated as validators. The remaining staff were unavailable due to off-site assignments.

The system was tested using 12 waste items, each representing distinct categories such as biodegradable, recyclable, or special waste. During this single trial run**,** the system’s detection and classification were observed in real time. Out of the 12 items, 11 were correctly identified and sorted, while 1 item which is a cylindrical battery was misclassified as a 9V battery.

The performance metrics were computed as follows:

- **Accuracy Rate**: $\frac{11}{12} \times 100 = 91.67\%$
- **Error Rate**: $\frac{1}{12} \times 100 = 8.33\%$

This indicates a high success rate, even under non-laboratory conditions.

4.4.3 Survey Results and Analysis

After the system demonstration, each validator completed the usability survey based on their experience. The table below summarizes the results across the 13 evaluation criteria:

Table 7. Evaluation Survey

	Strongly Disagree (1)	Disagree (2)	Neutral (3)	(Agree) (4)	Strongly Agree (5)	Mean
1.) The system provides accurate waste segregation results in real-time.				80%	20%	4.2
2.)THE WASTE SEGREGATION SYSTEM consistently performs without errors under various conditions.				60%	40%	4.4
3.) The system maintains performance levels even with large amounts of waste input.			40%	20%	40%	4
4.) The system is reliable when handling different types of waste (e.g., biodegradable, non-biodegradable).				60%	40%	4.4

	Strongly Disagree (1)	Disagree (2)	Neutral (3)	(Agree) (4)	Strongly Agree (5)	Mean
5.) The system effectively recovers from any detected errors or failures.			20%	20%	60%	4.4
6.) It is easy to identify the points where the system fails during waste segregation.			40%	20%	40%	4
7.) The system provides sufficient logs and feedback for diagnosing issues.			40%	20%	40%	4
8.) The system supports testing in a variety of environmental and operational conditions.			20%	40%	40%	4.2
9.) Test results from the system are reproducible and consistent.			40%	40%	20%	3.8
10.) The system is easy to test and debug, with clear interfaces for monitoring system behavior.			20%	60%	20%	4
11.) Do you believe the system contributes positively to reducing waste mismanagement and improving recycling efforts?				80%	20%	4.2
12.) Do you think the cost of implementing and maintaining the system is justified given its overall benefits and performance?			20%	60%	20%	4
13.) Do you think the cost of implementing and maintaining the system is justified given its overall benefits and performance?			20%	60%	20%	4
					Total:	4.12

Based on the survey responses, the system was rated highly in terms of accuracy, with 80% of respondents agreeing that it provides real-time results and 20% strongly agreeing, resulting in a mean score of 4.2. For performance consistency, the system achieved a mean score of 4.4, with 60% of respondents agreeing and 40% strongly agreeing. The system also received positive feedback regarding its reliability when handling different types of waste, reflected in a mean score of 4.4.

However, responses regarding the system's reproducibility showed some variation, resulting in a mean score of 3.8, indicating potential areas for improvement. The system's ability to recover from errors garnered a mean score of 4.4, suggesting that users felt confident in its error recovery capabilities.

Overall, the system was perceived as effective in facilitating waste management, with the mean score across all questions being 4.12, indicating general satisfaction with its performance.

5. Conclusion and Recommendation

This chapter presents the final insights from the development and evaluation of the IoT-based Waste Segregation System utilizing the YOLOv8 and DeepSort algorithms. It confirms the successful accomplishment of the study's main objectives, which included curating a diverse and representative waste dataset, training and evaluating the YOLOv8 model using performance metrics such as precision, recall, and F1 score, and integrating the detection system with IoT components to enable real-time waste classification. The chapter is organized into two sections: Section 5.1 (Conclusion) discusses the key outcomes of the project, including system performance and user feedback, demonstrating the system's effectiveness and practical potential. Section 5.2 (Recommendations) outlines suggested improvements to further enhance the system's accuracy, scalability, and operational reliability, offering guidance for future development and real-world application in waste management operations.

5.1. Conclusion

This paper presented the findings and results from the development, training, and testing of an IoT-based Waste Segregation system utilizing the YOLOv8 and DeepSort algorithms. The study successfully achieved its objectives, which included:

1. Dataset Curation: A comprehensive dataset was meticulously curated, encompassing various waste classes to enhance the effectiveness of object detection. This foundational step was crucial for training the model to recognize and classify different types of waste accurately. By ensuring diversity in the dataset, including common and less frequent waste materials that are available here in

Davao City, the model's robustness was significantly improved, allowing it to perform well under varied conditions.

2. Model Training and Evaluation: The YOLOv8 model was trained using the custom dataset, and its performance was rigorously evaluated through multiple metrics, including recall, precision, and F1 score. These metrics provided a comprehensive understanding of the model's accuracy in waste segregation tasks, highlighting its ability to minimize false positives and false negatives, which are critical in real-time applications.

3. Real-time Integration: The system effectively integrated real-time YOLOv8-DeepSort detection with various IoT components, enabling seamless monitoring and classification of waste as it passed through the segregation system. This real-time capability is vital for ensuring efficient waste processing, allowing for immediate response to any errors or misclassifications that may occur during operation.

The evaluation results indicated that the system operates efficiently, achieving an impressive accuracy rate of 91.67% during testing. This level of accuracy signifies the system's effectiveness in real-time waste segregation, showcasing its potential as a practical solution for addressing the growing challenges of waste management in urban environments.

Furthermore, user feedback collected through a comprehensive survey revealed a mean satisfaction score of 4.2. This positive response underscores the system's usability and acceptance among users, highlighting its potential to improve waste management practices in real-world scenarios. The feedback indicated that users found the system intuitive and beneficial, which is essential for encouraging adoption in municipal waste management operations.

5.2 Recommendations

To enhance the performance and effectiveness of the IoT-based Waste Segregation system further, the following recommendations are proposed:

Integration of Advanced IoT Technologies: The system could benefit from the integration of more advanced IoT solutions, such as smart sensors and machine learning analytics. These technologies can provide deeper insights into waste composition, track real-time waste flow, and improve the overall efficiency of the segregation process.

Addition of Multiple Cameras: Integrating additional cameras into the system setup is recommended to ensure broader field-of-view coverage. This would help detect waste items that may be missed due to limited angles or obstructions, thereby reducing blind spots and improving overall accuracy in object detection and classification.

Servo Motor Upgrade for Heavier Items: To handle a wider range of waste materials, including heavier or bulkier objects, the servo motors used in the system should be upgraded to models with higher torque. Stronger servos will improve mechanical reliability during sorting, reduce failure rates, and enhance the system's capability to segregate diverse waste types effectively.

Expansion of the Dataset: It is crucial to continuously improve and enlarge the dataset used for training the YOLOv8 model. Incorporating a wider variety of waste types, including local wastes, less common wastes or complex materials, will enhance the model's ability to classify waste accurately and adapt to different environments. Collaborating with local waste management authorities such as CNERO to gather a more extensive range of waste samples could significantly contribute to this effort.

Enhanced Camera Resolution: Investing in higher-resolution cameras will significantly improve the accuracy of object detection, especially for small or similar-looking waste items that may currently be misclassified. Improved visual clarity can lead to better recognition rates and reduced error margins.

Strengthened Conveyor System: Engineering a more robust and efficient conveyor belt system is essential for reliable operation. The conveyor should be designed to handle various waste types seamlessly, ensuring smooth processing and minimizing the risk of jams or operational failures. Considerations should include speed control, durability, and the ability to handle larger waste volumes without compromising segregation efficiency.

Regular Performance Reviews: Conducting periodic assessments of the system's performance will help identify areas for improvement. Regularly reviewing performance metrics and user feedback can guide future enhancements and ensure that the system remains effective over time. Establishing a feedback loop with users can facilitate continuous improvement and adaptation to changing waste management needs.

By implementing these recommendations, the IoT-based Waste Segregation system can significantly enhance its capabilities, thereby contributing to improved waste management practices and supporting sustainable development efforts in communities. As urbanization continues to increase, innovative solutions like this system will play a crucial role in addressing the challenges of waste management, promoting recycling efforts, and ultimately fostering a cleaner environment.

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Appendices

Appendix A. Letter to Validation

MAPÚA
MALAYAN COLLEGES
MINDANAO

September 14, 2024

Hon. Sebastian Z. Duterte
City Mayor
City Government of Davao

Thru: ENGR. MARIVIC L. REYES
Acting Department Head
City Environmental and Natural Resources Office
Ma-a Motorpool Compound, Brgy. Ma-a, Talomo Dist.,
Davao City, 8000, Philippines

Dear Ma'am/Sir

We hope this message finds you well. As a fourth-year students from Mapúa Malayan Colleges Mindanao – College of Computer and Information Science, we are conducting a thesis project titled "Improving Real-Time IoT-based Waste Segregation leveraging YOLOv8 and DeepSORT for Davao Material Recovery Facilities."

As part of our project, we have developed a system prototype aimed at enhancing waste segregation in Davao City's Material Recovery Facilities (MRFs). Our prototype uses a conveyor belt and advanced technology to sort waste items more accurately and efficiently.

We are humbly requesting your permission to test our system using a few sample waste items from your facility's trash bins. We would only need a small portion of your time to conduct the test and a brief survey, as we aim to gather key performance data such as the system's usability, performance, functionality, and accuracy. Your cooperation will greatly assist us in finalizing our prototype and contribute, even just a little, to improving waste management in Davao.

We would also like to acknowledge the kindness of your personnel, Mr. Orly Limpangog, who assisted us during a previous interview regarding the processes at your facility. His contributions have been very beneficial to our project, and we are thankful for the valuable time and information he shared. Additionally, we kindly request further cooperation, specifically asking if Mr. Orly or another suitable person from your team could guide us briefly for the testing process. This support would be crucial for us to ensure the successful operation of our prototype.

Should you have any questions or require further information, please do not hesitate to contact us using the details below. We deeply appreciate your time and consideration and look forward to your positive response.

Sincerely,

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