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An enhanced control solutions for efficient urban waste management using deep learning algorithms

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Abstract

This study focuses on developing an efficient urban waste management system using deep learning algorithms and Internet of Things (IoT) technology. The goal is to improve waste management in Ikot Ekpene municipality by enabling quick disposal responses to prevent environmental pollution. The researchers employed an Object-Oriented Analysis and Design (OOAD) methodology to develop a software system that integrates mobile GIS techniques and IoT sensors to monitor and manage waste. The system was trained using a dataset of 510 images of six classes of waste-related scenarios, with an 84% training set and 16% validation set. The results showed that the garbage bin half-full class had the highest F1 score (above 80%) at a confidence score of 0.4, indicating accurate detection. The average F1 score for all classes was 0.45 at a confidence score of 0.238. The system's API was designed using Python, supporting both web-based and Android-based applications. The integration of IoT sensors and mobile GIS techniques enables real-time monitoring and efficient waste management. This study demonstrates the potential of deep learning algorithms and IoT technology in improving waste management services, contributing to a cleaner and healthier environment. The system's effectiveness in detecting waste levels and triggering timely disposal responses can help prevent environmental pollution and enhance the well-being of citizens.

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1. Introduction

The search for information on safety and precautionary measures dates back to the Stone Age when various primitive and costly methods were used for purposes such as traveling to visit sites and obtaining required authorization [1]. From the Stone Age to the Computer Age, stakeholders visited refuge sites to gather information required by authorities to properly disseminate details

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about waste dumps and their locations [2–5]. Information was stored electronically in computer systems for further processing and decision-making [6–8]. This serves as a safeguard for proper waste disposal and management of information about waste. From the Computer Age to the Internet Age, the world has become interconnected and is often referred to as the global village [9, 10].

At this level, information is easily collected and disseminated to various authorities without stress. In the Internet age, GIS (Geographical Information System) technology conventionally tracks locations, distances, and geographical points of reference using ICT technology [11]. This computer-based system helps authorities analyze and display geographically referenced information by utilizing data attached to unique locations [12, 13]. Before the internet age, GIS was not utilized in waste management, which contributed to the poor operational services rendered by government authorities or agents [14–16].

For instance, in some major towns in developing and underdeveloped countries around the world, there are possibilities of waste dumps encroaching on walkways and waterways, causing traffic congestion, air pollution, and disease outbreaks. This may be principally because government agencies are unaware or have forgotten about them. Therefore, implementing proper ICT technology coupled with GIS would be beneficial in enabling the authorities to promptly identify illegal refuse sites and take proactive measures to mitigate the menace caused by illicit waste dumping sites, thus protecting the environment and its inhabitants.

Although it is widely acknowledged that waste management services are essential in every society, there is a lack of understanding about what constitutes waste. The concept of waste is highly subjective, as one person's waste can be another person's resource. Therefore, it is crucial to have a clear definition of what constitutes waste. As long as human activities continue, waste generation will persist and increase. The consequences of poor waste management are extremely harmful to the environment and human health, serving as a wake-up call to address this issue before it causes further damage [17]. This has led to a search for best practices and the latest technological trends to properly manage waste, giving rise to the idea of an enhanced control solution for urban waste management. This solution aims to improve the quality of waste management and collection.

A clean and healthy environment is a primary objective of every government, aiming to enhance the well-being of its citizens. To achieve this goal, governments engage in activities that promote environmental cleanliness, establishing agencies and parastatals to oversee these efforts. Effective waste disposal and management are crucial aspects of this endeavor. This research will support these agencies and parastatals in fulfilling their responsibilities efficiently, credibly, and reliably. Additionally, it will contribute to the academic community's understanding of waste management, an area previously overlooked despite its significance in maintaining a healthy environment and mitigating its impact on human health. This research will provide valuable insights, enhancing the academic world's comprehension of environmental importance and the necessary measures for its preservation.

Urban waste management is a significant challenge faced by cities worldwide, with inadequate waste management leading to environmental, health, and economic issues. Traditional waste management systems rely on manual data collection and rule-based systems, resulting in inefficiencies and inaccuracies. Urbanization and population growth have led to a significant increase in municipal solid waste, posing considerable challenges to urban waste management systems worldwide. The efficient management of urban waste is crucial for maintaining public health, environmental sustainability, and quality of life. However, traditional waste management practices are often inadequate, relying on manual data collection, rule-based systems, and simplistic estimation methods. These approaches result in inefficiencies, inaccuracies, and inadequate waste collection services, leading to; inadequate waste collection coverage, insufficient waste disposal capacity, environmental pollution through litter and unauthorized dumping, health risks associated with exposure to waste, and economic burdens due to waste management costs.

Recent advancements in deep learning algorithms offer a promising solution to address these challenges. Deep learning techniques have demonstrated exceptional capabilities in pattern recognition, prediction, and optimization, making them ideal for addressing the complexities of urban waste management. By integrating deep learning models with IoT sensors, GIS mapping, and real-time monitoring, it is possible to create a scalable, transferable, and intelligent urban waste management system. This research contributes to the development of sustainable, data-driven waste management practices, enhancing the quality of life for urban populations while mitigating environmental impacts.

This study proposes a novel deep learning-based approach for efficient urban waste management. The proposed system utilizes convolutional neural networks (CNNs) to analyze waste generation patterns, predict waste accumulation, and optimize waste collection routes. The system integrates with IoT sensors and GIS mapping to provide real-time monitoring and decision-making. The objectives are to reduce waste collection costs, increase efficiency, and minimize environmental impacts. The expected outcomes include a scalable and transferable framework for smart waste management, improved waste collection efficiency, and reduced environmental pollution. This research shall contribute to the development of sustainable and data-driven urban waste management systems.

Chen *et al.* [18] researched the development of smart technology that maintains a clean environment and ensures a healthy and hygienic environment. They successfully developed innovative technology that addressed the improper disposal and maintenance of household waste, which had been contributing to public health issues and environmental pollution. However, this machine was unable to remove rubbish from the bin in real time. However, in the past, several intelligent methods were applied to solve this problem. Among these methods are the ones explained below::

Stanislas [19] developed a dynamic and integrative model for waste management in emerging nations, utilizing a range of tools and multimedia capabilities. This model enhanced solid waste management by employing a matrix with various components, highlighting the complex and multi-level nature of waste management processes.

Thaseen *et al.* [20] developed an intelligent waste management application using IoT and a genetic algorithm-fuzzy inference system. By integrating fuzzy logic with a genetic algorithm, they overcame the probability of essential gene loss (referring to location information and waste-filling parameters), which could lead to inefficiency or accuracy loss. This approach preserved the interpretability of the fuzzy inference system (FIS) and minimized the cost of manual interpretation in the intelligent smart waste management system, compared to traditional methods. However, the complexity of the system was a significant drawback.

Resmi *et al.* [21] proposed a GPS-based information system that gathers location information, validates images using an image classification algorithm to roughly identify the type of accumulated waste, and utilizes a K-means clustering algorithm for route optimization. This system assists waste-collecting agencies in tracking waste-dumped areas and provides information on Waste Accumulation Areas (WAAs) to concerned authorities, enabling optimized route decision-making. The application is user-friendly, requiring no special knowledge beyond taking a simple photograph using a mobile camera. However, the system lacks an image classification and segmentation feature, which would have enabled segmenting images into different parts and identifying specific waste types, such as electronic, solid, organic, inorganic, or medical wastes.

Rahman *et al.* [22] proposed a novel solution implemented using an Arduino UNO microcontroller, ultrasonic sensor, and moisture sensor. This system utilizes image processing to measure the waste index of a particular dumping ground. It reduces infrastructure, maintenance, and rating costs by up to 30ensures timely waste collection when the maximum level is reached. However, the high installation cost of smart bins was a significant drawback.

Chukwu *et al.* [23] proposed an intelligent waste management system leveraging deep learning and IoT [24]. Their work presents a real-time waste monitoring system that utilizes a deep learning paradigm and IoT. However, the model has limitations, including only recognizing five categories of indigestible waste, utilizing only two sensors in the developed prototype, and being unable to detect various types of holes in the trash box. Moreover, the system may incorrectly indicate a full bin when it is not even half full due to the nature of the waste. Despite these limitations, the existing system is practical for real-time waste monitoring in household settings. This work can resolve the issue of detecting waste, even when the bin is not full, but litter is scattered on the ground or illegally dumped, posing a threat to the environment.

2. Materials and methods

2.1. Research methods

The following steps/techniques were used to achieve the aim and objectives of the study:

(i) Review of waste management and waste management techniques.
(ii) Human experts in various waste management agencies as well as other academics in the field of computing and waste management were interviewed.
(iii) Several works and journals on waste management and its techniques were consulted.
(iv) The Object-Oriented Analysis and Design (OOAD) system development method was used in developing the proposed system.
(v) The system was implemented with Python as the front programming tool and My SQL as the database engine.

The system implemented in (v) above, was tested in Ikot Ekpene town and the result was evaluated to assess the functionality and adequacy of the system.

The system performs real-time waste management processes via IoT technology, reporting overflow and unauthorized waste dumping to the waste management agency [3]. It captures images of offenders and sends warning text messages alerting them to the health implications of improper waste disposal. The system accurately tracks refuge sites within the metropolis, enabling timely notification to the waste management agency to prevent health hazards [4]. With the GIS component, precise positional data from GPS assists agencies in crustal and seismic monitoring of refuge sites in the town. Utilizing GPS fleet management software, it is possible to track not only the positions of a fleet of vehicles but also their initial positions, movement duration, and efficiency along assigned routes, enabling the evaluation of driver efficiency. By leveraging this capability, fleet managers can transform their waste management GPS tracking systems into time management systems, enabling drivers to stay focused and on-task, thereby reducing the waste of time, labor, and fuel in the field.

2.2. Design methodology

The process of defining a system's components, modules, interfaces, and data to meet specific requirements is known as system design [5]. System design can be understood as the application of systems theory to the creation of finished products. The knowledge and data provided will enhance the system architecture by serving as a resource for implementing the system elements. The proposed system is presented in this section.

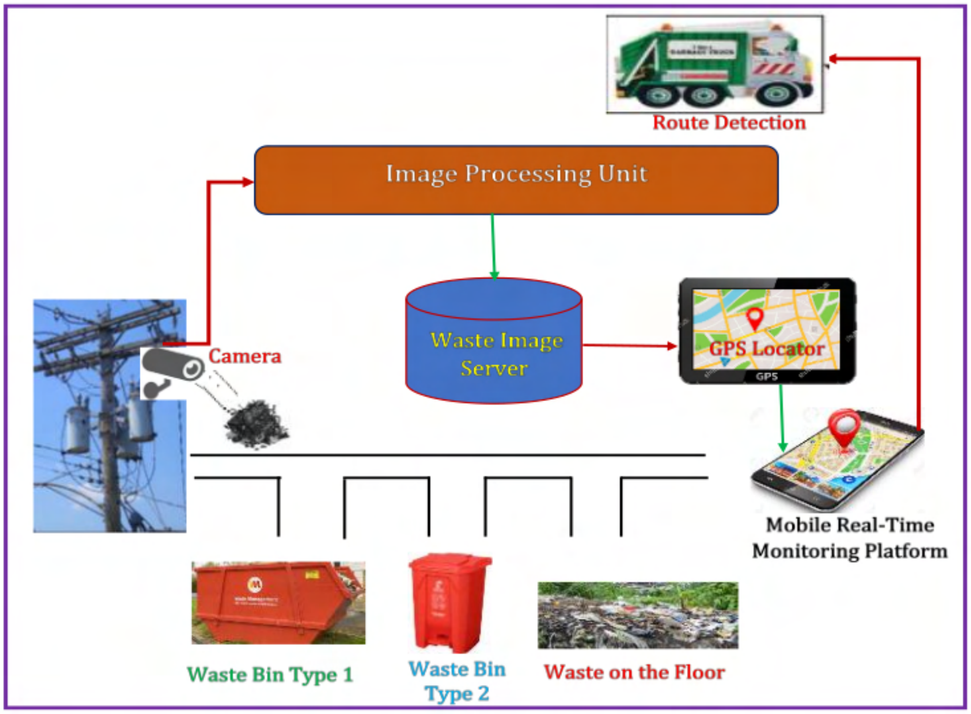

Figure 1: Framework of the proposed intelligent sensor-based control solution for efficient waste management system (Adapted from Wahidur *et al.* [18]).

2.2.1. The framework of the PISBCSEWM

Figure 1 shows the framework of the enhanced control solution for efficient urban waste management. The framework consists of sensitive devices and equipment that embody the IoT approach of the system, facilitating the transaction of information via the Internet. The sensitive components comprise Street Bin 1, Street Bin 2, the Ground bin site (representing the solid waste image source), a Sensor positioned on an electric pole, powered by general electricity, an Image processing component, a Waste processing server, GPS location component. These components work together to enable the efficient management of solid waste.

When the sensor captures images of the waste bin and waste dumped on the ground, it forwards them to the image processing unit, which is built on deep learning algorithms. This image-processing component analyzes the bin and processes the image through a pre-trained model to determine if the bin requires evacuation or not [24, 25]. The output of the image processing unit is hosted on the waste processing server, likely located at the approved waste management agency's facility. The GPS locator receives this output and uses geographical distance measurements to track the exact location of the overflow solid waste or illegal dumping site. A report is then sent via the mobile platform to the stationed truck, prompting evacuation of the waste.

In the proposed framework, the image-capturing module scans the waste material, and after every successful scanning and image-capturing process, a preprocessing component performs real-time processing of the captured images taken by the camera [26]. The proposed methodology consists of the integration of two crucial components: waste classification in the image processing unit through convolutional neural networks and the GPS location system, which enables real-time geographical monitoring using IoT [27].

2.2.2. Framework of the PISBCSEWM image processing unit

The framework for the image processing unit, as shown in Figure 2, consists of the following components: data collection, data warehouse, and data pre-processing, model implementation, comparative analysis of the training algorithms, results evaluation, and the GPS locator. After receiving the analyzed solid waste images, the GPS locator computes the geographical distance to the waste location and directs the truck driver to evacuate the waste.

Data collection

Evaluating solid waste images using Convolutional Neural Networks (CNNs) is a valuable application for automating waste management and environmental monitoring. CNNs are capable of learning to identify different types of waste materials, assisting in sorting, recycling, and managing waste more efficiently [4, 9]. Collecting data for this research involves gathering a diverse dataset of images depicting various types of solid waste, such as plastic, bottles, paper, metal, cans, organic waste, and trash. Each image is labeled with the appropriate waste category. The dataset for this work was obtained using two methods, enabling the researcher to

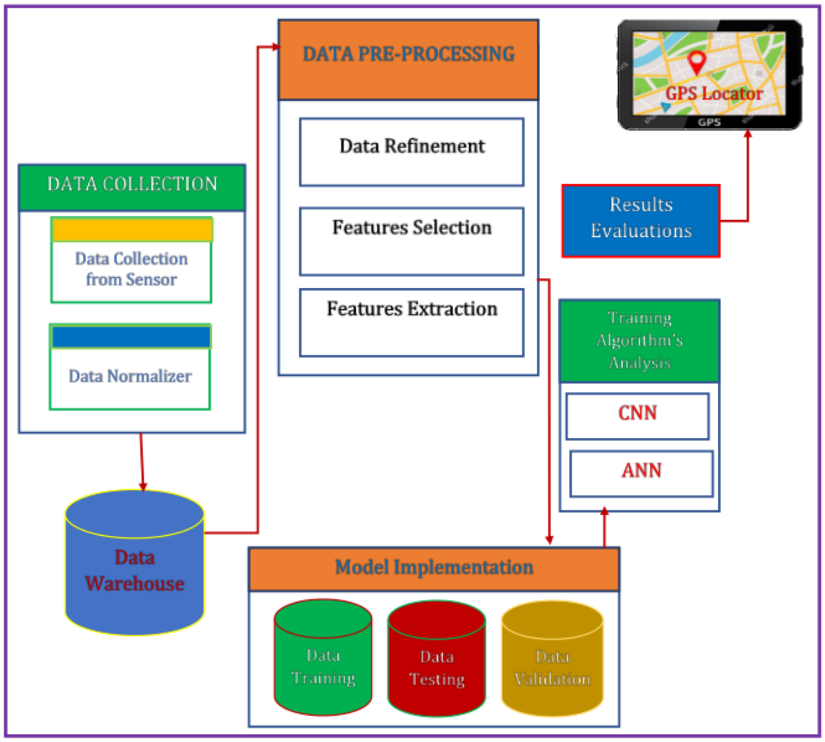

Figure 2: Framework of the image processing unit.

Figure 3: Image of dump site at market Road, Ikot Ekpene, Akwa Ibom State, Nigeria.

gather a large dataset of labeled solid waste images. Firstly, images of garbage bins on the road and at home, as well as garbage sites on bare ground representing unauthorized refuge sites, were captured. Secondly, the publicly available ImageNet dataset, already labeled, was downloaded from the Kaggle site. The ImageNet dataset contains six classifications: cardboard (393), glass (491), metal (400), paper (584), plastic (472), and trash (127).

However, since the scope of this work, in terms of waste management, only focused on evacuation by truck drivers to avoid air pollution, rather than recycling, the features considered during training were textures, colors, shapes, conditions, and sizes. In addition to the already captured images used for simulations, a live camera will be stationed at the garbage sites to capture images in real time, which will be recorded on the system. The system will then use the captured images to train the already trained model to determine the likelihood that the waste requires immediate evacuation or not. These features are scaled through data

Figure 4: Image of the location where people are barred from dumping refuse.

Figure 5: Image of a site showing randomly dumped refuse at Urua Akpan Junction, Ikot Ekpene, Akwa Ibom State, Nigeria.

normalization to standardize the range of features or variables, ensuring that different features with different scales or magnitudes do not disproportionately affect the performance of the CNN algorithm. A Min-Max Scaling with Unit vector scaling (L2 normalization) was used for normalization. Min-Max scaling transforms the data to a specific range, often between 0 and 1, using the formula:

$$\mathrm{X}_{\text{normalized}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}}, \tag{1}$$

where X represents the original feature value, $X_{\min}$ represents the minimum value of the feature, and $X_{\max}$ represents the maximum value of the feature.

The L2 normalization scales each data point so that its magnitude, measured by the L2 norm, becomes 1. This is helpful since both the direction and magnitude of the data are required. The diagrams in Figures 3 to 9 show sample images captured from Ikot Ekpene town in Akwa Ibom State.

Figure 3 shows an image of the dump site, captured to enhance the system with a sample of the dump site. This means that whenever the system receives an image of such a site from the sensor, it will automatically report the dump site to the agencies.

Figure 4 shows the location where people are barred from dumping refuse, which was evacuated by the Agency, and a notice was manually placed to warn the area's occupants against dumping waste on the site. This figure will enhance the system with the

Figure 6: Image of a waste bin captured in Chubb Road Ikot.

Figure 7: Image of a half-filled waste bin captured in Ikot Abia-Idem in Ikot Ekpene, Akwa Ibom State, Nigeria.

knowledge of an empty ground without waste. Figure 5 shows a picture of the image of a site with randomly dumped refuse, which equipped the system with knowledge of the waste's location.

Figure 6 shows a waste bin. This bin indicates that the system does not need to alert the agency. Figure 7 shows a half-filled waste bin. At this point, the waste bin does not pose a health hazard to the environment, and therefore, the system does not need to alert the agency. Figure 8 shows an image of a waste bin surrounded by a littered environment. At this point, although the bin is not filled, the littered waste poses a health hazard to the environment, and thus, the system alerts the agency for evacuation.

Figure 9 shows an image of a waste bin surrounded by a severely littered and disgusting environment. At this point, the waste bin and its surroundings pose a significant health hazard to the environment, and thus, the system alerts the agency for immediate evacuation.

Figure 8: Image of a waste bin with a littered environment.

Figure 9: Image of a waste bin with refuse carelessly dumped at the site.

Data pre-processing

Similar to other image processing and predictions, preprocessing solid waste images by resizing them to a consistent size, normalizing pixel values, and applying data augmentation techniques (such as rotation, flipping, and cropping) is essential to ensure an increase in the dataset's diversity and improve the model's generalization. Data preprocessing is a crucial step in preparing data for machine learning tasks. It involves cleaning, transforming, and organizing raw data into a format suitable for modeling.

The data used in this work was cleaned by handling inconsistencies, errors, and outliers. Data entry mistakes were corrected, duplicate entries were removed, and outliers that could affect the model were adequately handled. To make the data suitable for modeling, feature extraction was performed by creating new features based on existing ones, and transforming the data into a suitable format.

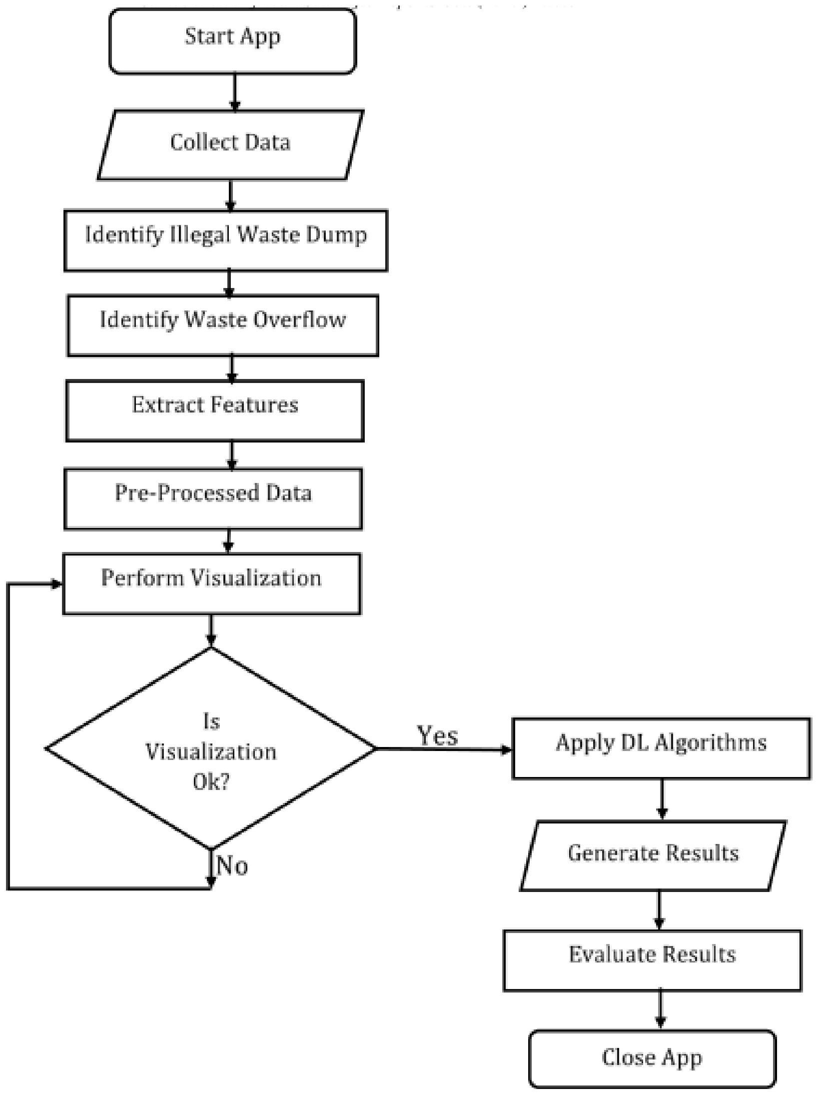

Figure 10: Activity diagram.

Algorithm for the proposed framework
STEP 1: Collect data
STEP 2: Identify illegal waste dumps
STEP 3: Identify waste overflow
STEP 4: Carry out feature extraction
STEP 5: Carry out data pre-processing
STEP 6: Perform visualization
STEP 7: Apply Deep Learning to waste image data
STEP 8: Evaluate results

Activity diagram

An activity diagram is used to graphically depict the sequential flow of activities in either a business process or a use case [28]. Figure 10 illustrates the activities of the system, showing the sequential flow of actions and decisions involved in the process.

3. Discussion of results

3.1. Model implementation reports

The training dataset consisted of a total sample of 510 images, representing six classes: piles of garbage, litter on the ground, garbage bin full, garbage bin half full, garbage bin full and litter on the ground, and empty garbage bin. When training a deep

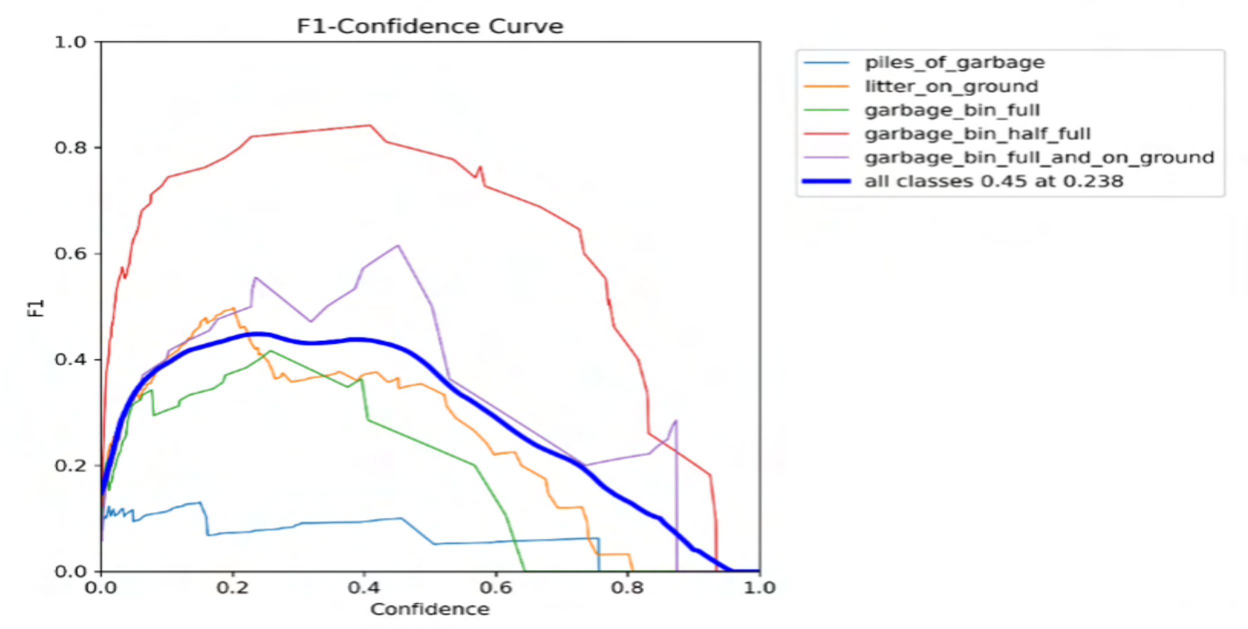

Figure 11: F1-confidence curve on training data.

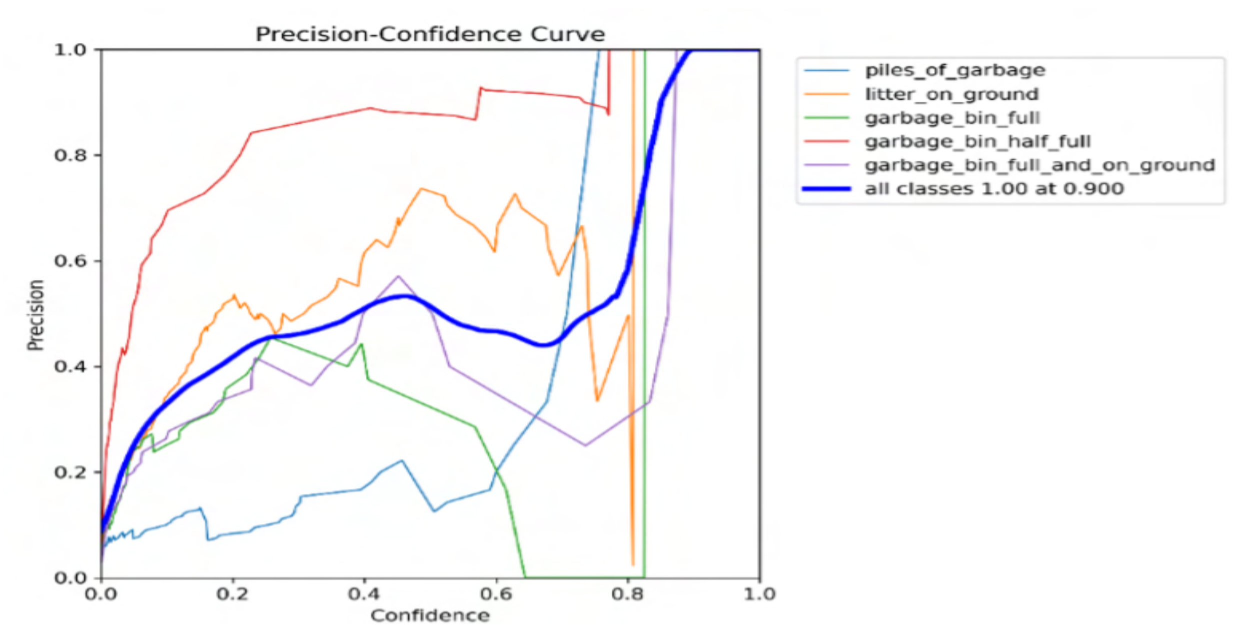

Figure 12: Precision-confidence curve.

learning model, the dataset is required to be split into three parts: a training set, a validation set, and a testing set. In this project, the dataset was split into 84 % training samples and 16 % validation samples.

3.2. *Model performance evaluation*

Predictive modeling often involves training multiple models, applying each to a holdout sample, and assessing its performance. Object detection models are typically evaluated using various performance metrics to assess their accuracy and effectiveness, which help measure how well the model identifies and localizes objects in an image. In this research, we present some of the metrics used to evaluate the performance of the garbage detection model as follows:

a. F1 Score: The F1 score is the harmonic mean of precision and recall, and is a metric used to evaluate the trade-off between precision and recall [29]. It is particularly useful in scenarios where there is an imbalance in the dataset [30]. Figure 11 shows the

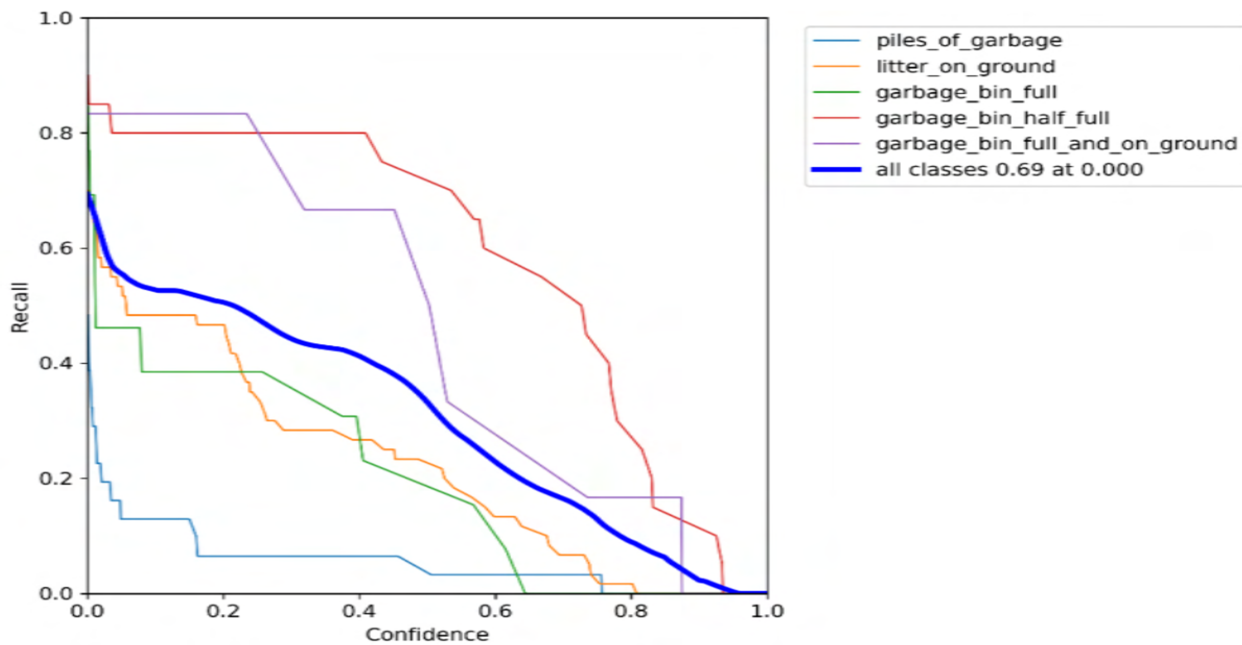

Figure 13: Recall-confidence curve.

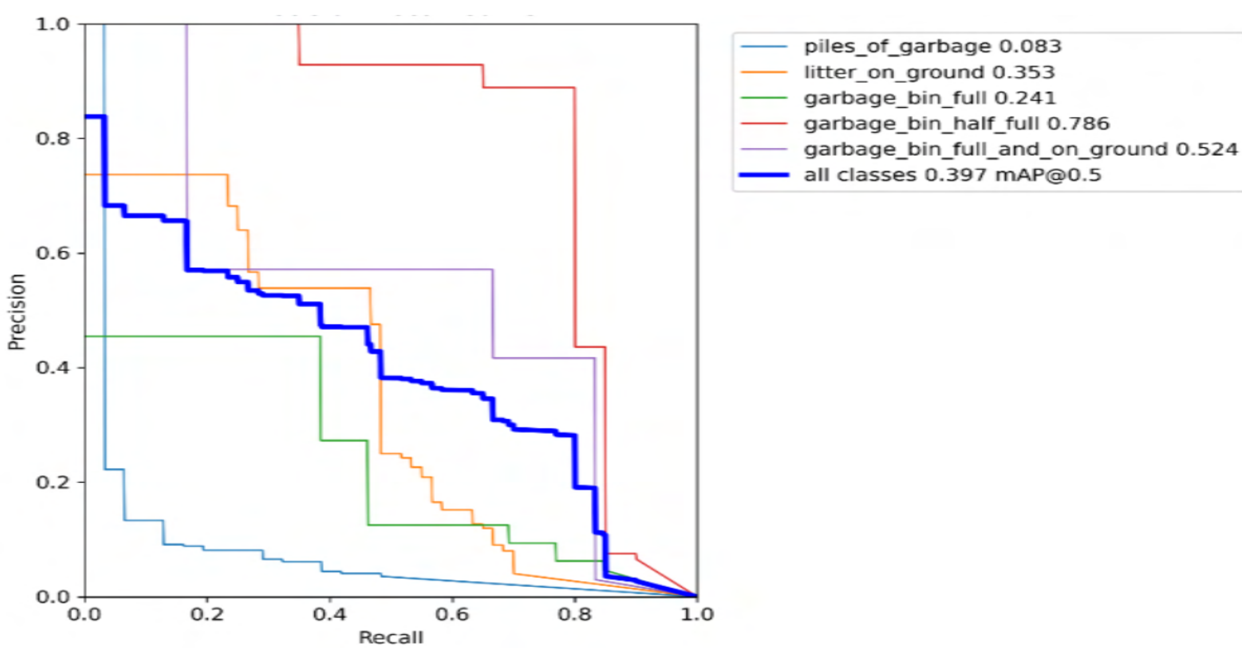

Figure 14: Precision-recall curve.

F1 score obtained from the validation data. Figure 12 shows the curve of the F1 score as a function of the confidence score of the object detection. From the diagram, it can be deduced that the garbage bin half-full class achieved the highest F1 score, exceeding 80 % at a confidence score of 0.4. The average F1 score for all classes was obtained as 0.45 at a confidence score of 0.238.

b. Precision, Recall, and Precision-Recall curves: Precision is the ratio of true positive predictions to the total positive predictions, while recall is the ratio of true positive predictions to the total ground truth positives [**?**]. These metrics provide insights into the model's ability to avoid false positives (precision) and not miss true positives (recall). Figures 12, 13, and 14 illustrate the results of precision, recall, and precision-recall curves during model evaluation. In Figure 14, a precision-confidence curve is presented, showing an average score of 1.0 at a confidence interval of 0.9. As stated earlier, the precision score measures the proportion of true positives among all predicted positive instances, representing how many of the positively identified instances (true positives) are correct out of the total instances predicted as positive (true positives plus false positives). Mathematically, it is expressed

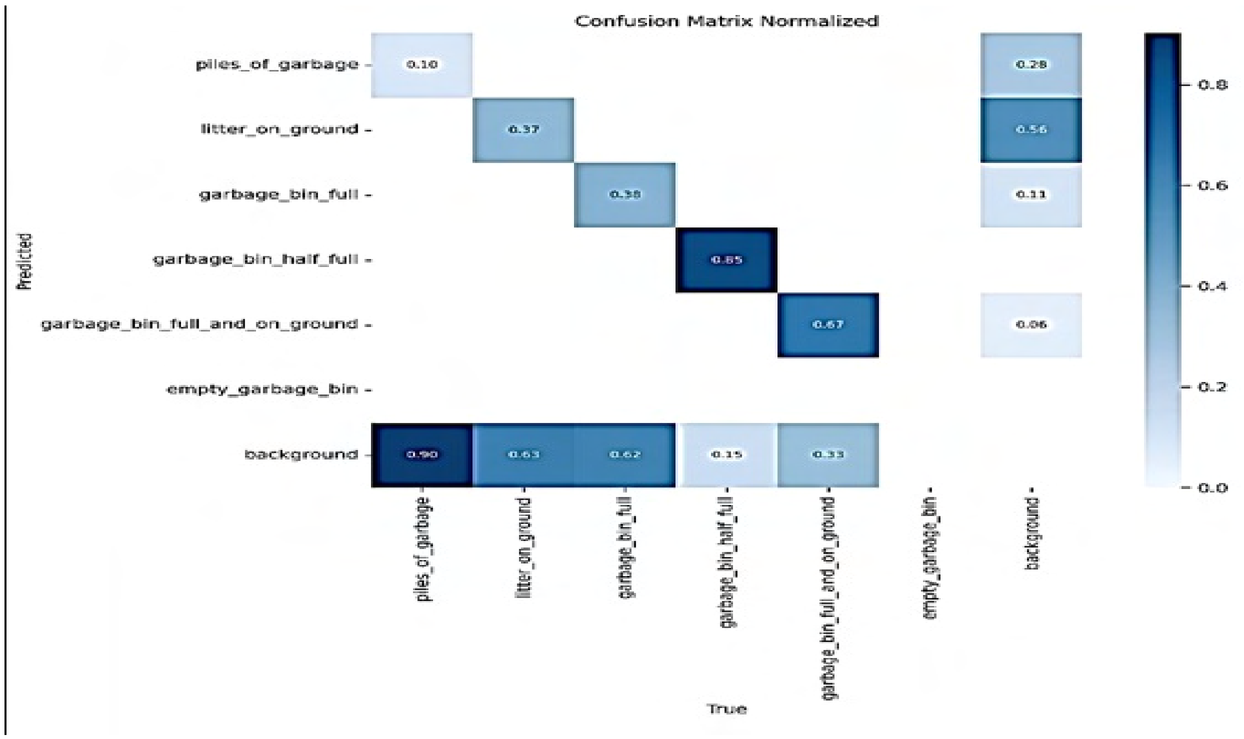

Figure 15: Normalized confusion matrix.

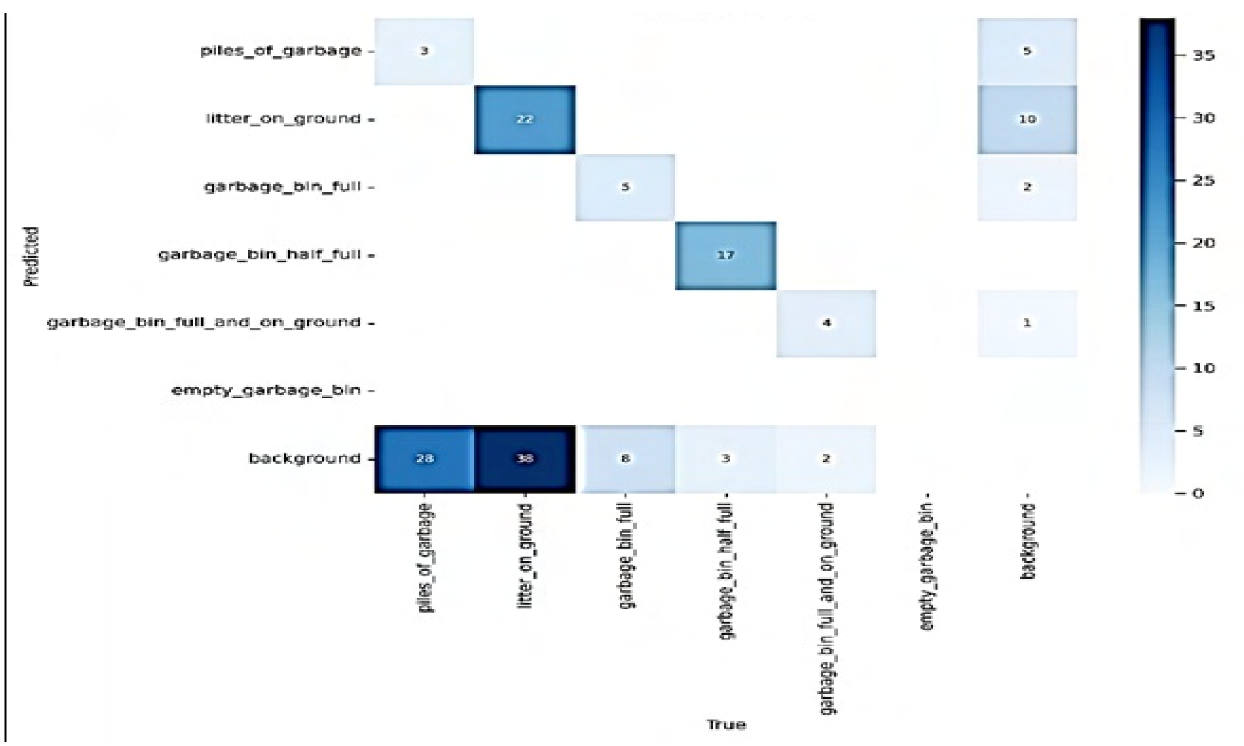

Figure 16: Unnormalized confusion matrix.

as Precision = $\frac{T_p}{T_p+F_p}$. However, we cannot solely rely on the precision score to assess the accuracy of the model; instead, it is considered alongside recall. Figure 14 shows a recall score of 0.69 at a confidence score of 0. Recall measures the proportion of actual positive instances (true positives) that the model correctly identified and is expressed mathematically as Recall = $\frac{T_p}{T_n+F_p}$. A combination of precision and recall is illustrated in Figure 13, which depicts the precision-recall curve.

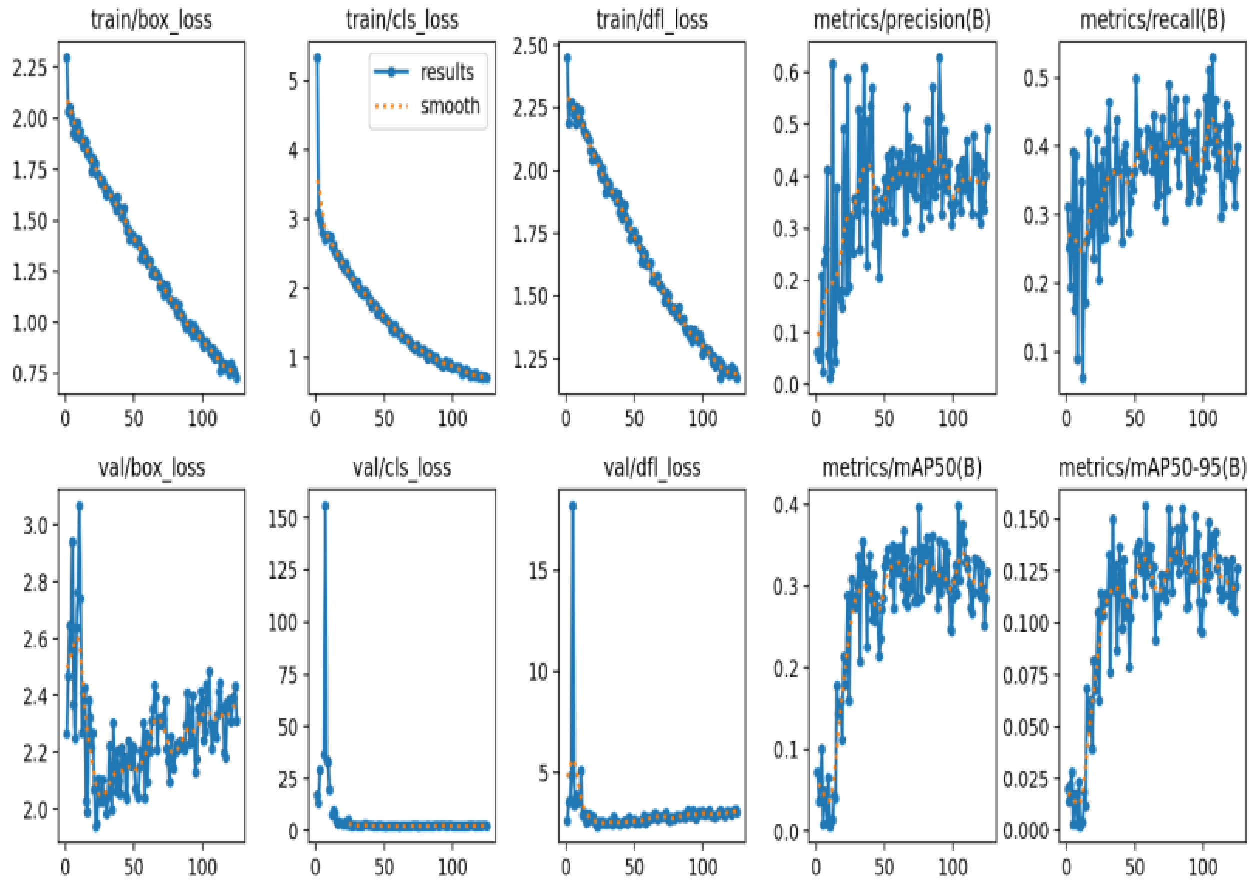

Figure 17: Result of the training and evaluation.

Figure 18: Sample batch 1 validation results.

c. Confusion Matrix: A confusion matrix is a tabular representation commonly used to evaluate the performance of a machine learning model, particularly in classification tasks [31, 32]. It provides a detailed breakdown of the model's predictions and their

Figure 19: Sample batch 2 validation data.

Figure 20: Sample batch 2 prediction results.

comparison to the actual ground truth [33]. While the confusion matrix is particularly useful for binary classification, it can also be extended to multi-class classification [34]. Figures 15 and 16 show the normalized and unnormalized confusion matrices, respectively, for the object detection model evaluation.

d. Model Training result: The object detection model developed in this research was trained for 120 epochs, and the results of the training and evaluation are illustrated in Figure 17.
e. Sample training and validation results: Some sample training and validation results obtained from the model evaluation are presented in Figures 18, 19, and 20, respectively.

3.3. Application interface (API)

The API was designed using Python. The API supports both web-based and Android-based applications. The API can be accessed by clicking the link (link unavailable), which will display the GUI platform shown in Figure 21.

Figure 21: The main API environment.

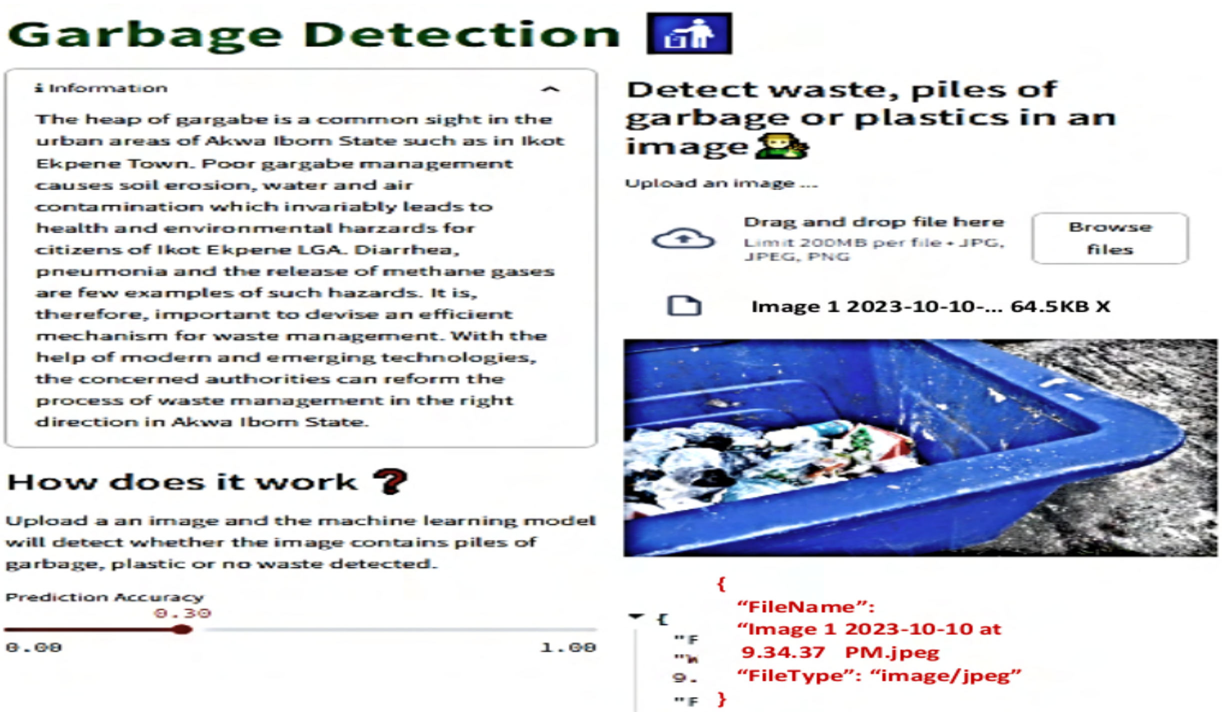

Figure 22: The main API environment with a captured garbage bin.

When the capturing is complete and the captured images are dropped into the waste or garbage box, the captured image will be displayed as shown in Figure 22.

Upon reaching this point, the 'Detect Garbage' button is clicked, and the model will detect and evaluate the garbage, reporting its findings as shown in Figure 23.

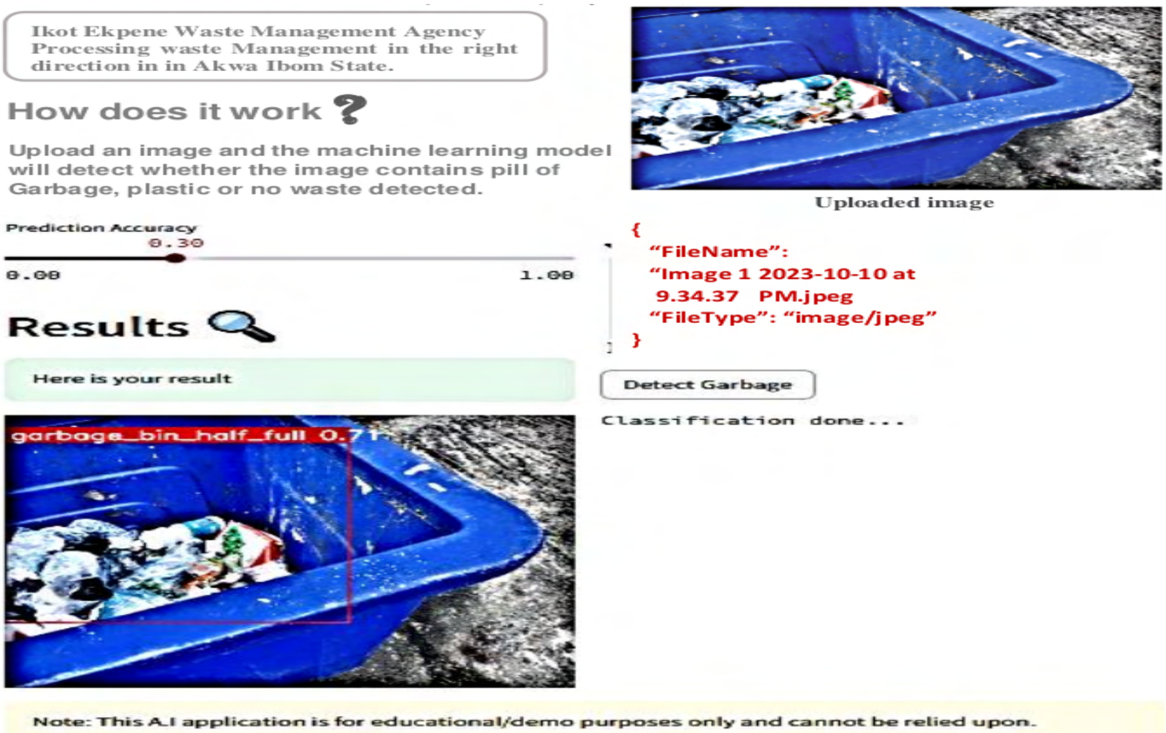

Figure 23: The main API environment with a garbage detection report.

Table 1: Training results.

e	train	train	train	metric	metric	metric	metric	val	val	val	lr	lr	lr	pg2
1	2.3	5.33	2.45	0.06	0.31	0.07	0.02	2.27	16.98	2.6	0.09	0.001	0.001	0.012
2	2.03	3.08	2.19	0.05	0.25	0.04	0.01	2.47	13.26	3.5	0.07	0.003	0.004	0.014
3	2.05	2.99	2.26	0.06	0.19	0.06	0.02	2.65	29.3	3.61	0.06	0.005	0.021	0.005
4	2.02	2.91	2.27	0.21	0.28	0.1	0.01	2.94		4.85	0.05	0.001	0.001	0.006
5	1.98	2.8	2.26	0.02	0.39	0.01	0.02	2.37		18.23	0.03	0.004	0.002	0.009
6	1.93	2.77	2.22	0.23	0.16	0.05	0.02	2.25	36.49	3.36	0.02	0.021	0.005	0.001
7	1.91	2.7	2.19	0.26	0.39	0.05	0.01	2.64	155.9	3.85	0.01	0.001	0.005	0.002
8	1.98	2.73	2.25	0.41	0.09	0.01	0.02	2.77	38.78	3.48	0.01	0.002	0.005	0.012
9	1.98	2.76	2.24	0.06	0.3	0.07	0.01	3.07	19.67	3.52	0.01	0.003	0.005	0.023
10	1.9	2.75	2.19	0.01	0.3	0.01	0.01	2.74		3.59	0.01	0.005	0.001	0.253
11	1.93	2.73	2.24	0.03	0.35	0.01	0.01	2.27	7.65	5.07	0.01	0.005	0.001	0.041
12	1.89	2.6	2.19	0.62	0.06	0.01	0.02	2.26	9.79	2.87	0.02	0.005	0.003	0.025
13	1.86	2.63	2.16	0.08	0.24	0.04	0.01	2.41	8.69	2.95	0.05	0.005	0.005	0.014
14	1.89	2.54	2.14	0.04	0.17	0.04	0.01	2.43	2.93	2.93	0.01	0.001	0.001	0.008
15	1.88	2.48	2.15	0.38	0.26	0.19	0.07	2.03	4.99	2.52	0.02	0.001	0.004	0.009

3.4. Evaluation of results

The model results show that the validation loss increases as the epochs increase, while the accuracy level improves drastically to 92 %. Table 1 displays the training results.

4. Conclusion

Upon full implementation of this technology, waste management agencies will be notified on time to prevent health disasters. The training dataset consisted of a total of 510 images, divided into six classes: piles of garbage, litter on the ground, garbage bins full, garbage bins half full, garbage bins full and on the ground, and empty garbage bins. When training a deep learning model, the dataset is typically split into three parts: a training set, a validation set, and a testing set. Our project dataset was split into 84 % training samples and 16 % validation samples. It can be deduced that the garbage bin half-full class achieved the highest F1 score, exceeding 80 % at a confidence score of 0.4. The average F1 score for all classes was 0.45, with a confidence score of 0.238. Garbage heaps are a common sight in some urban areas. Poor garbage management leads to soil erosion, and water and air contamination, resulting in health and environmental hazards for citizens [10, 11]. Examples of these hazards include diarrhea, pneumonia, and methane gas emissions. Therefore, it is crucial to develop an efficient waste management mechanism [35–37]. By leveraging modern and emerging technologies, concerned authorities can reform the waste management process in these towns.

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