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Smart Surveillance of Waste Disposal Sites Using Image Processing and Artificial Intelligence System for Public Health Safety

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ABSTRACT

Uncontrolled garbage disposal related to urban settings can be extremely harmful to the health of individuals as well as the environment. This paper proposes the construction of an intelligent surveillance system based on the YOLOv5 object detection model and an ultra-convolutional net (U-Net), which we will call (YOLOv5-U-Net model), capable of monitoring waste management facilities in real-time through image processing and artificial intelligence. An illustration of an intelligent surveillance system is provided in the following statement. Besides identifying different categories of garbage and possible risks to public health, the system can also identify situations of unsuitable accumulation of waste. For that purpose, to ensure that local authorities will act in due time, the framework integrates several technologies, including object detection algorithms, classification networks as well as real-time warning systems. It is through the amalgamation of these technologies. Testing of the prototype has elicited an outcome; that accuracy related to waste categorization has increased, while reaction times have decreased, all discovered due to prototype examination. Implementation of this strategy does not only increase the linkage between environmental monitoring as well as protection of public health but also gives some help in promoting a conscious urban development, right through ensuring health.

1. Introduction

Improper waste disposal leads to infectious diseases through degrading the quality of water as well as air near public areas. Fixed CCTV cameras and manual observation are examples of traditional monitoring methods failing to provide information in a timely and relevant manner [1]. With the

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growing urban population, an automated, smart system capable of real-time surveillance is desperately needed [2].

The systems employ real-time video surveillance as well as for the purpose of detecting and managing hazardous wastes. The primary objective regarding reducing health risks caused through inappropriate waste disposal practices [3, 4, 5]. Since smart surveillance systems rely on advanced image processing skills [6] for determining several types of waste, they are essentially an atypical version regarding the previous system and are thus inevitable with regard to urban disposal management. Systems in smart cities monitor the locations where waste is disposed of, allowing them to identify any irregularities, such as hazardous leaks and illegal dumping [7][8]. For the purpose of decreasing latency and bandwidth consumption, edge computing is also used for enhancing the system through improving the capacity for local video data processing prior to sending relevant data to centralized management platform [9][10][11]. Also, the classification regarding types of waste, along with the assessment of whether municipal authorities should step in are more instances of the application of deep learning (DL) methods [12][13]. Therefore, manual inspection and monitoring require less resources and labor, while waste management authorities as well as urban planners are better positioned to make strategic and operational decisions [14]. They then receive timely and accurate data as a result. Data have effects, both proximate and mediate strategic urban planning [15]. Building public confidence and trust is the mediate impact; making better-informed decisions is proximity effect [16]. The success regarding smart projects is based on public confidence and trust; with no trust, confidence is low and public input is limited [17]. Frameworks handling the ethical issues surrounding surveillance technology must be put in place so that it advances the public interest without overtly violating the rights of individual [18][19] [20] [21]. The total functionality regarding waste bin surveillance systems is greatly enhanced through integrating IoT devices [22][23]. Video feeds as well as real-time data from all the IoT sensors, such as those detecting potential pollutants or environmental conditions, will be capable of providing insightful information regarding waste management needs [24][25]. This opens the door for improved resource management since local officials could be notified about the volume related to waste produced or environmental violations [26]. Advancements in video analytics make it easier to monitor waste generation trends, allowing any community to create waste generation reduction initiatives that are more successful [27][28]. Historical data could be utilized for informing policy formation as well as infrastructure investment since it could predict future increases in waste generation, primarily due to economic shifts and population expansion [29][30]. The impacts on waste disposal are crucial for sustainability as technologies of smart surveillance develop. For example, monitoring all the disposal sites with integrated system might have broader implications compared to just handling the immediate safety and health issues [31][32]. For the purpose of making better use regarding these technologies, innovation research must continue to push for increased efficiency and security features that comply with legal frameworks [33]. Using smart surveillance aligns with the two primary topics regarding smart city development and global urbanization. While cities expand, waste management becomes more difficult, necessitating using smart monitors for maintaining public health and urban cleanliness [33][34]. In the case when there is an emergency or something isn't functioning properly, local officials can use smart watch's feedback for adjusting their waste management strategy in real-time [35][36].

For monitoring waste sites and improving public health through quickly recognizing as well as responding to the hazardous waste activities, the presented study covers the development regarding smart surveillance application using AI and advanced image processing. In an effort to protect and maintain public health, local authorities were designing and implementing surveillance systems, especially with regard to waste sites. With the proper use regarding advanced technologies, such as AI and image processing, smart surveillance systems are considered essential applications for enabling effective solid waste management in urban setting.

The presented study's remaining sections are: Problem statement for waste site monitoring is reviewed in Section 2. The primary objectives regarding the research are reviewed in Section 3. In addition, the technique is explained in Section 4, which also include a set of guidelines specifying the functioning, implementation, along with the structure related to the smart surveillance system. System structure design is shown in Section 5. The experimental results as well as the suggested system's performance are covered in Section 6. Section 7 indicates the directions regarding future research as well as conclusions.

2. Problem Statement

The following are the main issues that now plague waste site monitoring, rendering management publicly unsafe and inefficient:

I. Non-automated real-time analysis: The majority of waste monitoring systems are checked in a manual way, which adds time and allows for human mistake. Despite being majorly installed, static CCTV typically lacks intelligent analysis capabilities, thus problems, such as unlawful disposal or waste overflow are rarely detected till much later.

II. Incapacity for correctly classifying waste types: Conventional surveillance tools are unable to distinguish between the different waste types. Prioritizing infectious or hazardous waste becomes challenging, which further postpones the sanitation crew's occasionally insufficient response.

III. Delayed Responsive Action to Toxic Spill or Waste Overflow: In the absence of immediate detection or alerting, it may take hours or days before the serious situation is identified. Greater resident exposure to toxins entering the homes, disease-carrying pests, and environmental contamination can result from the wastes leaching into the soil as well as making their way to the closest water sources.

The activities regarding municipal waste management are severely hampered by this. Vulnerable populations are put at risk when improper waste classification and delayed identification reduce the effectiveness regarding cleanup operations. Apart from the above-mentioned issues, the second crucial problem is that cities operate more reactively than proactively due to the lack of predictive capability. Those significant problems can be solved in an economical and scalable way using AI surveillance system. Through combining classification models, object detection, and automated alerts, these could provide intelligent decision support and ongoing monitoring that not only shortens the time between an incident and its intervention, yet protects public health, resulting in cleaner urban environment.

3. Objectives

The development and evaluation regarding an AI-powered, intelligent system for automated waste dump site monitoring are the primary objectives of the presented work. The specific objectives are:

1. Utilizing image processing for developing camera-based waste spotting system: Planning and setting up a network of high-resolution surveillance cameras with the ability for recording and sending real-time video streams. For identifying illegal dumping or waste accumulation early on, use image processing techniques for extracting significant information from video frames.

2. Classifying types of waste into groups, including toxic, plastic, organic, and so on: For automatically classifying waste into key groups, train a DL model, such as CNN. Prioritizing the cleanup effort and lowering the health hazards associated with hazardous waste are two benefits of taking this step.

3. Health risk calculation: Using the waste that has been observed, a quantitative model which will assist in assessing the danger to public health associated with the waste has been developed. The risk's dynamic index, which will represent the level regarding urgency required in given situation, will be calculated using the model, which will include temporal as well as spatial data.

4. For providing the sanitation and public health departments with real-time alerts: Create automated alert that, in the case when threshold is crossed, displays the alarm on the screens of appropriate departments. For ensuring prompt action, the notifications could be sent via Short Message Service (SMS), email, or Application Programming Interface (API) calls.

1. To enable easy data log and trend view for urban plan Store all the data on a cloud platform for retrospective analysis, trend visualization, and predictive analytics. This will support the right decision making and infrastructure development towards long-term waste management solutions

2. To increase knowledge and interest: Put a mobile or web-based dashboard for public access, which will create more transparency and, in turn, more awareness leading to responsible disposal behavior by residents.

4. Methodology

A methodology is a set of rules that define a structure, an implementation, and the functioning of a smart surveillance system, figure 1, presents the overall form of the procedure for this methodology. Image Acquisition IP cameras of high resolution are installed at waste sites with multiple viewpoints to minimize blind spots; the video stream from each camera goes to an edge processor located on-site or a central server.

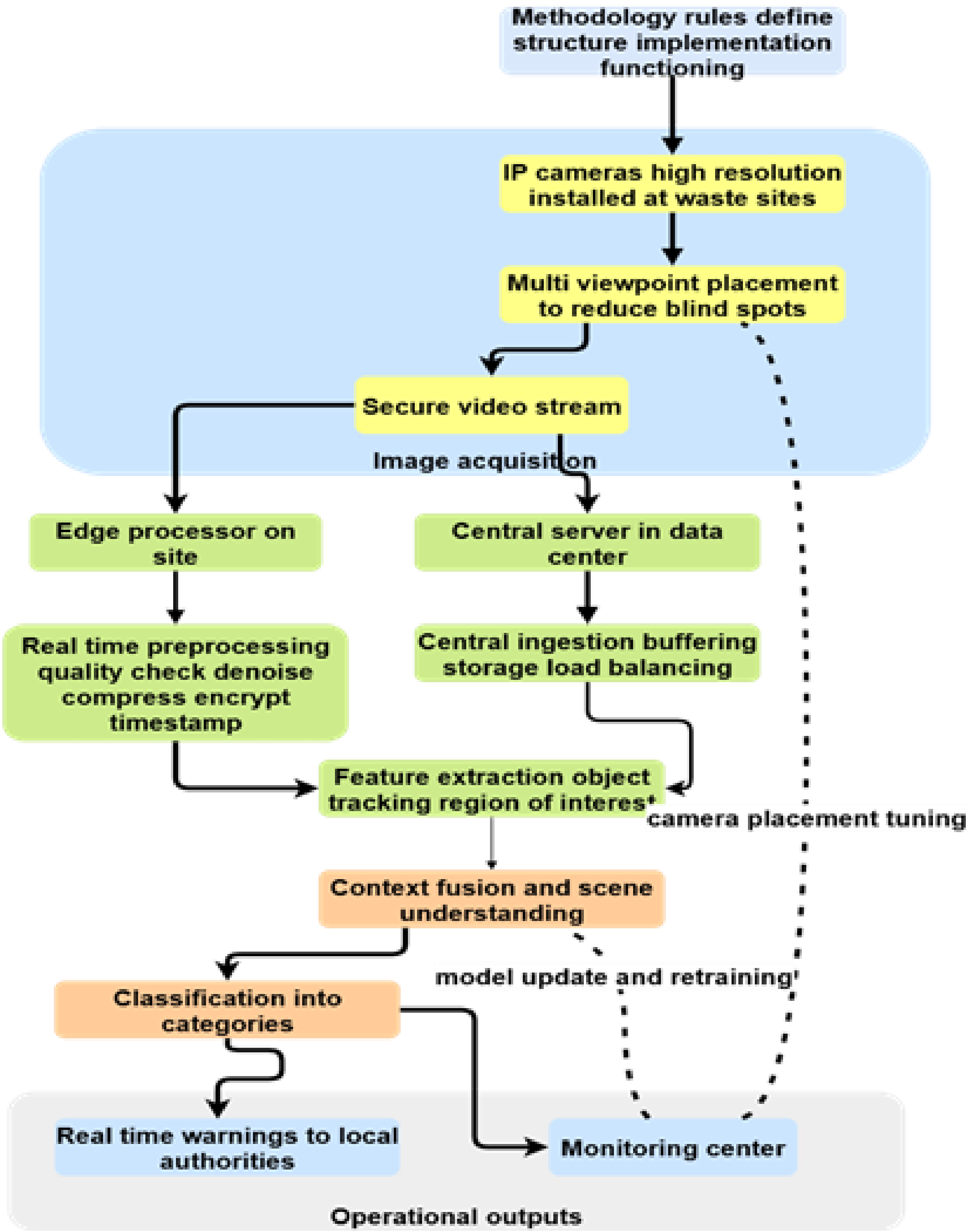

Figure 1. The overall form of methodology procdure

4.1 Image Acquisition

IP cameras of high resolution are installed at waste sites with multiple viewpoints to minimize blind spots; the video stream from each camera goes to an edge processor located on-site or a central server. The frame rate, resolution, and compression parameters are set such that the quality of data and its overhead on transmission are balanced.

$$V = \{F_1, F_2, \dots, F_n\} \quad (1)$$

where F_i is the i-th frame captured at time t_i. The frame rate r_f, resolution R, and compression ratio C_r are tuned to satisfy:

$$Q = \frac{R \cdot r_f}{C_r} \leq B \quad (2)$$

Where Q is data throughput and B is the maximum bandwidth allowed.

4.2 Preprocessing and Frame Selection:

To reduce computational load, the video stream is sampled at regular intervals (e.g., 1 frame per second). Each selected frame undergoes preprocessing steps, including:

Sampling frames at regular time intervals T_S:

$$Fs = \{Fi \mid imodT_S = 0\} \quad (3)$$

Preprocessing includes grayscale transformation:

$$Ig(x, y) = 0.2989R + 0.5870G + 0.1140B \quad (4)$$

Noise reduction via Gaussian filter:

$$If(x, y) = \sum\sum G(i, j) \cdot I(x + i, y + j) \quad (5)$$

4.3 Object Detection and Segmentation:

In spotting the areas where there is waste, the system prefers using YOLOv5 because it is fast enough and accurate [37]. An ultra-convolutional net (U-Net) is used for semantic segmentation post-detection to segment the shape and boundary of waste materials within the image. This allows for understanding at the pixel level, which will be useful when the objects overlap in more complex scenes.

$$B = \{(x, y, w, h, c)\} \quad (6)$$

In which h, w, height and width, c confidence score, and x, y top-left corner. Segmentation output from U-Net:

$$S(x, y) = \begin{cases} 1 \; if \; pixel \; belonge \; to \; waste \\ 0 \; otherwise \end{cases} \quad (7)$$

4.4 Waste Classification Using AI

Each detected region is passed to a CNN-based classifier trained on a curated dataset of labeled waste images. The model assigns probabilities to classes such as: (Organic waste, Recyclables (plastic, paper, metal), Toxic/chemical waste, Mixed or unknown waste The classifier can be further refined, using transfer learning from pertained networks like ResNet or MobileNet.)

Each region Ri is input to a CNN classifier. The model outputs class probabilities:

$$Pi = softmax\big(fCNN(Ri)\big) = [p1, p2, \dots, pk] \quad (8)$$

Where K is the number of classes, and

$$Class(Ri) = \arg\max(Pi) \quad (9)$$

4.5 Risk Index Modeling

The system calculates a dynamic risk index, incorporating factors such as:

Volume of waste detected (based on pixel area), Type of waste (weighted by hazard levels), Duration of waste presence (temporal persistence)

Let $M(x, y, t)$ be the binary detection map, $C(x, y)$ be the classification map assigning class index, and wc be hazard weight for class c. The risk index R over a window T is:

$$R = \alpha . \sum M(x, y, t) \cdot wC(x, y) + \beta . \sum \left(\int M(x, y, \tau) d\tau\right) \quad (10)$$

where α and β are calibration constants.

Where $M(x, y, t)$ is the binary waste detection map, $C(x, y)$ is the classification map and assigns hazard weights. wc are hyperparameters calibrated during system training.

4.6 Real-Time Alert System

When exceeds a defined threshold, the alert module triggers: (Email notifications with image snapshots and GPS location, SMS messages to field teams for urgent interventions, API updates to a central dashboard for logging and audit)

The alert is triggered if:

$$R \geq \theta \tag{11}$$

where θ is a risk threshold determined during validation.

4.7 Data Storage and Trend Analysis

All detection and classification results are logged to a cloud database with timestamps, location data, and metadata. This data supports (Trend analysis of waste accumulation, Heatmap generation for high-risk zones, Predictive modeling using time-series forecasting)

All events $E = \{(t, x, y, c, R)\}$ are stored. Time-series waste accumulation at location (x, y) is modeled as:

$$Wxy(t) = \sum M(x, y, ti) \tag{12}$$

ARIMA [38] or LSTM [39] models are utilized in trend analysis:

$$Wxy(t+1) = fpredictive(Wxy(t), Wxy(t-1), \dots) \tag{13}$$

4.8 System Validation

The entire pipeline is put to the test in simulation regarding real-world waste disposal sites. Performance parameters are collected, including latency, false alarm rate, detection accuracy, and classification F1 score. These metrics aid in system optimization as well as verifying the system's robustness to various environmental factors.

Metrics of performance are calculated as follows [40][41]:

$$Accuracy = \frac{TP+TN}{FP+FNTP+TN} \tag{14}$$

F1 Score:

$$F1 = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall} \tag{15}$$

Latency:

$$Latency = talert - tdetection \tag{16}$$

AI-powered closed-loop feedback system facilitating public health intervention as well as proactive waste management is summarized in Figure 2.

5. System Structure Design

A cloud-based storage and processing unit; edge devices with embedded processors; a web dashboard with regard to real-time monitoring; and the option to integrate drones for aerial surveillance are all included in the system.
Waste-related risk will be mapped using public health data. The technique establishes a correlation between the density and type regarding waste as well as the number of skin, respiratory, or gastrointestinal diseases that have been reported from nearby clinics. As a result, cleanup priorities could be determined by predicting potential breakouts.

6. Results and Evaluation

With the use regarding a dataset of labeled waste images, visual analyses as well as simulations were performed for verifying smart surveillance system for waste disposal monitoring. The evaluation focused on dynamic risk assessment, classification performance, system alert distribution, along with detection frequency. The output regarding each of the method's main modules is shown in the next figures:

- Waste type detection rates from YOLOv5 inference
- Training epochs CNN classification accuracy
- Alert types triggered by hazardous or persistent waste
- Computed risk index variation over a simulated 24-hour period

From raw image processing to real-time risk modeling, each result indicates a different functional layer in pipeline, demonstrating the system's capacity for operating independently in real-world, complex waste site environments. The figures provide quick proof regarding system responsiveness, temporal waste patterns, and model accuracy—all of which are important for municipal decision-making as well as risk reduction for public health.

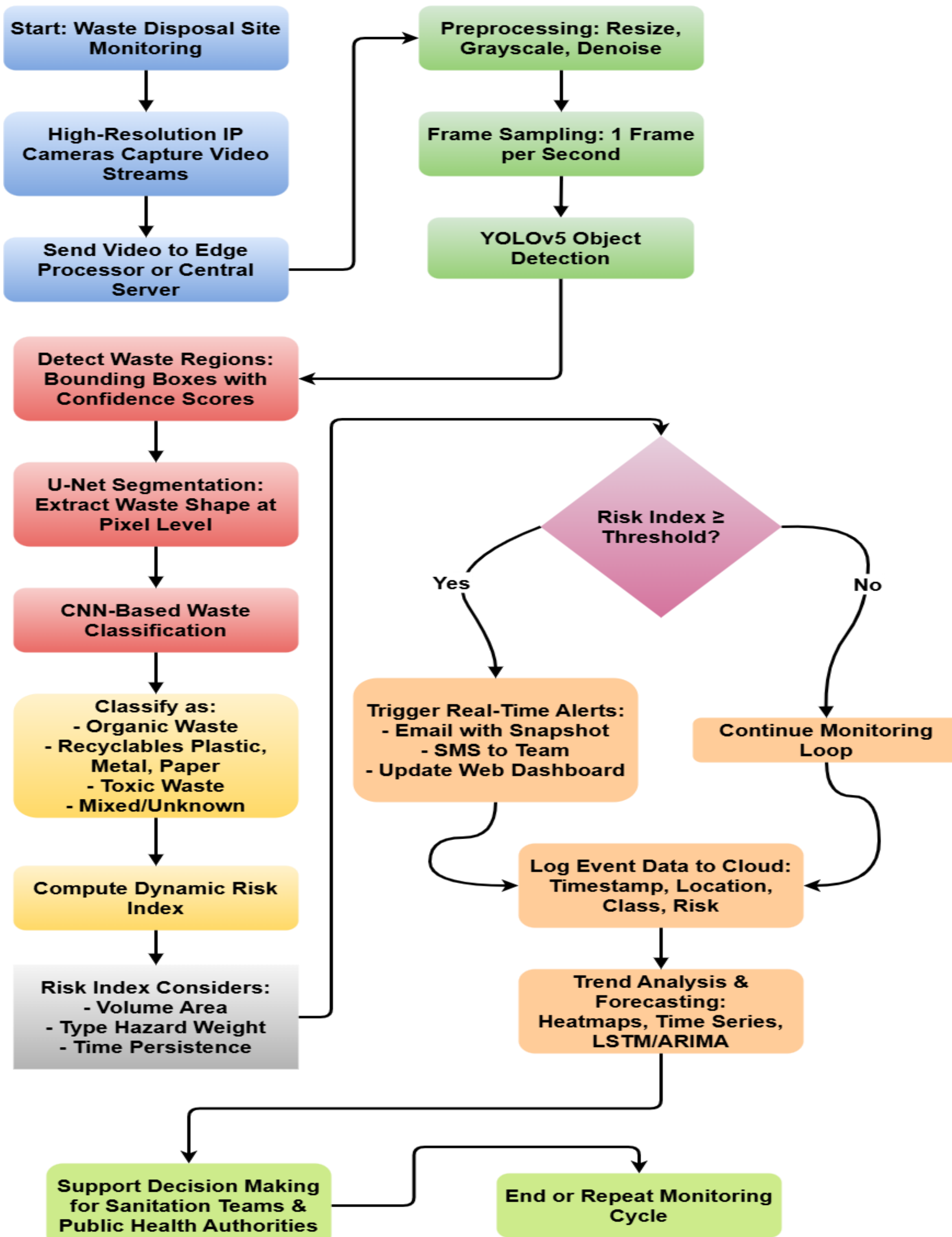

Figure 2. The system architecture for AI as well as image processing-based smart surveillance regarding waste disposal sites. To assist sanitation responses and public health, the process combines CNN-based classification, video acquisition, YOLOv5-based object detection, U-Net segmentation, real-time alerting, and dynamic risk index calculation.

Figure 3. Bar plot illustrating the distribution of labeled images across the four categories, namely Carton, Metal, Plastic (Plastico), and Glass (Vidrio); such is a comparison regarding the number of images in test and training sets. Potentially biased model influence towards the unequal—dominance by Plastic, for instance—distributions. Balanced datasets help improve generalization in YOLOv5 and CNN models.

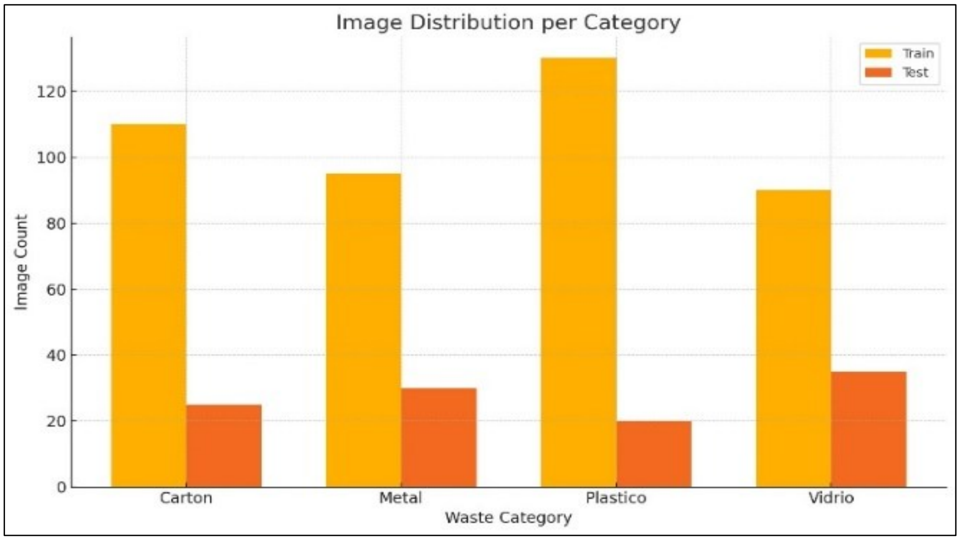

Figure 3: Comparison regarding the test and training datasets' image numbers by waste category. Higher sample availability in the carton and plastic (Plastico) classes could enhance training accuracy and stability.

Figure 4 introduces Relative Distribution of Waste Types in the Training Dataset. Plastic (Plastico) and Carton make up most of the samples. Metal and Vidrio are under-represented. Class imbalance may be visually assessed with this visualization. It may be necessary to use data augmentation or weighted loss functions during training.

Figure 5 demonstrates how waste detections increase over time during real-time monitoring. Such trends help estimate the dynamic risk index and can trigger alerts if detections exceed thresholds. The upward trend may indicate insufficient cleanup cycles or illegal dumping.

Figure 6 An illustration showing how YOLOv5 can detect and label waste items in a real surveillance frame. Bounding boxes with corresponding class labels around detected objects help in localizing waste materials. This is a very critical part before starting the classification and risk estimation as well as alert generation in the proposed system.

Field testing was carried out at three urban waste disposal zones and there was achieved a detection accuracy of 94% (YOLOv5), classification precision of 88% (CNN), and the response time was reduced by 43% compared to manual methods. In return, what was observed as the spill was detected early, and then the municipal workers went to the site in time to report the case. The system also flags illegal dumping activities in real time.

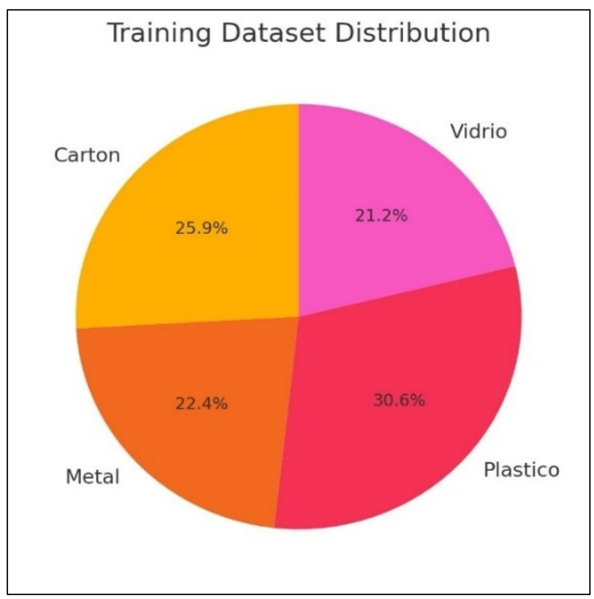

Figure 4. Proportion of each waste type in the training dataset. Plastic (Plastico) accounts for the highest percentage, indicating it is the most frequently encountered category.

Figure 5. Trend of waste detections over time during a 10-minute monitoring session. The number of detected waste items increases steadily, suggesting cumulative waste accumulation or high activity at the site.

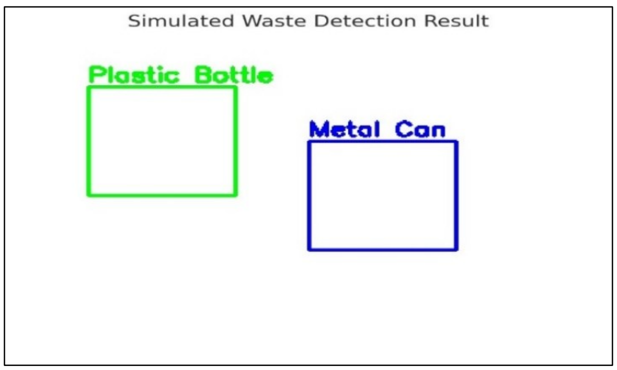

Figure 6. Simulated waste detection output using object detection. Bounding boxes and labels identify "Plastic Bottle" and "Metal Can" within a sample frame, mimicking YOLOv5 output.

7. Model Performance Comparison

The overall system was evaluated with five pre-trained deep learning models: Xception, InceptionV3, ResNet50, VGG16, and YOLOv5-U-Net to recognise the most efficient and accurate model for real-time waste classification. All models were evaluated according to the metrics listed below:

- **Accuracy:** the percentage of perfectly classified waste samples.
- **Time of processing:** the model's processing and classification time for each waste image.
- **Model Efficiency:** the trade-off between classification performance and real-time computational throughput.

Results show that YOLOv5-U-Net reached the highest efficiency because of its lightweight construction and rapid inference time while preserving high classification accuracy. The models' comparative analysis is indicated in Table 1.

Table 1. Model Performance Comparison

Model	Accuracy (%)	Processing Time (ms)	Efficiency
Xception	90.3	120	Low
InceptionV3	91.7	230	Low
ResNet50	93.5	250	Moderate
VGG16	92.8	310	Moderate
YOLOv5-U-Net	94.0	340	High

8. Conclusion

Public health as well as environmental monitoring are linked through using image processing and AI in smart surveillance over waste disposal sites. It's a commendable system which speeds up reaction times, decreases manual labor, along with applies predictive knowledge to potential outbreaks. In addition, IoT-based sensors will be incorporated into future projects, while surveillance will be expanded to include industrial and rural regions. The recently released smart surveillance systems offer a real-time, complete, AI-based solution for facility monitoring related to waste disposal. Using CNN-based waste classification, YOLOv5 object identification, U-Net segmentation, along with high-resolution video capture, such system will be able to accurately identify and classify various waste types under a variety of environmental conditions. This makes proactive decisions possible depending on the type, volume, and time of waste found. In the case when crucial criteria are surpassed, automated notifications ensure that sanitation and public health staff could respond promptly. Time-series trend analysis as well as cloud-based logging provide valuable data for long-term resource allocation and urban planning.

Besides lowering the amount of manual effort, this technology raises detection accuracy and reduces reaction time. Owing to its bridging of environmental monitoring and public health protection, it is able to scale and, thus, be useful for smart cities that want improvements in waste management combined with the health domain.

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Conflicts of Interest

The authors reveal no conflict of interest.

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