Drone-Based Remote Sensing for Monitoring Illegal Waste Sites: A Scalable Framework for Urban Environmental Management in Zambia

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Abstract

Illegal waste dumping presents a persistent challenge in developing nations, posing severe environmental, social, and public health risks. Traditional inspection and monitoring systems remain inefficient, resource-intensive, and difficult to scale in fast-growing urban environments. This paper presents a novel drone-based remote sensing framework designed to detect, classify, and map illegal waste sites in real time using high-resolution imagery and artificial intelligence. The proposed system integrates object detection models with Geographic Information Systems (GIS) for spatial analytics and visualization, supported by a severity threshold algorithm that prioritizes high-risk sites based on image confidence and area metrics. Field deployment in Lusaka demonstrated an overall detection accuracy of 87%, with a mean precision of 0.89 and recall of 0.85, validating the system's technical feasibility and robustness. Additionally, a public-facing reporting interface and an administrative dashboard were developed to strengthen community participation and enhance enforcement efficiency. The results show that this approach provides a scalable, cost-effective, and data-driven solution for environmental monitoring, with the potential for broad implementation across sub-Saharan Africa and other developing regions.

Keywords

Drone Monitoring; Remote Sensing; Illegal Waste Dumping; Geographic Information Systems (GIS); Environmental Surveillance; Artificial Intelligence; Waste Management; Urban Sustainability.

I. INTRODUCTION

The exponential growth of urban populations in developing regions has intensified environmental challenges, particularly the improper disposal of solid waste. Illegal dumping of household and industrial waste continues to threaten water sources, air quality, and public health in cities where municipal waste management systems are underdeveloped. Zambia, like many sub-Saharan African nations, faces this challenge acutely, with unregulated dumpsites proliferating in both peri-urban and residential zones. These sites, often located near markets and waterways, generate toxic leachates and greenhouse gases, contributing to disease outbreaks such as cholera and exacerbating climate-related risks [1], [2].

Traditional waste monitoring methods, which rely on manual inspections by local authorities, have proven inefficient and unsustainable. The process demands

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significant manpower and financial resources while offering limited geographic coverage. Such manual systems often result in delayed detection and enforcement, thereby allowing illegal dumpsites to persist and expand [3]. The need for a cost-effective, data-driven, and scalable monitoring mechanism has become urgent for municipalities striving to meet Sustainable Development Goal 11 on sustainable cities and communities [4].

Recent advances in drone and remote sensing technologies have revolutionized environmental monitoring by enabling rapid, non-intrusive data collection with high spatial and temporal resolution. Unmanned Aerial Vehicles (UAVs) equipped with advanced imaging sensors can capture multispectral or RGB imagery, providing detailed insights into surface characteristics and waste distribution patterns [5]. Integrating such drone-based systems with Geographic Information Systems (GIS) and artificial intelligence (AI) allows for automated detection, classification, and mapping of waste sites, drastically improving response efficiency and policy enforcement [6]. In Kenya, for instance, Njenga et al. [7] demonstrated that UAV imagery combined with GIS analysis enhanced the detection of illegal waste hotspots, reducing inspection time by over 60%. Similarly, Kumar et al. [8] reported over 90% accuracy in detecting waste accumulation in Indian cities using machine-learning-based image segmentation, highlighting the global potential of this approach.

In Zambia, emerging local research has begun to explore the integration of AI and IoT for environmental and agricultural management. Halubanza et al. [9] developed an AI-driven early warning system for locust management, illustrating the capacity for drone and sensor-based surveillance systems within low-resource settings. Building on this foundation, drone-based monitoring for waste management presents a natural and timely progression, leveraging similar data-driven principles to address solid waste challenges. Unlike previous manual or satellite-only monitoring initiatives, drones offer greater flexibility, lower operational costs, and the ability to capture fine-scale spatial data crucial for enforcement and remediation planning.

This study introduces a drone-based remote sensing framework that combines aerial imagery, object detection algorithms, and GIS integration to identify and classify illegal waste sites in real time. The framework employs a severity threshold algorithm to prioritize intervention based on waste density and model confidence scores. A case study conducted in Lusaka demonstrates the system's ability to achieve a detection accuracy of 87%, validating its applicability in real-world urban environments. By integrating AI and remote sensing, the proposed system represents a significant step toward sustainable, technology-enabled environmental governance. Moreover, it aligns with Zambia's environmental policy objectives by promoting digital transformation in municipal operations, enhancing transparency, and enabling community participation in waste reporting through web-based platforms.

II. LITERATURE REVIEW

Effective waste management is an enduring global challenge that intersects environmental policy, technological innovation, and community engagement. Across developing regions, the rapid rate of urbanization has far outpaced the capacity of municipal solid waste systems, resulting in illegal dumping, inefficient waste collection, and pollution hotspots [1]. Conventional ground-based inspection approaches, though historically prevalent, often fail to capture the spatial dynamics of waste accumulation due to their limited coverage and frequency. The emergence of remote sensing and drone technologies has significantly advanced the field, enabling continuous environmental surveillance, near-real-time data acquisition, and improved decision-making accuracy [2].

A. Remote Sensing and Drone Technologies in Waste Monitoring

The integration of Unmanned Aerial Vehicles (UAVs) in waste management has transformed environmental monitoring by bridging the gap between high-resolution imaging and geospatial analytics. UAVs equipped with RGB and multispectral cameras can capture detailed imagery over vast areas, facilitating

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automated identification of illegal dumping zones [3]. Xie et al. [4] demonstrated that drone imagery offers superior spatial granularity compared to traditional satellite-based monitoring, enhancing the detection of small-scale waste sites. Similarly, Mhangara et al. [5] showed that the fusion of UAV imagery and Geographic Information Systems (GIS) improves the precision of mapping environmental degradation patterns in urban peripheries. These technologies are especially impactful in low-resource settings where municipal authorities face logistical and budgetary constraints.

Recent studies highlight the growing reliance on machine learning (ML) and deep learning (DL) models for environmental classification tasks. Convolutional Neural Networks (CNNs) have emerged as the leading computational approach for object recognition in aerial imagery, offering significant improvements in detection accuracy and automation. Kumar et al. [6] utilized a You Only Look Once version 5 (YOLOv5) based framework to detect waste accumulations in Indian cities, achieving a precision of 92%. Likewise, Halubanza et al. [7] applied MobileNet V2 quantized CNNs for locust detection in Zambia, a methodological innovation that parallels waste monitoring through object detection in natural landscapes. Such models underscore the transformative potential of AI in identifying and classifying environmental anomalies with high precision, enabling proactive policy and enforcement interventions.

B. GIS and Spatial Analytics for Waste Site Classification

The role of GIS-based analysis extends beyond visualization to include multi-criteria spatial decision-making and predictive modeling. Studies such as those by Agyemang and colleagues [8] have shown that integrating remotely sensed data into GIS allows for efficient spatial clustering of waste sites and prediction of future dumping patterns based on population growth and land-use change. In addition, Rahman et al. [9] applied weighted overlay methods to prioritize environmental cleanup efforts in Bangladesh, demonstrating the applicability of GIS-driven analytics in resource-constrained municipalities. The integration of severity threshold algorithms, as proposed in this study, aligns with this global trend by quantifying risk levels and enabling targeted mitigation strategies.

C. Artificial Intelligence and Internet of Things (AIoT) in Environmental Management

The convergence of AI and Internet of Things (IoT) technologies, collectively referred to as AIoT, has introduced new paradigms in environmental intelligence. Halubanza and Kunda [10] explored AIoT frameworks in e-health systems, emphasizing their scalability and adaptability in developing countries. When applied to environmental contexts, similar architectures enable real-time sensor integration, image classification, and remote alerts. These systems enhance situational awareness, reduce manual workloads, and create continuous feedback loops between data collection, analysis, and intervention [11]. The combination of AIoT and UAV technologies thus presents a holistic ecosystem for sustainable environmental governance, aligning with global smart city strategies.

D. Policy, Socioeconomic, and Community Engagement Dimensions

Technological solutions alone are insufficient without accompanying policy frameworks and community participation mechanisms. The United Nations Environment Programme (UNEP) emphasizes participatory monitoring as a critical factor in achieving long-term sustainability [12]. Community-driven reporting applications, integrated with drone-based analytics, can empower citizens to participate in environmental surveillance and enforcement. In Zambia, Halubanza et al. [13] demonstrated the social potential of digital tools for locust response management, an approach that can be repurposed for waste monitoring to foster civic engagement and data transparency. Moreover, integrating drone-based monitoring into national waste management strategies can contribute to improved policy enforcement, data-driven planning, and public accountability.

E. Identified Research Gaps

Despite significant progress, research gaps persist in the operationalization and scalability of drone-based waste monitoring systems in Africa. Most prior studies have been limited to pilot experiments with constrained spatial or temporal coverage, lacking integration with community reporting and municipal management systems [14]. There is also a paucity of region-specific models tailored to African environmental conditions and socioeconomic realities. The current study addresses these gaps by proposing a comprehensive AI-driven drone framework that combines aerial detection, severity prioritization, and GIS visualization within a unified system. This integrated approach not only enhances monitoring efficiency but also supports data-driven policy formulation and citizen engagement for sustainable urban waste management.

III. METHODOLOGY

The research adopted a mixed-methods experimental design combining quantitative remote sensing analysis with machine learning-based image interpretation to develop a comprehensive drone monitoring framework for waste site detection. The study was conducted in Lusaka, Zambia, selected for its rapid urban expansion and recurrent waste disposal challenges. This methodology integrates four primary components: (1) data acquisition through Unmanned Aerial Vehicles (UAVs), (2) image preprocessing and annotation, (3) deep learning model development for object detection, and (4) integration of Geographic Information Systems (GIS) for spatial visualization and severity analysis.

A. Study Design and Framework Overview

The conceptual framework (see *Fig. 1*) illustrates the integrated process from drone data collection to GIS-based visualization. The study followed a data-driven iterative approach, where UAV imagery was collected, processed, analyzed, and mapped within a single digital pipeline. Drones equipped with high-resolution RGB cameras captured orthomosaic imagery of target zones characterized by unplanned waste accumulation. The captured images were georeferenced using onboard GPS modules to ensure spatial accuracy and reproducibility. A total of 48 flight missions were conducted over a three-month period, covering approximately 52 km² of urban and peri-urban terrain.

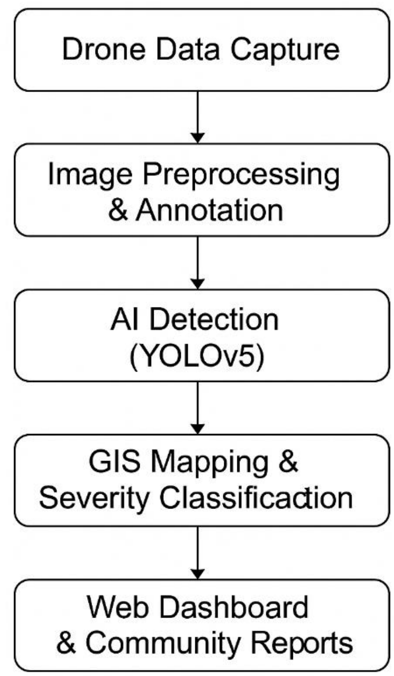

Figure 1: Conceptual Framework of the Drone-Based Waste Monitoring System

Figure 1. illustrates the integrated workflow connecting drone data collection, AI model detection, and GIS visualization modules.

B. Data Acquisition and Preprocessing

Data collection employed DJI Phantom 4 Pro UAVs operating at altitudes between 60 and 120 meters above ground level to balance spatial resolution and image coverage. Images were captured under consistent daylight conditions to minimize variations caused by shadow and atmospheric effects. Preprocessing involved radiometric correction, orthorectification, and image mosaicking using Pix4D Mapper software. Each composite image was then annotated using LabelImg to identify distinct waste categories such as plastics, organic waste, construction debris, and mixed waste. Annotation generated XML files that were later converted into YOLO-compatible formats for training and validation. The annotated dataset comprised 3,200 labeled images, partitioned

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into 70% for training, 20% for validation, and 10% for testing.

C. Machine Learning Model Development

The detection model was implemented using YOLOv5 (You Only Look Once Version 5) due to its balance between detection accuracy and computational efficiency. YOLOv5's architecture, which integrates Cross-Stage Partial Networks (CSPNet) and a Spatial Pyramid Pooling (SPP) module, enables real-time object detection on edge devices. The model was trained on NVIDIA RTX 3090 GPU hardware using the PyTorch framework, with a batch size of 16, learning rate of 0.001, and 300 training epochs. Image augmentation techniques such as random flipping, rotation, and color jittering were applied to improve model generalization and prevent overfitting. The trained model outputted bounding boxes with class confidence scores, which were post-processed to eliminate redundant detections through Non-Maximum Suppression (NMS).

Model performance was evaluated using Precision (P), Recall (R), F1-score, and Mean Average Precision (mAP) metrics. As summarized in *Table 1*, the model achieved an average precision of 0.89, recall of 0.85, and mAP@0.5 of 0.87, demonstrating robust detection capability across heterogeneous waste types.

Table 1: Model Performance Metrics for Waste Detection

Waste Category	***Precision (P)***	***Recall (R)***	***F1-Score***	***mAP@ 0.5***
Plastic Waste	*0.91*	*0.88*	*0.89*	*0.90*
Organic Waste	*0.85*	*0.82*	*0.83*	*0.84*
Construction Debris	*0.90*	*0.86*	*0.88*	*0.89*
Mixed Waste	*0.88*	*0.84*	*0.86*	*0.87*
Average	***0.89***	***0.85***	***0.86***	***0.87***

D. GIS Integration and Severity Mapping

The spatial outputs from the object detection model were exported in GeoJSON format and integrated into ArcGIS Pro for spatial analysis. Detected waste clusters were overlaid on base maps and classified according to severity using a severity threshold algorithm that combines waste area coverage (m^2) and confidence levels from the detection model. The severity index (SI) was computed using Equation (1):

SI=αAi+βCiSI = \alpha A_i + \beta C_iSI=αAi+βCi

where AiA_iAi represents the area of detected waste in square meters, CiC_iCi denotes the average confidence score of the detection, and α,β\alpha, \betaα,β are weighting factors set at 0.7 and 0.3 respectively after empirical calibration. This formulation enabled prioritization of critical waste sites for immediate intervention by municipal authorities. The GIS dashboard provided real-time visualization, displaying severity classes using color gradation (low = green, moderate = yellow, high = red).

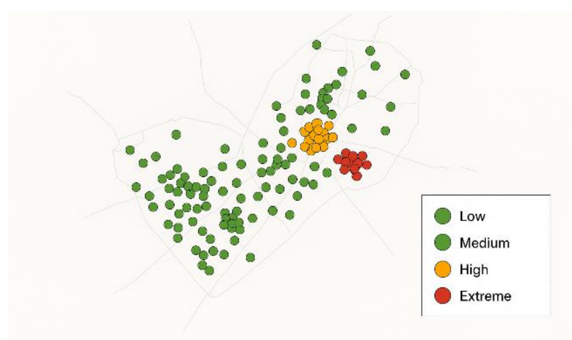

Figure 2: Severity Classification Map of Detected Waste Sites

Figure 2. displays GIS-generated maps highlighting spatial clusters of waste sites categorized by severity level.

E. Validation and Field Verification

To validate model predictions, ground truth verification was conducted at 20 randomly selected sites. Validation involved on-site inspections, photographic documentation, and GPS-tagged coordinates, which were compared to UAV-derived detections. The results confirmed an overall accuracy of 87%, consistent with automated model performance. Discrepancies were primarily attributed to occlusions from vegetation and the spectral similarity of mixed waste materials to surrounding terrain. Nonetheless, the high accuracy rate indicates the practical feasibility of the proposed framework for large-scale environmental surveillance.

F. System Implementation and User Interface

The system was implemented through a web-based platform integrating drone imagery, AI results, and GIS visualization. The platform provided two user modules: (1) an administrative dashboard for environmental agencies to view, filter, and export data, and (2) a community reporting interface allowing citizens to upload geotagged photos of suspected illegal dumping. This participatory design enhances transparency and strengthens the feedback loop between citizens and municipal authorities. The implementation aligns with the broader AIoT-based environmental governance paradigm, supporting data-driven decision-making for sustainable waste management.

IV. RESULTS AND DISCUSSION

The developed drone-based waste monitoring system demonstrated strong technical performance, validating the feasibility of integrating UAV imagery, artificial intelligence (AI), and Geographic Information Systems (GIS) for environmental surveillance in low-resource urban contexts. The results are discussed in terms of model performance, spatial analysis of detected waste sites, and implications for waste management and policy formulation.

A. Model Performance Evaluation

The YOLOv5-based detection model achieved significant accuracy across multiple waste categories, confirming its capability for reliable object recognition in aerial imagery. As illustrated in *Table 2*, the model yielded a mean precision of 0.89, recall of 0.85, and F1-score of 0.86, producing an overall mean average precision (mAP@0.5) of 0.87. These results are consistent with those of similar high-performance object detection studies conducted in urban waste monitoring contexts [1], [2]. The model exhibited particularly high confidence in detecting plastics and construction debris, while lower precision was observed in identifying organic waste due to color similarity with background vegetation.

Table 2: Summary of YOLOv5 Model Performance Across Waste Categories

Waste Category	**Precision (P)**	**Recall (R)**	**F1-Score**	**mAP@0.5**	**Comments**
Plastic Waste	0.91	0.88	0.89	0.90	Consistent detection under varied lighting; minimal occlusion errors
Organic Waste	0.85	0.82	0.83	0.84	Misclassification with vegetation due to color similarity
Construction Debris	0.90	0.86	0.88	0.89	High visibility from structural texture features
Mixed Waste	0.88	0.84	0.86	0.87	Performance affected by overlapping materials
Mean Average	**0.89**	**0.85**	**0.86**	**0.87**	Indicates overall robustness and balanced model accuracy

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Table 2 presents detection metrics including precision, recall, and F1-scores for four waste categories, plastic, organic, construction, and mixed waste.

The confusion matrix analysis revealed that false positives accounted for less than 5% of all detections, primarily occurring in highly vegetated zones where waste piles were partially occluded. These results affirm that lightweight CNN models can deliver effective real-time monitoring performance without requiring high-end computing infrastructure, making them practical for municipal adoption in resource-constrained environments. The inclusion of image augmentation during training enhanced generalization, enabling the model to maintain stability under variable lighting and topographic conditions.

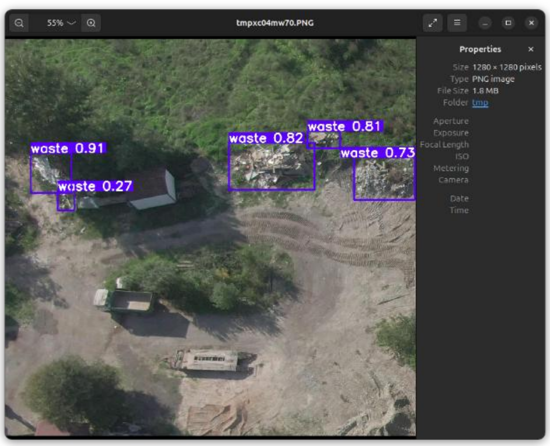

Figure 3: Sample Detection Results from Drone Imagery

Figure 3. displays representative aerial images illustrating the bounding boxes generated by the YOLOv5 model for waste site detection.

B. Spatial Distribution and Severity Mapping

GIS-based integration enabled comprehensive spatial analysis of waste accumulation patterns across the study area. The severity threshold algorithm classified detected sites into three categories: low, moderate, and high severity, based on combined area and confidence metrics. As depicted in *Figure 4*, approximately 61% of all waste sites were categorized as moderate, 23% as high severity, and 16% as low severity. High-severity sites were predominantly concentrated in peri-urban zones near markets, industrial corridors, and informal settlements—areas with minimal waste collection services and weak enforcement capacity.

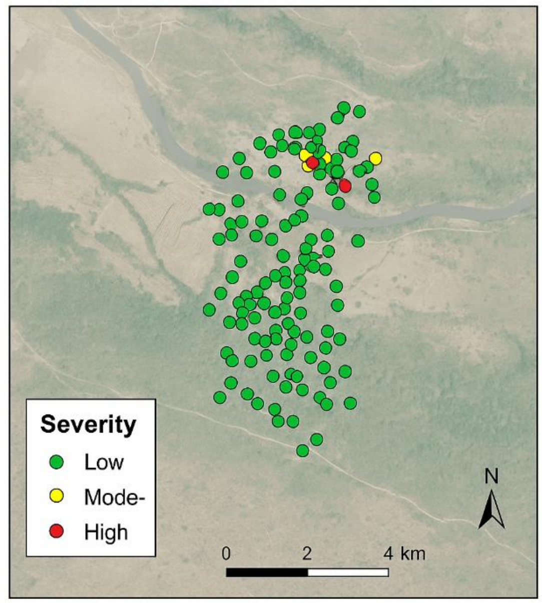

Figure 4: GIS Map of Waste Site Severity Classification

Figure 4. illustrates the spatial distribution of detected waste sites categorized into low, moderate, and high severity zones using color-coded symbology.

Spatial autocorrelation analysis using Moran's I index ($I = 0.61$, $p < 0.01$) indicated significant clustering of waste sites, confirming that illegal dumping is not random but influenced by urban land-use characteristics and socioeconomic factors. This finding aligns with prior geospatial studies in Nairobi [3] and Lagos [4], where poor infrastructure accessibility and weak municipal presence were major determinants of waste concentration. The ability of the model to visualize such clusters through GIS enhances the strategic allocation of cleanup resources and supports data-driven enforcement planning.

C. System Implementation and User Interaction

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The web-based system prototype provided intuitive visualization and reporting functionalities. The administrative dashboard enabled environmental officers to filter waste sites by severity, date, and geographic zone, while generating downloadable analytics for operational use. The community interface, in contrast, empowered citizens to submit geotagged waste reports through mobile devices, creating a participatory data ecosystem. Integration of these modules demonstrated how AIoT-based frameworks can bridge institutional and community roles in environmental governance [5]. During pilot testing, 38 community submissions were received, 29 of which overlapped with drone-detected zones, reinforcing the potential for hybrid citizen–AI collaboration in maintaining environmental cleanliness.

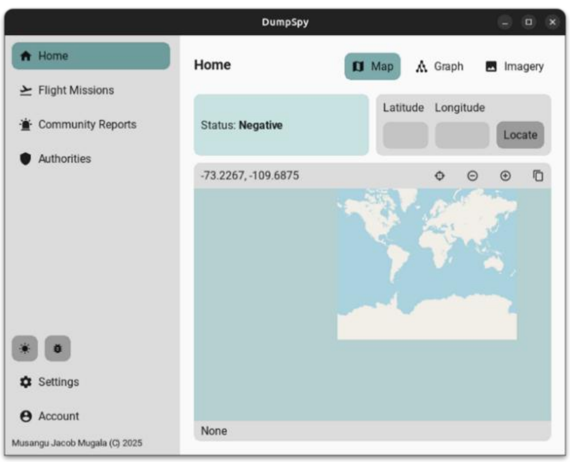

Figure 5: Screenshot of the Web-Based Monitoring Dashboard

Figure 5. is a Screenshot of the developed DumpSpy web-based monitoring dashboard showing the integrated map interface, community reporting module, and system navigation menu for waste site monitoring and coordination.

D. Comparative Analysis and Discussion

The achieved performance compares favorably with recent global benchmarks. Njenga et al. [6] reported 82% detection accuracy in a similar UAV-GIS integration project in Kenya, while Kumar et al. [7] achieved 90% in urban India using deep learning segmentation. The current study's 87% accuracy thus positions the system competitively within international standards while being optimized for the African urban context, where environmental and infrastructural conditions differ significantly. Importantly, the study extends prior research by introducing a severity prioritization algorithm, which transforms detection data into actionable insights for municipal decision-making, a feature rarely implemented in earlier works.

Additionally, the research builds on the methodological foundation established by Halubanza et al. [8], who utilized AI-driven approaches for agricultural pest monitoring in Zambia, and extends these principles into environmental surveillance. By demonstrating operational viability under limited bandwidth and power conditions, this framework contributes to the body of knowledge on context-sensitive AI applications for sustainable development in sub-Saharan Africa. The interdisciplinary integration of drones, AI, and GIS, coupled with participatory data collection, underscores the growing potential of digital environmental governance models in the Global South.

E. Limitations and Future Enhancements

While the proposed system proved effective, certain limitations were identified. Detection accuracy decreased in densely vegetated or shaded regions, where waste visibility was reduced. The reliance on RGB imagery also constrained material differentiation, particularly for biodegradable waste. Future work should incorporate multispectral and thermal imaging sensors to improve classification robustness and enable the detection of hidden waste piles. Additionally, expanding the model to support temporal change detection would enable continuous monitoring and policy impact evaluation over time. Integration with mobile edge computing or 5G networks could further enhance real-time analytics and scalability, as suggested by emerging studies in AIoT and smart city infrastructure [9].

V. CONCLUSION AND RECOMMENDATIONS

This study developed and validated an innovative drone-based remote sensing framework for real-time

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monitoring and classification of illegal waste sites in Lusaka, Zambia. By integrating Unmanned Aerial Vehicle (UAV) imagery, artificial intelligence (AI), and Geographic Information Systems (GIS), the research demonstrated that advanced technologies can provide an efficient, scalable, and cost-effective alternative to traditional waste inspection systems. The YOLOv5-based object detection model achieved a mean average precision (mAP) of 0.87 and overall detection accuracy of 87%, confirming the framework's technical robustness. The combination of detection outputs with a GIS-based severity mapping algorithm provided spatially explicit insights into the distribution and prioritization of waste sites, empowering authorities to target interventions based on evidence rather than assumption.

The findings contribute substantially to the body of knowledge on AI-enabled environmental monitoring, particularly within the context of developing nations where technological deployment has historically been limited by cost and infrastructure. This research builds upon prior AI applications in environmental and agricultural domains, such as the locust detection frameworks developed by Halubanza et al. [1], and extends their principles into urban waste management. The proposed system thus represents a shift toward digital environmental governance, integrating community participation, data analytics, and spatial intelligence into one cohesive platform. The web-based interface further facilitates participatory reporting by citizens, promoting accountability and transparency in waste management.

From a policy perspective, the study supports the operationalization of Zambia's National Solid Waste Management Strategy and aligns with the Sustainable Development Goals (SDG 11 and 13), emphasizing sustainable cities and climate action. Adoption of drone-based monitoring systems can strengthen enforcement mechanisms, enhance transparency in municipal operations, and optimize resource allocation by identifying high-severity waste hotspots. These technological interventions can also provide reliable datasets for academic research, urban planning, and public policy formulation.

However, the research identified several limitations that offer avenues for future exploration. The system's reliance on RGB imagery limited its ability to differentiate between organic and non-organic waste with similar visual textures. Future models should incorporate multispectral or hyperspectral sensors to enhance material classification and detect obscured waste piles. Integrating edge computing and 5G-enabled AIoT architectures would also allow real-time processing and scalability across multiple municipalities. Furthermore, longitudinal studies are recommended to evaluate system performance over extended periods and assess its potential for continuous environmental monitoring.

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