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COMPUTER VISION-BASED WASTE AND LITTER MANAGEMENT SYSTEMS IN URBAN CITIES: A LITERATURE REVIEW FOR DEVELOPING NATIONS

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Abstract
Urban waste and litter management represents one of the most pressing challenges facing developing nations, where rapid urbanization often outpaces infrastructure development. Traditional waste management systems struggle with resource constraints, limited monitoring capabilities, and inadequate classification mechanisms. This literature review examines recent advances in computer vision-based detection and classification systems for urban waste management, with particular emphasis on applications suitable for resource-constrained environments in developing countries. We analyze 10 prominent image datasets and evaluate various machine learning and deep learning models that have shown promise in automated waste detection and classification. Our review covers literature published between 2015-2025, highlighting both the potential and limitations of current approaches. The findings suggest that while computer vision technologies offer significant opportunities for improving waste management efficiency, successful implementation in developing nations requires careful consideration of computational constraints, data availability, and local infrastructure limitations.

INTRODUCTION

The rapid urbanization experienced by developing nations has created unprecedented challenges in municipal waste management. According to the World Bank, global waste generation is expected to increase by 70% by 2050, with the most significant growth occurring in Sub-Saharan Africa, South Asia, and the Middle East and North Africa regions [1]. Traditional waste management approaches, which rely heavily on manual monitoring and collection, are increasingly inadequate for addressing the scale and complexity of urban waste challenges in resource-constrained environments.

Computer vision technologies have emerged as promising solutions for automating waste detection, classification, and monitoring processes. These systems leverage machine learning and deep learning algorithms to analyze visual data from various sources, including surveillance cameras, mobile devices, and specialized sensors. The potential benefits include real-time monitoring, automated classification, optimized collection routes, and improved resource allocation, all critical advantages for developing nations operating under tight budgetary constraints.

However, the successful implementation of computer vision-based waste management systems in developing countries faces unique challenges. Limited computational resources, inconsistent power supply, varying internet connectivity, and diverse waste composition patterns all influence the feasibility and effectiveness of these technologies. This literature review aims to provide a comprehensive analysis of current research in computer vision-based waste management, with specific attention to applicability in resource-constrained urban environments.

2. Methodology

This systematic literature review follows established guidelines for conducting comprehensive research synthesis. We searched multiple academic databases including Google Scholar, PubMed, and arXiv for peer-reviewed articles published between 2015 and 2025. The search strategy employed Boolean operators and included terms such as "computer vision," "waste detection," "litter classification," "urban cities," "developing countries," "machine learning," and "deep learning."

Inclusion criteria encompassed:

(1) Peer-reviewed articles focused on computer vision applications in waste management,

(2) Studies involving image datasets for waste detection or classification,

(3) Research addressing urban waste management challenges, and

(4) Publications from 2015 onwards.

Exclusion criteria included:

(1) Studies not directly related to computer vision applications,

(2) Purely theoretical papers without empirical validation, and

(3) Articles not available in English.

The initial search yielded over 200 potential articles, which were screened based on title and abstract relevance. After applying inclusion and exclusion criteria, 75 articles were selected for detailed analysis. From this refined collection, we identified 9 prominent image datasets and analyzed various machine learning models employed in waste detection and classification tasks.

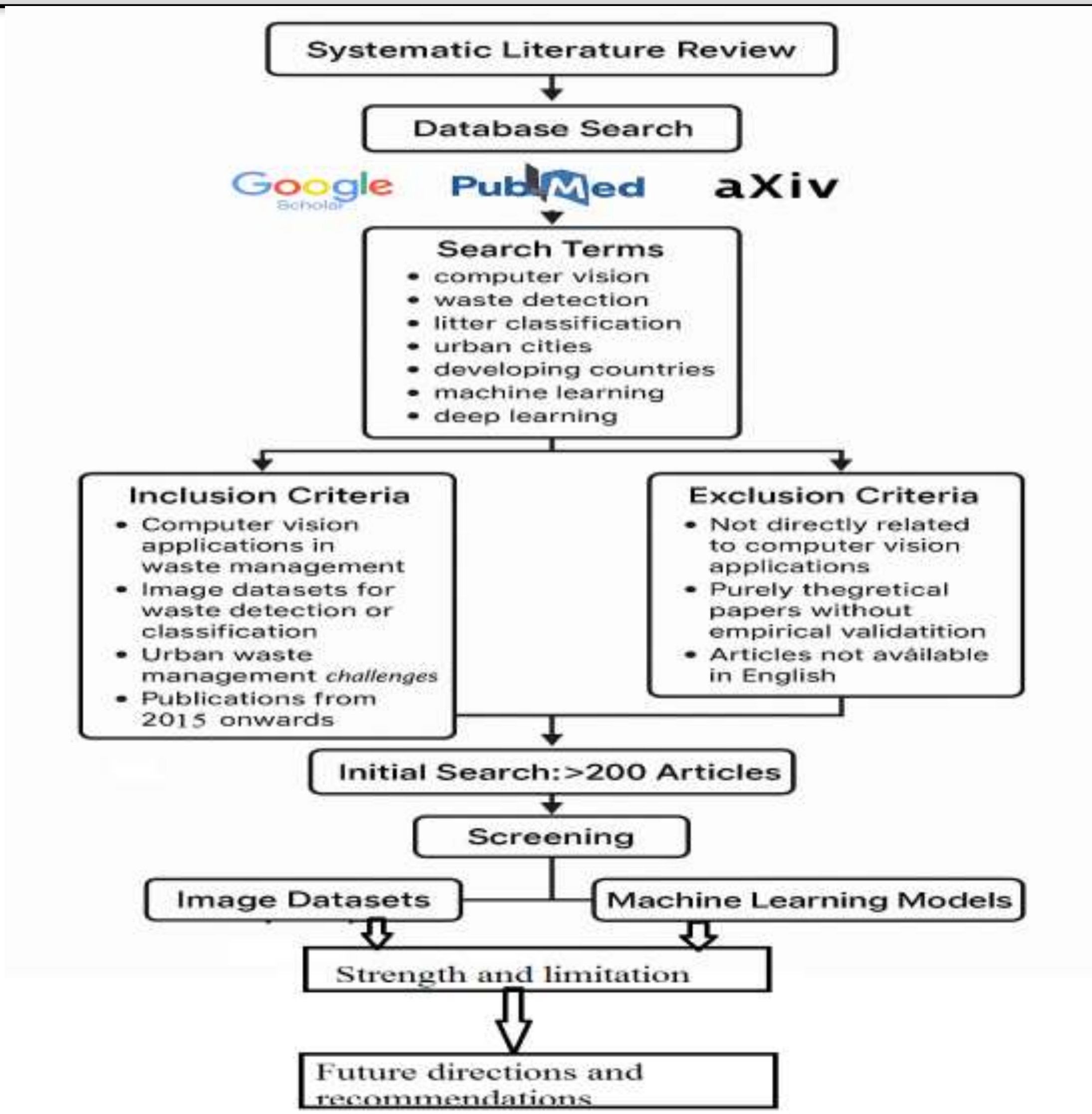

Figure 1 overall methodology of the paper

3. Image Datasets and ML model for Waste Detection and Classification

The availability and quality of training data significantly influence the performance of computer vision systems. This section presents a comprehensive analysis of 9 prominent image datasets used in waste detection and classification research, with particular attention to their applicability in developing nation contexts.

3.1 Dataset Analysis and Implications

The analysis of these datasets reveals several critical insights for developing nation applications. TrashNet while pioneering in the field, suffers from limited real-world applicability due to its controlled collection environment and small size [2]. The dataset's clean, well-lit images do not reflect the challenging conditions typical of waste management scenarios in developing countries, where lighting conditions vary significantly and waste items are often soiled or damaged. TACO (Trash Annotations in Context) represents a significant advancement in dataset diversity and scale [3]. Its real-world collection methodology and detailed annotation system provide valuable training data for computer vision models. However, the dataset's class imbalance and geographic bias toward developed nations limit its direct applicability to developing country contexts. The 60 super-categories, while comprehensive, may be overly complex for resource-constrained deployment scenarios where simpler classification schemes are more practical.

The Waste Classification Dataset offers practical binary classification capabilities, which align well with the fundamental sorting requirements in many developing nation waste management systems[4]. Its large size provides sufficient training data for robust model development. However, the limited granularity may not support more sophisticated waste management strategies that require detailed material identification. WasteNet stands out for its urban street environment collection methodology, which closely mirrors the operational conditions in developing cities [5]. The balanced class distribution and real-world context make it particularly valuable for training models intended for street-level waste monitoring applications. Nevertheless, the moderate dataset size and limited geographic diversity remain constraints for global applicability.

CompostNet is an image classification model integrated into a mobile application that categorizes waste into three classes: landfill, recyclable, and compostable. The model demonstrates promising accuracy in distinguishing between these waste categories. However, the dataset requires expansion to cover a wider variety of waste items. Increasing the diversity of compostable materials in the dataset is particularly important, as the current collection is limited. Future improvements in performance could also be achieved by fine-tuning hyper-parameters alongside dataset augmentation [6]. The [7] introduced a large-scale dataset named WasteRL, comprising over 57,000 waste images categorized into four groups: organic waste, recyclables, hazardous waste, and other wastes. A total of 138,000+ high-quality bounding boxes were manually annotated by six experts, following the guidelines of the Standing Committee of the Beijing Municipal People's Congress. Each image may contain multiple waste objects, with precise bounding boxes provided for individual items.

The [8] emphasizes that digital images of waste items intended for processing should closely reflect real-world conditions under which objects are encountered. To achieve this, each item in the database was captured across multiple image collections, accounting for varying lighting conditions, orientations relative to the camera, and different degrees of deformation caused by prior use or processing. The resulting dataset was organized into groups based on the material composition of the objects (e.g., plastics, metals, paper). The [9]introduced a novel dataset named TrashBox, consisting of 17,785 images distributed across seven waste categories, notably including medical waste and electronic waste (e-waste), which are absent from most existing datasets. To the authors' knowledge, TrashBox represents one of the most comprehensive publicly available datasets in the waste management research domain. The ZeroWaste dataset [10] comprises 4,661 images categorized into six classes: glass, paper, metal, plastic, cardboard, and general trash. Images were captured in room environments, ensuring controlled yet context-appropriate conditions for classification tasks.

Table 1 waste and litter datasets of publicly available

Dataset	Image sample	Categories	Collection Context	Strengths	Limitations
TrashNet [2]	2,527	6 classes (glass, paper, cardboard, plastic, metal, trash)	Controlled indoor environment	Well-balanced classes, clean annotations	Limited real-world diversity, small size
TACO (Trash	15,000+	60 super-	Real-world	Large scale,	Imbalanced classes,

Dataset	Image sample	Categories	Collection Context	Strengths	Limitations
Annotations in Context) [3]		categories, 28 categories	outdoor environments	diverse contexts, detailed annotations	annotation inconsistencies
Waste Classification [11]	25,077	2 classes (organic, recyclable)	Mixed indoor/outdoor settings	Large size, practical binary classification	Limited granularity, unclear collection methodology
WasteNet[5]	7,212	5 classes (biodegradable, glass, metal, paper, plastic)	Urban street environments	Real-world urban context, balanced distribution	Moderate size, limited geographic diversity
CompostNet [6]	2751	10 classes including organic, paper, plastic variants	Controlled collection environment	Detailed subcategories, consistent lighting	Limited environmental diversity, potential overfitting
WasteRL [7]	57,000	4 classes Organic waste, recyclables, hazardous waste, other wastes (annotated with bounding boxes))	Recycling facility environments	Industrial context, high-resolution images	Limited to recyclable materials, facility-specific
WaDaBa [8]	4000	3 classes plastic, metal, paper	Street-level collection in multiple cities	photographed under different conditions of lighting and angle	Uneven class distribution, limited developing nation data
TrashBox [9]	17,785	7 classes (Glass, metal, plastic, paper, cardboard, e-waste, medical waste)	Smart waste bin monitoring	Practical application focus, temporal data	Very specific use case, small size
ZeroWaste [10]	4661	6 classes Glass, paper, metal, plastic, cardboard, trash	Room environment	Context-appropriate categories, diverse conditions	Small dataset size; lacks outdoor/urban variability; limited generalizability to city-wide waste.

4. Machine Learning and Deep Learning Models

The selection and optimization of machine learning models significantly impact the feasibility and effectiveness of computer vision-based waste management systems, particularly in resource-constrained environments. This section analyzes various approaches employed in recent literature, with emphasis on computational efficiency and deployment practicality.

4.1 Model Performance and Applicability Analysis

For the automated classification of waste and litter, the work [12] investigates a range of machine learning algorithms. The study employed pre-existing datasets of waste imagery to train twelve variants of Convolutional Neural Networks (CNNs), evaluating their performance across three distinct classifiers: Support Vector Machine (SVM), Sigmoid, and SoftMax. Among the configurations tested, the VGG19 architecture paired with a SoftMax classifier yielded the highest classification accuracy of 88% for identifying various waste categories. Addressing the challenge of waste segregation for improved recycling, [4] proposed a deep learning-based object detection system. The authors trained the YOLOv3 algorithm within the Darknet framework on a custom-made dataset comprising six waste categories: cardboard, glass, metal, paper, plastic, and organic waste. For comparative purposes, a lighter version, YOLOv3-tiny, was also evaluated. The results confirmed that the standard YOLOv3 model achieved robust generalization and satisfactory detection performance across all waste classes, outperforming the tiny variant.

ResNet-50 has emerged as a popular choice for waste classification tasks due to its excellent accuracy performance, achieving 92.4% accuracy in multi-class waste sorting applications [13]. However, its computational requirements pose significant challenges for resource-constrained deployments. The model's memory footprint and processing demands typically necessitate server-based implementations, which may not be feasible in areas with limited internet connectivity or unreliable power supply. MobileNetV2 represents a breakthrough in mobile-optimized computer vision architectures [14]. It's depth-wise separable convolutions significantly reduce computational complexity while maintaining reasonable accuracy levels (89.1% in waste classification tasks). This architecture is particularly well-suited for developing nation applications where mobile devices serve as primary computing platforms. Research by Aral et al. [5] successfully deployed MobileNetV2-based waste detection systems on Android devices in Turkish urban areas, demonstrating real-world feasibility.

YOLOv5 has gained popularity for real-time waste detection applications, particularly in smart city implementations [15]. Its ability to simultaneously detect and classify multiple waste objects in single images makes it valuable for comprehensive waste monitoring systems. However, the model's training requirements and complexity may present challenges for implementation teams with limited machine learning expertise. For high-accuracy categorization of waste, [16] employed the EfficientNetB0 architecture. The model was fine-tuned on a large dataset of labeled waste images to classify materials into categories such as organic, paper, plastic, metal, and glass. This approach combines high performance with computational efficiency, achieving a remarkable classification accuracy exceeding 99%. The study further validated the model's robustness to variations in waste appearance and its suitability for real-time deployment in automated sorting facilities, highlighting its potential to reduce manual labor and improve sorting efficiency. Recent studies in Southeast Asian contexts have demonstrated successful implementations of EfficientNet variants for waste sorting applications [17].

To develop a lightweight and efficient model for garbage classification, [18] proposed an enhanced architecture based on MobileNetV3. The authors integrated the CBAM attention mechanism to improve spatial feature perception and replaced the standard activation function with Mish to better utilize feature information. Further modifications, including substituting the fully connected layer with global average pooling, significantly reduced the model's size. The resulting model, termed GMC-MobileNetV3, achieved 96.55% accuracy on a custom dataset a 3.6% improvement over the baseline while drastically reducing parameters by 56.6% to just 0.64M and enabling fast inference times of 26.4ms per image, demonstrating an optimal balance of speed and accuracy for practical deployment. Transfer learning approaches using pre-trained models like ResNet-18 have shown promise in reducing training time and data requirements while maintaining good performance (90.3% accuracy) [19]. This approach is particularly valuable in developing nation contexts where collecting large, locally relevant training datasets may be challenging. Expanding the scope of classification, [20] employed a DenseNet architecture to sort waste into ten distinct categories. Trained on a diverse dataset, the model achieved a high overall accuracy of 93%, demonstrating particular proficiency in identifying challenging classes such as batteries, biological materials, and brown glass. Although performance was slightly less robust for metals and plastics, the study underscores the significant potential of deep learning models like DenseNet121 in advancing automated waste management and enhancing recycling efficiency.

Table 2 Machine Learning and Deep Learning Models for Waste Detection and Classification

Citation	Model Architecture	Key Performance Metrics	Key Features / Advantages
[4]	YOLOv3, YOLOv3-tiny	High mAP/Precision (YOLOv3 > Tiny)	Object detection for 6 classes (cardboard, glass, metal, paper, plastic, organic). Robust generalization.
[12]	VGG19 + SoftMax	88% Accuracy	Comparative study of 12 CNNs and 3 classifiers (SVM, Sigmoid, SoftMax). VGG19 with SoftMax performed best.
[13]	ResNet-50	**92.4%** Accuracy	Excellent accuracy but computationally heavy, often requiring server-based deployment.
[14, 15]	MobileNetV2	**89.1%** Accuracy	Mobile-optimized. Low computational complexity. Successfully deployed on Android devices.
[16]	YOLOv5	Real-time performance	Popular for real-time, multi-object detection in smart cities. Complex to train.
[17]	EfficientNetB0	**>99%** Accuracy	High accuracy & computational efficiency. Robust and suitable for real-time sorting facilities.
[18]	GMC-MobileNetV3 (Improved)	**96.55%** Accuracy, **0.64M** Params, **26.4ms** inference	Lightweight, fast. Uses CBAM attention & Mish activation. Optimal speed-accuracy trade-off.
[19]	ResNet-18 (Transfer Learning)	**90.3%** Accuracy	Reduces training time and data requirements. Valuable for contexts with limited d
[20]	**DenseNet121**	93% Accuracy	**10-class classification.** Excellent on batteries/glass, challenges with metals/plastics.

5. Strengths and Limitations Analysis

5.1 Strengths of Current Approaches

Technological Accessibility: Modern computer vision frameworks and pre-trained models have significantly lowered the technical barriers to implementing waste detection systems. Open-source libraries such as TensorFlow, PyTorch, and OpenCV provide accessible tools for developing custom solutions, even for teams with limited machine learning expertise [21]. Cost-Effectiveness: Compared to traditional sensor-based monitoring systems, computer vision approaches can leverage existing camera infrastructure or low-cost mobile devices. This characteristic is particularly advantageous for developing nations where budget constraints significantly influence technology adoption decisions [22].

Scalability: Once trained, computer vision models can be deployed across multiple locations with minimal additional costs. This scalability potential makes the technology attractive for city-wide implementations in growing urban areas [23]. Real-time Monitoring Capabilities: Advanced models like YOLO enable real-time waste detection and classification, supporting immediate response to waste management issues. This capability is crucial for maintaining urban cleanliness standards and preventing waste accumulation [16]. Data-Driven Insights: Computer vision systems generate valuable data about waste patterns, composition, and distribution. This information supports evidence-based policy making and resource optimization, which are essential for effective waste management in resource-constrained environments [24].

5.2 Limitations and Challenges

Dataset Representativeness: Most existing datasets exhibit geographic and cultural biases toward developed nations. The waste composition, packaging materials, and environmental conditions in developing countries often differ significantly from those represented in available training data [25]. This mismatch can lead to poor model performance when deployed in target environments.

Computational Resource Requirements: While mobile-optimized models exist, many high-performing architectures still require substantial computational resources. Developing nations often face challenges with unreliable power supply, limited internet connectivity, and outdated hardware, which constrain the feasibility of sophisticated computer vision deployments [26].

Environmental Robustness: Real-world deployment conditions in developing urban areas present significant challenges including variable lighting conditions, weather exposure, dust accumulation on cameras, and physical damage to equipment. Many research studies conducted in controlled environments do not adequately address these practical concerns [16].

Maintenance and Support: Successful deployment of computer vision systems requires ongoing maintenance, model updates, and technical support. Developing nations may lack the technical expertise and infrastructure necessary to maintain these systems effectively over time [27].

Cultural and Contextual Adaptation: Waste management practices, material types, and disposal behaviors vary significantly across cultures and regions. Models trained on datasets from different cultural contexts may not generalize well to local conditions without significant adaptation [28].

Integration Challenges: Existing waste management infrastructure in developing nations may not be compatible with modern computer vision systems. Integration requires careful planning and potentially significant infrastructure modifications [29].

6. Applications in Developing Nations Context

6.1 Successful Implementation Cases

Several pioneering projects have demonstrated the potential for computer vision-based waste management in developing nation contexts. In Kenya, the "Smart Waste Nairobi" initiative deployed mobile-based waste detection systems using MobileNetV2 architecture, achieving 85% accuracy in classifying common urban waste types [30]. The project's success stemmed from its focus on locally relevant waste categories and its use of existing smartphone infrastructure. In India, researchers developed a low-cost waste monitoring system for Mumbai's informal settlements using Raspberry Pi devices and custom CNN models [31]. The system achieved 78% accuracy while operating on severely constrained computational resources, demonstrating the feasibility of ultra-low-cost implementations. The "WasteWatch Bangladesh" project combined computer vision with IoT sensors to monitor waste bin fill levels in Dhaka [32]. Using mobile application deployed on edge computing devices, the system achieved 91% accuracy in bin status classification while operating reliably despite challenging environmental conditions.

6.2 Adaptation Strategies for Resource-Constrained Environments

Model Optimization Techniques: Successful implementations in developing nations have employed various model optimization strategies including pruning, quantization, and knowledge distillation to reduce computational requirements while maintaining acceptable accuracy levels [33]. These techniques enable deployment on low-cost hardware platforms commonly available in developing regions.

Hybrid Approaches: Combining computer vision with simple sensor technologies can enhance system reliability while managing costs. For example, integrating basic ultrasonic sensors with image classification can improve waste bin monitoring accuracy while reducing computational load [34].

Progressive Deployment: Rather than attempting comprehensive city-wide implementations, successful projects have adopted progressive deployment strategies, starting with pilot areas and gradually expanding based on lessons learned and available resources [35].

Community Engagement: Effective implementations have incorporated community participation in data collection and system monitoring. This approach not only reduces operational costs but also builds local ownership and sustainability [36].

Local Partnership Development: Collaborations with local universities, NGOs, and government agencies have proven essential for successful technology transfer and long-term sustainability [37].

7. Future Directions and Recommendations

7.1 Research Priorities

Context-Specific Dataset Development: There is an urgent need for comprehensive image datasets that accurately represent waste composition and environmental conditions in developing nations. Future research should prioritize collaborative data collection efforts that involve multiple developing countries and address regional variations in waste types and disposal practices [38].

Ultra-Efficient Model Architectures: Research into extremely lightweight model architectures that can operate on microcontroller-based systems while maintaining reasonable accuracy is crucial for enabling deployment in areas with severe resource constraints [39].

Robustness and Reliability: Future studies should focus on developing models that can maintain performance despite challenging environmental conditions, including variable lighting, weather exposure, and equipment degradation [40].

Integration and Interoperability: Research into seamless integration of computer vision systems with existing waste management infrastructure and practices in developing nations is essential for practical deployment success [41].

7.2 Policy and Implementation Recommendations

Capacity Building: Developing nations should invest in building local technical capacity for computer vision system development, deployment, and maintenance. This includes training programs for local engineers and partnerships with international research institutions [42].

Regulatory Frameworks: Governments should develop appropriate regulatory frameworks that support the deployment of computer vision technologies while addressing privacy concerns and data security issues [43].

Public-Private Partnerships: Collaboration between government agencies, private technology companies, and international development organizations can provide the resources and expertise necessary for successful large-scale implementations [44].

Incremental Implementation: Rather than attempting comprehensive system overhauls, cities should consider incremental implementations that build on existing infrastructure and gradually introduce computer vision capabilities [45].

8. Conclusion

Computer vision-based waste and litter management systems offer significant potential for addressing urban waste challenges in developing nations. Our review of recent literature reveals substantial progress in both dataset development and model optimization, with several architectures demonstrating feasibility for resource-constrained deployments. The availability of 10 prominent image datasets provides valuable training resources, while optimized models like MobileNetV2 and EfficientNet-B0 offer practical deployment options for mobile and edge computing platforms. However, successful implementation in developing nation contexts requires careful consideration of unique challenges including limited computational resources, diverse waste composition patterns, challenging environmental conditions, and infrastructure constraints. The most promising approaches combine technological innovation with contextual adaptation, community engagement, and progressive deployment strategies.

Future research should prioritize the development of context-specific datasets, ultra-efficient model architectures, and robust integration frameworks. Policy makers and implementation teams should focus on capacity building, appropriate regulatory frameworks, and sustainable partnership models. While significant challenges remain, the potential benefits of computer vision-based waste management systems – including improved monitoring capabilities, cost-effective scaling, and data-driven decision making – make continued research and development efforts highly worthwhile. The successful deployment of these technologies in developing nations will require sustained collaboration between researchers, policy makers, technology developers, and local communities. By addressing current limitations and building on demonstrated successes, computer vision-based waste management systems can contribute significantly to sustainable urban development in resource-constrained environments.

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