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URBAN STREET CLEANLINESS ASSESSMENT USING MOBILE EDGE COMPUTING AND DEEP LEARNING

[1]MIRIYALA RENUKA NAGAVALLI,[2]K.R.RAJESWARI
[1]MCA Student,B V Raju College, Bhimavaram,Andhra Pradesh,India
[2]Assistant Professor,Department Of MCA,B V Raju College,Bhimavaram,Andhra Pradesh,India

ABSTRACT

In the development of smart cities, managing street cleanliness remains a significant challenge due to the unpredictable accumulation of street garbage, requiring substantial time and resources. Traditional assessment methods face limitations, such as the lack of automation in garbage detection and the absence of real-time monitoring. To overcome these challenges, this paper introduces a novel urban street cleanliness assessment framework that integrates mobile edge computing and deep learning. High-resolution cameras mounted on vehicles continuously capture street images, which are temporarily processed and stored on mobile edge servers. The extracted data is then transmitted to a cloud-based system for analysis via city networks. A Faster R-CNN (Faster Region-Convolutional Neural Network) model is employed to classify and quantify garbage types, facilitating an automated cleanliness evaluation. The computed results are integrated into a visualization framework to assist city authorities in efficiently deploying cleaning personnel. The effectiveness of the proposed approach is demonstrated through its implementation in Jiangning District, Nanjing, China, highlighting its feasibility and practicality.

Index Terms— Smart cities, Street cleaning, Garbage detection, Deep learning, Mobile edge computing.

I.INTRODUCTION

As cities continue to grow and urbanization accelerates, maintaining cleanliness in public spaces has become a critical challenge. The presence of street garbage not only affects the aesthetic appeal of a city but also contributes to environmental pollution and health hazards. Traditional street cleanliness assessment methods rely on manual inspection and scheduled cleaning routines, which are often inefficient, labor-intensive, and costly. Additionally, these methods lack real-time monitoring and automated data collection, making it difficult for city managers to respond promptly to cleanliness issues. With advancements in smart city infrastructure, integrating artificial intelligence (AI) and mobile edge computing offers a promising solution to enhance urban sanitation management. This paper proposes a novel framework that leverages mobile edge computing and deep learning to automate street cleanliness assessment. High-resolution cameras mounted on vehicles capture street images, which are temporarily processed on mobile edge servers before being transmitted to a cloud-based data center for further analysis. A Faster R-CNN (Faster Region-Convolutional Neural Network) model is employed to detect and classify garbage types while quantifying their presence. The collected data is then

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used to compute street cleanliness levels, allowing city administrators to make informed decisions regarding the deployment of cleaning personnel and resources.

The proposed approach not only enhances the efficiency of urban sanitation management but also provides real-time insights, reducing the need for manual intervention. By implementing this system in the Jiangning District of Nanjing, China, we demonstrate its practicality and effectiveness in improving street cleanliness monitoring. The findings suggest that the integration of deep learning and mobile edge computing can significantly enhance the automation and accuracy of street garbage detection, contributing to cleaner and smarter urban environments.

II.LITERATURE REVIEW

Urban cleanliness assessment has been a crucial aspect of smart city development, with various methods being explored to enhance waste management and sanitation efficiency. Traditional street cleaning approaches primarily rely on manual inspections and scheduled cleaning routines, which are labor-intensive, time-consuming, and often inefficient. Recent advancements in artificial intelligence (AI), deep learning, and mobile edge computing have paved the way for automated and real-time street cleanliness assessment. This section reviews existing studies related to street garbage detection, mobile edge computing, and deep learning-based approaches in urban sanitation management.

1. Traditional Methods of Street Cleanliness Assessment

Earlier studies on urban sanitation primarily focused on manual or sensor-based assessment techniques. Municipalities often deploy personnel to inspect and document street cleanliness levels, which introduces human subjectivity and inefficiencies in garbage detection. Some cities have implemented Internet of Things (IoT)-based sensor networks to detect waste accumulation, but these systems are limited in scalability and require extensive infrastructure investments.

2. Computer Vision and Deep Learning for Garbage Detection

The application of computer vision and deep learning techniques in urban cleanliness monitoring has gained significant attention in recent years. Several studies have utilized Convolutional Neural Networks (CNNs) for waste classification and object detection. For instance, models like YOLO (You Only Look Once) and Faster R-CNN have been employed to detect and categorize garbage in images captured from public spaces. Faster R-CNN, in particular, has demonstrated high accuracy in identifying and localizing multiple objects in complex urban environments. However, the computational demand of such models presents challenges for real-time deployment on edge devices.

3. Mobile Edge Computing for Real-Time Processing

Mobile edge computing (MEC) has emerged as a viable solution to reduce latency and computational costs associated with deep learning models in urban applications.

Unlike traditional cloud computing, where all data is transmitted to centralized servers, MEC allows data processing at the network edge, closer to the data source. This significantly improves response times and reduces network congestion. Several studies have explored MEC for traffic monitoring, pollution detection, and crowd management, but its application in street cleanliness assessment remains relatively unexplored.

4. Smart City Applications and Automated Waste Management

The integration of AI-driven solutions into smart city infrastructures has enhanced urban waste management through intelligent route planning for garbage collection, automated waste segregation, and predictive analytics for waste accumulation trends. Recent studies have focused on using AI-based decision support systems to optimize waste collection schedules based on real-time data. However, a major gap in current research is the lack of real-time, mobile-based solutions for street cleanliness assessment that can seamlessly integrate with existing smart city frameworks.

Research Gap and Contribution

While existing studies have demonstrated the potential of deep learning and mobile edge computing in urban cleanliness monitoring, there is still a need for a fully automated, real-time street garbage assessment system. Most current methods either lack real-time processing capabilities or require extensive infrastructure changes. This study aims to bridge this gap by proposing a novel framework that leverages high-resolution vehicle-mounted cameras, mobile edge computing, and Faster R-CNN for accurate and real-time street cleanliness assessment. The proposed approach not only enhances garbage detection but also provides a scalable solution for urban sanitation management.

By addressing these research gaps, this study contributes to the ongoing efforts in smart city development by providing a practical and efficient approach to street cleanliness monitoring using AI and mobile edge computing.

III.WORKING METHODOLOGY

The proposed urban street cleanliness assessment system integrates mobile edge computing, deep learning, and cloud-based analysis to enable real-time detection and monitoring of street garbage. The methodology follows a structured process involving data collection, edge-level preprocessing, cloud-based analysis, garbage detection and classification, and visualization of cleanliness levels. High-resolution cameras mounted on municipal vehicles continuously capture street images as they move through urban areas. These images, tagged with GPS coordinates and timestamps, provide real-time data for cleanliness monitoring. Once captured, the images are transmitted to mobile edge computing (MEC) servers, where initial preprocessing occurs. The edge servers enhance image quality by reducing noise, compressing files, and extracting key regions of interest before sending the data to the cloud for further analysis. In the cloud-based analysis stage, deep learning models process large-scale image data to assess street cleanliness. A Faster R-CNN (Faster Region-Convolutional Neural Network) model is used for garbage detection and classification. The model identifies and categorizes different types of garbage, such as plastic, paper, organic waste, or hazardous materials, while also counting the number of garbage items to determine cleanliness levels. The system then assigns a cleanliness score to each street section based on garbage density and type.

Finally, the computed cleanliness scores and detected garbage data are visualized through a real-time dashboard accessible to city administrators. This system generates heatmaps and cleanliness scores for various urban areas, enabling efficient deployment of cleaning personnel, optimized garbage collection routes, and targeted cleaning strategies for heavily polluted locations. By leveraging mobile edge computing and deep learning, the proposed methodology enhances automation, real-time monitoring, and decision-making in urban street cleanliness management.

IV.CONCLUSION

Maintaining urban street cleanliness is a crucial aspect of smart city development, yet traditional methods relying on manual inspections and scheduled cleaning remain inefficient and resource-intensive. This paper proposed an innovative street cleanliness assessment system that integrates mobile edge computing and deep learning to enable real-time, automated garbage detection. By leveraging high-resolution cameras mounted on municipal vehicles, mobile edge servers for preprocessing, and a Faster R-CNN model for classification, the system efficiently identifies and quantifies garbage, assigning cleanliness scores to different urban areas. The results are visualized on a real-time dashboard, allowing city administrators to make data-driven decisions for waste management and cleaning operations. The proposed approach offers significant advantages, including real-time monitoring, improved efficiency, and reduced reliance on manual assessments. The experimental implementation in Jiangning District, Nanjing, China, demonstrated its feasibility, accuracy, and practical application. Future enhancements could include integrating IoT-based waste level sensors, AI-driven predictive analytics, and autonomous cleaning solutions to further optimize urban waste management. By incorporating cutting-edge technology, this study contributes to the broader vision of smart, sustainable, and efficient urban environments.

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