

Smart Image-Based Detection and Reporting of Unclean Public Spaces Using CNN

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Abstract

The rate of increasing cleanliness issues has been considered as a biggest problem in today's modern scenario. The issue has created a serious impact on the overall well-being of many citizens in both rural and urban areas. The traditional checking of cleanliness methods needs manual checking, which results in poor progress and no effective methodology. Since India is a vast country, checking each place manually is an impossible act. To overcome these drawbacks, we have introduced a software solution that uses CNN to automatically detect and report unclean public places. In regard to this, the system uses an Android mobile to take pictures of public areas. So, this would be simpler, and there is no special equipment needed. Here, these photos are fed into a CNN model that uses the patterns to identify trash. The system generates a report with the photo, GPS location, and time details when it detects a dirty area. The municipal authorities can receive the report directly. The system keeps these records for a while, so the authorities can track the patterns and identify problems in cleanliness maintenance. As per this project, mobile data collection and CNN analysis are combined regarding urban cleanliness management. This can be a very efficient solution for cities. It reduces human work and improves detection. Further, this system helps in quick action for the maintenance of clean and healthier cities. When a person uploads a photo, they will get some rewards. This will make the work more efficient. By this approach, we can conclude that if this is made as a daily technology, then it becomes easier to solve practical problems in city management.

Keywords: CNN; GPS

1. Introduction

Maintaining cleanliness in contemporary urban environments has become an increasing concern. Municipal authorities are tasked with monitoring hygiene conditions, yet traditional practices rely heavily on manual labor. These methods are often slow, labor-intensive, and unable to provide an accurate, real-time assessment of cleanliness. Consequently, many unclean locations remain undetected, negatively impacting public health and overall quality of life. Simultaneously, the proliferation of mobile devices and advancements in Artificial Intelligence present new opportunities for urban cleanliness monitoring. Image-based algorithms can substantially reduce manual effort and deliver faster, more consistent results. Convolutional Neural Networks (CNNs), recognized for their robust

image recognition capabilities, can be trained to detect dirt, litter, and waste patterns from standard photographs without requiring specialized equipment. This work introduces a system that combines mobile images with CNN-based analysis to support real-time cleanliness monitoring. Users can take photos of public locations, and the system automatically evaluates the image and determines whether the area is clean or not. When unclean regions are found, the system records essential details such as location, timestamps, and image evidence, and allows authorities to take action. By this approach, the study demonstrates how AI tools can assist in addressing practical civic challenges and contribute to building cities that are more hygienic, responsive, and eco-friendly.

1.1. Related Works

Urban cleanliness monitoring has evolved significantly over the past decade, driven by rapid urbanization, increasing population density, and the need for more efficient public health management. Traditional waste monitoring practices rely heavily on manual inspections conducted by municipal workers. However, these methods are slow, inconsistent, and incapable of providing continuous real-time data, especially in large cities. This limitation has encouraged researchers to explore automated digital solutions using computer vision, deep learning, and smart city technologies. Dyuthi et al. (2025) introduced *CleanSpot*, a web-based application designed to encourage citizen involvement in maintaining urban cleanliness. The platform enables users to upload photographs of areas where waste has accumulated, helping civic authorities quickly locate and respond to sanitation issues [1]. While the system proved effective in improving reporting efficiency through public participation, it largely depended on manual verification of the submitted images. Since it lacked automated image-based cleanliness assessment, this limitation highlighted the need for advanced solutions. As a result, it paved the way for further research into the use of artificial intelligence for automatic and real-time analysis of environmental images. Hasan et al. (2022) extended research in this area by developing a deep learning-based waste classification model for smart city waste segregation systems [2]. Their approach employed convolutional neural networks (CNNs) to automatically classify waste into categories such as recyclable, organic, and hazardous materials. Although the model demonstrated strong classification performance, it was mainly evaluated in controlled waste-bin settings and did not address cleanliness detection in open or public environments. Even so, the study clearly demonstrated the superiority of CNN-based methods over traditional image processing techniques and confirmed the practicality of deploying deep learning solutions in civic and urban management applications. Research on image-based anomaly and outlier detection has also made an important contribution to this domain. Liu and Hentschel (2011) presented one of the earliest comprehensive

surveys on detecting anomalous instances using deep learning techniques [3]. Their work provides a strong conceptual basis for cleanliness assessment, where elements such as litter, waste, or dirt can be interpreted as anomalies within otherwise clean environments. This viewpoint supports the development of models that can effectively differentiate between clean and unclean scenes, even under diverse real-world conditions. Additional progress is evident in studies like Mittal et al. (2021), who proposed a CNN-based method for garbage detection. Their findings confirmed the effectiveness of deep learning in recognizing waste from images; however, the dataset primarily included close-up images of individual waste items, limiting its applicability for large-scale or street-level cleanliness evaluation [4]. Similarly, Rajesh et al. (2020) developed a CNN-driven automated waste segregation system with a strong focus on image preprocessing and model optimization [5]. Although their approach was mainly designed for indoor waste management environments, several of the techniques they employed—such as data augmentation and background noise reduction—are highly relevant for outdoor cleanliness monitoring applications. More recent studies have shifted attention toward mobile platforms and real-time detection capabilities. Nguyen et al. (2023) developed a lightweight litter detection system by integrating the YOLO object detection framework with smartphones, enabling real-time analysis directly on mobile devices [6]. Their work demonstrated that advanced deep learning models can be efficiently deployed on resource-constrained hardware with minimal impact on performance. This approach closely relates to the objectives of the present study, in which users capture images through mobile devices and the system automatically detects and reports cleanliness-related issues.

1.2. Problem Statement

As urban areas continue to expand, managing cleanliness in public and community spaces has become increasingly challenging due to the growing volume of waste [7]. Although many locations are monitored through CCTV systems and citizens regularly capture images of their surroundings, much of this visual information remains underutilized

because automated analysis mechanisms are lacking. Consequently, sanitation authorities often depend on manual inspections or delayed, complaint-driven responses, which can result in unhygienic areas remaining unnoticed and unaddressed for extended periods. As urban areas continue to expand, managing cleanliness in public and community spaces has become increasingly challenging due to the growing volume of waste. Although many locations are monitored through CCTV systems and citizens regularly capture images of their surroundings, much of this visual information remains underutilized because automated analysis mechanisms are lacking. Consequently, sanitation authorities often depend on manual inspections or delayed, complaint-driven responses, which can result in unhygienic areas remaining unnoticed and unaddressed for extended periods [8]. Relying solely on human monitoring is insufficient for analyzing the large number of images captured every day. Similarly, conventional rule-based systems are ineffective because waste does not exhibit consistent or predictable visual patterns. Its appearance can vary significantly in terms of shape, color, size, lighting conditions, occlusion, and background. Therefore, to accurately identify such complex and irregular features, an effective system must be capable of learning these visual patterns automatically rather than depending on manually defined rules. Recent progress in deep learning, particularly in Convolutional Neural Networks (CNNs), has demonstrated strong capability in extracting and interpreting complex visual features. By learning spatial hierarchies such as edges, textures, shapes, and contextual information, CNNs are able to accurately detect garbage, litter accumulation, overflowing bins, and generally unclean environments. Despite these advantages, deploying such models in real-world cleanliness monitoring systems remains challenging due to variations in real-world data, the demand for consistent and reliable classification, and the need for solutions that function effectively with minimal human intervention. A further limitation observed in existing cleanliness reporting platforms is the lack of sustained user participation. Most systems rely entirely on voluntary contributions, which often decrease after the initial

period of use. In the absence of well-defined incentive or reward mechanisms, users tend to lose motivation, resulting in low long-term engagement within the cleanliness monitoring framework. To address these challenges, this project introduces a smart image-based system for reporting unclean areas using Convolutional Neural Networks (CNNs). The proposed system analyzes uploaded images to automatically detect cleanliness issues, assesses the severity of the identified waste, and promotes sustained community involvement through a reward-based participation model. By combining automation with user engagement, the approach offers a scalable, efficient, and socially driven solution for enhancing cleanliness monitoring and response mechanisms [9].

1.3. Proposed Work

The proposed work leverages Convolutional Neural Networks (CNNs) to automatically identify littered or unhygienic areas within urban environments and generate structured reports for civic authorities. The system is designed to function on standard mobile devices, ensuring ease of use and broad accessibility for both citizens and field personnel. When a user captures an image of a public location, the photograph is instantly analyzed by a trained CNN model that examines visual patterns to determine the presence of garbage, litter, waste buildup, or other indicators of unclean conditions. Compared to manual inspection processes, which are often time-consuming and inconsistent, the CNN-based approach enables faster and more reliable image evaluation with high accuracy [10]. When waste is detected by the model, the system automatically generates a comprehensive cleanliness report. This report contains the captured image, precise GPS location details, the time at which the image was recorded, and a cleanliness classification label produced by the CNN. The generated report is transmitted in real time to municipal cleaning teams or the appropriate authorities, enabling prompt action. By providing visual evidence along with accurate location information, the system helps cleaning personnel reach the affected area quickly and carry out focused cleaning activities without unnecessary delays or uncertainty. Beyond generating individual reports, the system also maintains a centralized database that stores

information on all detected unclean locations over time [11]. This historical data enables authorities to analyze cleanliness patterns, identify areas with recurring waste accumulation, and plan manpower deployment or cleaning schedules more effectively. Over extended periods, such as weeks or months, the accumulated reports help reveal persistent garbage hotspots, supporting improved urban planning decisions and proactive cleanliness management strategies [12]. Overall, the proposed approach presents an effective and practical solution for cleanliness monitoring by minimizing reliance on manual inspections, enhancing detection accuracy, and facilitating rapid reporting and response. Through the integration of AI-based CNN analysis with mobile image capture and automated reporting mechanisms, the system offers a scalable framework that contributes to cleaner, healthier, and better-managed public spaces [13].

2. Method

2.1. User Interface

The system primarily relies on mobile phones or other camera-enabled devices for data collection. Users capture images of public areas using these devices and upload them to the platform. After submission, the images are transmitted to the backend server, where they are securely stored and prepared for subsequent processing and analytical tasks.

2.2. Backend Processing

The web server or API server functions as the central processing component of the system. It handles images uploaded by users and applies essential preprocessing steps, including image resizing and noise reduction. Once preprocessing is complete, the images are properly formatted and prepared for analysis, after which they are forwarded to the CNN-based analysis module for waste detection and classification.

2.3. CNN-Based Image Analysis

The Convolutional Neural Network (CNN) module performs the core image analysis by examining the preprocessed images received from the server. It identifies signs of unclean conditions, including trash, litter, or spills, and classifies each image as either clean or unclean. The classification outcomes are subsequently forwarded to the result and storage

module, where they are used for reporting, follow-up actions, and long-term record maintenance.

2.4. Result Generation & Storage

The database or cloud storage component stores the uploaded images along with their corresponding analysis outcomes, including cleanliness classifications. It also maintains historical records of all collected data, supporting long-term monitoring and trend analysis. These stored results are later retrieved and supplied to the display and reporting module for visualization, reporting, and decision-making purposes.

2.5. Display & Reporting

The user dashboard, admin dashboard, and notification system together form the interface layer of the system. This component displays the analysis results to users by indicating whether an area is clean or unclean. When unclean areas are detected, it automatically generates reports and sends alerts to the concerned authorities, ensuring timely action and effective response (Figure 1).

3. Results and Discussions

3.1. Results

The system was evaluated using images from various public locations, including roadsides, parks, bus stands, and open areas. The performance of the CNN model and the reporting process was assessed based on accuracy, processing time, and usability (Figure 2).

1.1. Discussion

The computational performance of the proposed system is largely influenced by the CNN-based image analysis module. Since the model processes images through multiple convolutional layers, inference time increases with image resolution, kernel size, and the number of filters and layers used. This makes CNN inference the dominant factor affecting system latency, especially when handling high-resolution images or deeper network architectures. In contrast, backend operations such as report generation, storage, and task assignment introduce minimal overhead, typically exhibiting linear time complexity relative to the number of reports. Similarly, space complexity is mainly governed by the storage of trained model weights and intermediate feature maps, which scale with image size and network depth. From a system perspective, this trade-off between accuracy

and computational cost is expected in deep learning-based visual inspection systems. While the current architecture provides reliable cleanliness detection across varied environments, optimization techniques such as lightweight CNN models, image resolution scaling, or hardware acceleration could further enhance real-time performance and scalability. Beyond performance considerations, the system demonstrates strong potential for practical urban deployment. By maintaining historical cleanliness data, it supports trend analysis and hotspot identification, enabling data-driven decision-making for municipal authorities. However, the current implementation relies on static image uploads, which limits continuous monitoring. Future extensions of the system could address these limitations by integrating live video streams from CCTV cameras to enable real-time surveillance. Enhancing the CNN to

perform multi-class waste classification—such as identifying plastic, metal, or organic waste—would further support targeted waste management and recycling strategies. Additionally, incorporating predictive analytics could help identify litter-prone hotspots in advance, allowing authorities to take preventive action. Further improvements may include integrating citizen engagement platforms to encourage public participation through incentives and gamification, as well as optimizing cleanup operations using GPS-based routing and traffic-aware scheduling. Expanding the framework to include other environmental monitoring tasks, such as air or water pollution detection, could transform the system into a comprehensive urban sustainability platform.

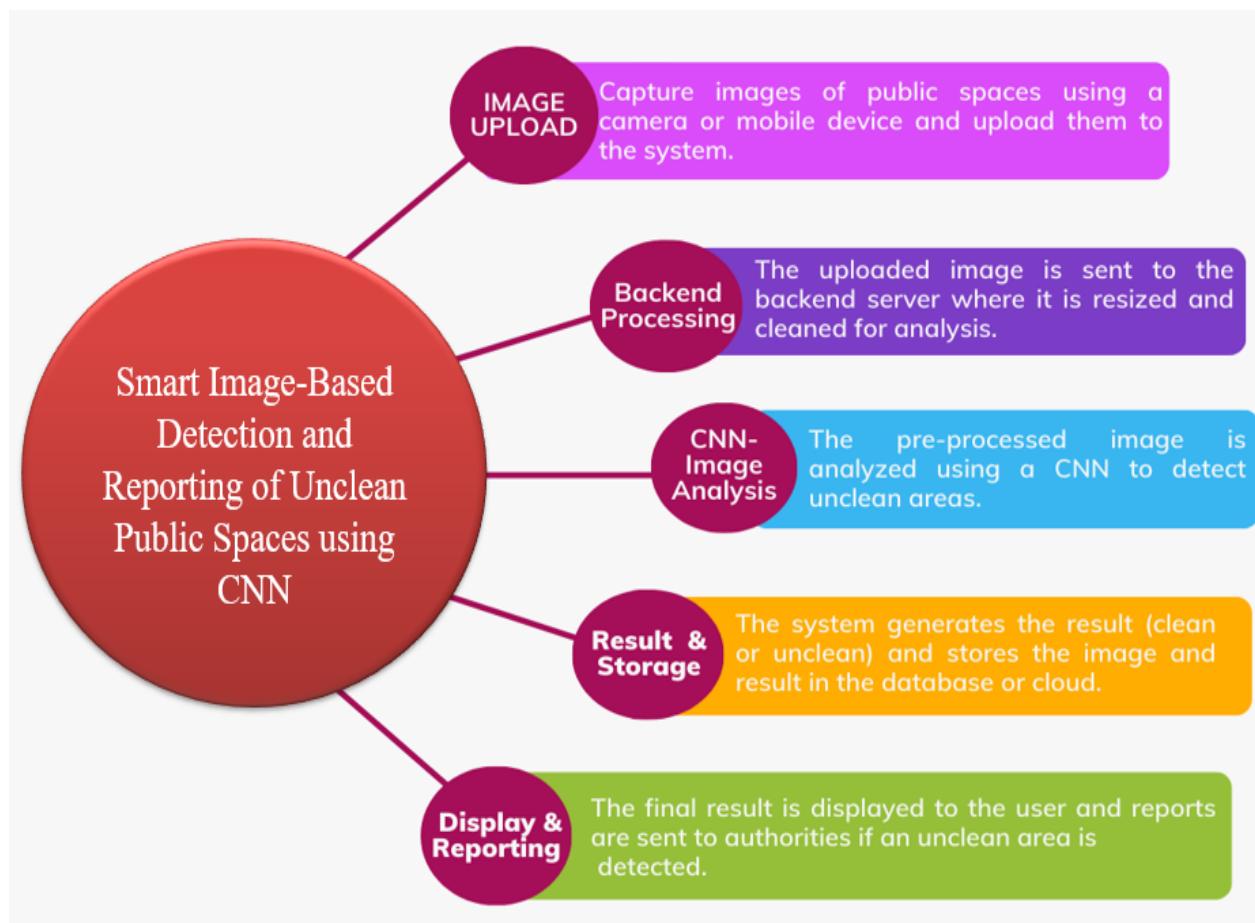
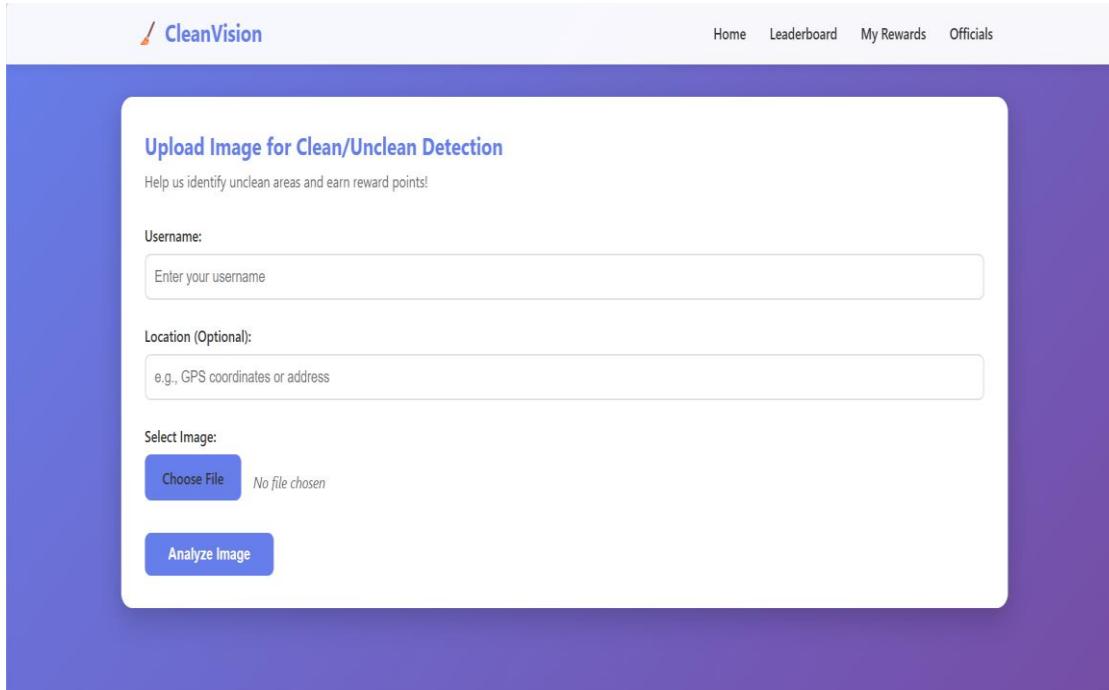


Figure 1 Methodology

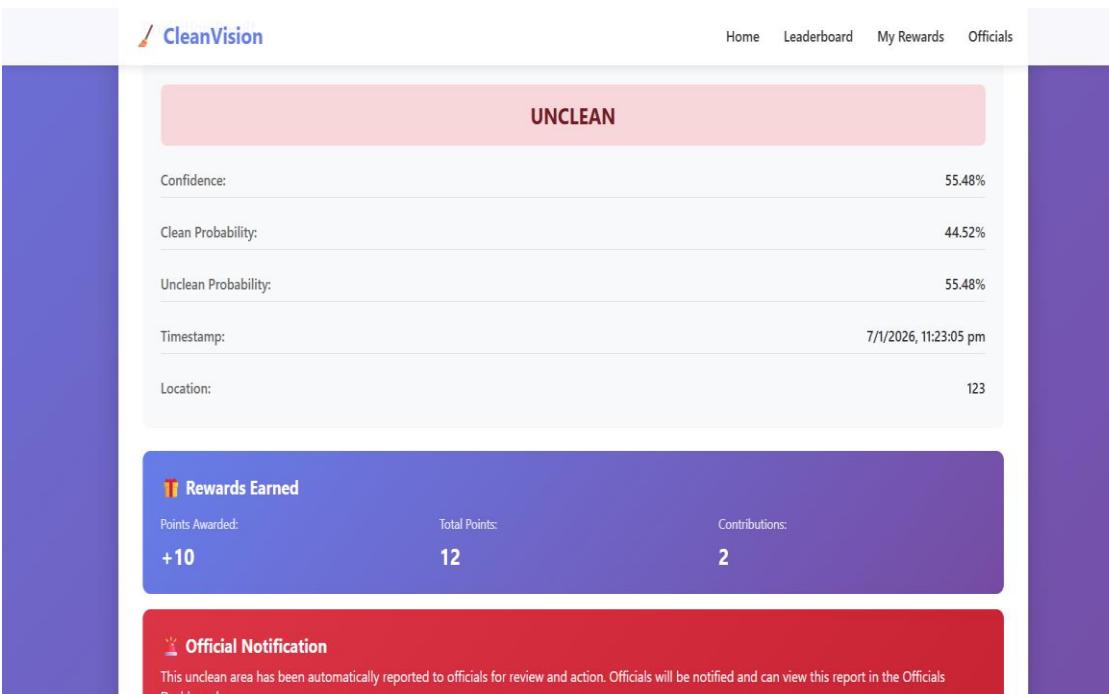


Upload Image for Clean/Unclean Detection
 Help us identify unclean areas and earn reward points!

Username:

Location (Optional):

Select Image:



UNCLEAN

Confidence:	55.48%
Clean Probability:	44.52%
Unclean Probability:	55.48%
Timestamp:	7/1/2026, 11:23:05 pm
Location:	123

Rewards Earned

Points Awarded:	Total Points:	Contributions:
+10	12	2

Official Notification

This unclean area has been automatically reported to officials for review and action. Officials will be notified and can view this report in the Officials Dashboard.

Figure 2 Accuracy of the System

Conclusion

This paper is about a way to check how clean urban spaces are. We want to use intelligence to do this job. Now people have to do this job by hand which is not very good. Our new method uses a computer system

that looks at pictures taken with a phone. This system is very good at finding public spaces. It can see litter remember where it is and make a report that's easy to understand. This means that the people in charge of the city can respond faster and make decisions based

on facts. The system is also very good at giving us the information we need to keep our city clean. Urban spaces, like parks and streets will be cleaner because of this method. The performance results show that the model is good in different environments and lighting conditions so it can be used in the real world. The system does a lot more than just find things it also helps with keeping things clean over a time by saving what happened in the past and showing us where the problems are that happen the most. The model is really good at doing this. In total this work shows how Artificial Intelligence can be used in the things we do every day to make our cities cleaner, healthier and smarter. The model is very useful, for this. With some improvements and more training samples, this system has the potential to become a powerful platform for urban management and sustainable city management.

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