A Lightweight Mobile Monitoring System for Detection of Small-Scale Road Debris

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Abstract

Road debris poses a significant threat to traffic safety, particularly small-scale objects that are difficult to detect under complex road conditions. Traditional manual inspection methods suffer from low efficiency, limited coverage, and delayed response. To address these challenges, this study proposes a lightweight mobile monitoring system for small-scale road debris detection based on vehicle-mounted sensing and dynamic data transmission. The system integrates a lightweight image acquisition device, a self-developed mobile monitoring software, and an improved lightweight detection model termed Dynamic-YOLOv8n. The model introduces dynamic convolution and attention mechanisms to enhance feature representation while maintaining computational efficiency. In addition, a dynamic compression transmission mechanism is designed to adaptively adjust image compression and transmission frequency under fluctuating network bandwidth, ensuring stable data transfer between the front-end terminal and the backend platform.

A dedicated debris dataset was constructed from field-collected images covering diverse road types and environmental conditions. Experimental results show that the proposed model achieves a mean Average Precision (mAP) of 93.2% while maintaining real-time detection performance. Field tests conducted on urban road networks further demonstrate that the system significantly improves detection efficiency compared with manual inspection and enables reliable real-time monitoring of road debris. The proposed framework provides an effective solution for intelligent road inspection and digital road maintenance.

1 Introduction

In recent years, the rapid expansion of highway networks and the continuous growth of traffic volume have led to increasingly complex road operating environments. In addition to traditional pavement distresses such as potholes and cracks, road debris has gradually become an important safety hazard affecting traffic operations. Road debris refers to foreign objects scattered on road surfaces due to transportation, construction, natural processes, or human activities, including cargo residues, vehicle components, construction fragments, and domestic waste. These objects may cause tire damage, vehicle avoidance maneuvers, or secondary accidents during driving, posing direct risks to traffic safety (Arya et al., 2021).

Compared with large obstacles, this study focuses on small-scale road debris, typically ranging from 1–15 cm in size. Such objects, including gravel, screws, glass fragments, and plastic debris, are characterized by irregular shapes, weak reflectivity, and random spatial distribution. Due to their visual similarity to pavement backgrounds and their small size, they are difficult to detect under complex lighting conditions and dynamic driving scenarios. Even though these objects are small, they may be crushed or projected by vehicle tires at high speeds, potentially causing injuries to pedestrians or vehicles behind them and even leading to tire punctures or vehicle damage (Mo et al., 2024). Because of their high occurrence frequency and unpredictable distribution, traditional manual inspection approaches are inefficient and cannot meet the demands of modern road safety management (Rathee et al., 2023).

With the rapid development of computer vision and deep learning technologies, intelligent road inspection systems have been increasingly applied to pavement condition monitoring and traffic environment perception. Vehicle-mounted cameras, unmanned aerial vehicles, and LiDAR sensors have been widely adopted to automatically detect road damages and traffic facilities (Maeda et al., 2020; Arya et al., 2021). In particular, deep learning–based object detection algorithms such as the YOLO family have demonstrated strong performance in real-time traffic scene analysis (Redmon et al., 2016; Wang et al., 2023). Several studies have explored lightweight neural networks and edge computing techniques to improve real-time road damage detection performance on embedded platforms (Liang et al., 2022; Yang et al., 2024).

Despite these advances, most existing studies focus on large-scale road defects or infrastructure elements, while the detection of small-scale road debris remains challenging due to weak visual features, small object size, and complex backgrounds (Tong et al., 2023). Furthermore, deep learning models often require substantial computational resources, which limits their deployment on vehicle-mounted embedded devices (Howard et al., 2019; Tan and Le, 2020). In addition, large-scale inspection data generated during mobile monitoring may suffer from unstable network bandwidth, leading to delays in data transmission and processing (Erfanian et al., 2022).

To address these challenges, this study proposes a lightweight mobile monitoring system for small-scale road debris detection. The proposed system integrates vehicle-mounted vision sensing and GNSS positioning to achieve real-time detection, localization, and recording of road debris. A lightweight detection model combined with a dynamic compression transmission mechanism is developed to ensure efficient detection and stable data transmission under fluctuating network conditions. The system adopts a modular architecture that supports continuous image acquisition and real-time detection during mobile inspections without manual intervention.

The contributions of this study are twofold. First, a lightweight visual detection model tailored for small-scale road debris is proposed, significantly reducing computational complexity while maintaining detection accuracy. Second, an integrated vehicle-mounted monitoring platform is developed to support synchronized image acquisition, debris detection, and spatial localization. The proposed approach provides an efficient and cost-effective solution for intelligent road inspection and digital highway maintenance.

2 Methodology

2.1 Overall System Architecture and Workflow

This study develops a hardware–software integrated lightweight mobile monitoring system for small-scale road debris, aiming to achieve real-time detection, localization, and recording of minor foreign objects on highways and urban roads, such as gravel, glass fragments, metal debris, plastic pieces, and rubber residues. Compared with traditional manual inspection methods—where maintenance personnel rely on visual observation and manual recording, resulting in high labor intensity, low efficiency, and subjective bias—the proposed system enables automated and standardized monitoring. The overall architecture consists of four components: a front-end lightweight acquisition module, a data processing and detection module, a data transmission module, and a backend management module (Figure 1).

The front-end acquisition module employs multi-sensor collaboration to continuously capture pavement images while simultaneously recording GNSS positioning information and timestamps, with images temporarily stored locally. The data processing and detection module utilizes a deep learning–based object detection framework to perform inference and identify the spatial characteristics of small-scale debris in the captured images. The data transmission module applies an adaptive compression mechanism that dynamically adjusts image compression ratios and transmission frequency according to real-time network bandwidth, ensuring stable data transfer under limited bandwidth conditions. The backend module receives, parses, and manages the transmitted data, and provides a visualization interface for result display and management.

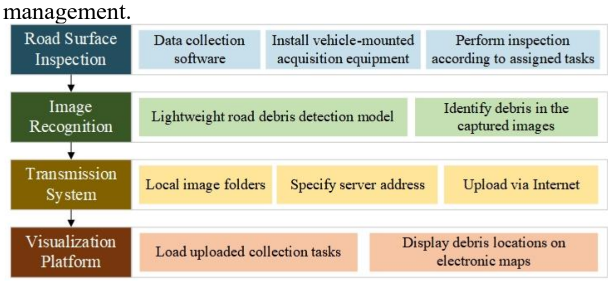

Figure 1. Workflow of the Lightweight Mobile Monitoring System for Minor Road Surface Debris

2.2 Mobile Monitoring Terminal Hardware Design

The lightweight image acquisition device consists of a high-resolution industrial camera, a centimeter-level GNSS receiver, an industrial control computer, and an integrated touch-screen terminal, as shown in Figure 2.

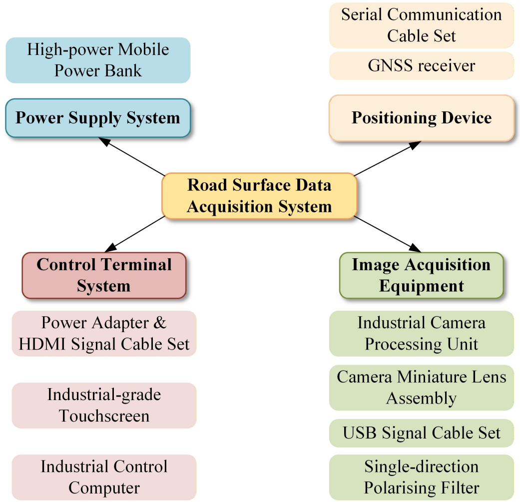

Figure 2. Lightweight Collection Equipment

The industrial camera is responsible for capturing high-quality pavement images, while the GNSS receiver provides high-precision spatiotemporal information to enable accurate localization of detected debris. The industrial control computer performs on-site image processing and data management, and the touch-screen terminal supports visualization, system monitoring, and parameter adjustment, facilitating real-time human–machine interaction.

2.3 Software Design of the Mobile Monitoring Terminal

The software system was developed on the Python platform and is responsible for coordinated control of front-end sensors and cameras, image acquisition, and data transmission, enabling automated road inspection. By ensuring real-time acquisition and data integrity, the system supports continuous road image collection and remote data communication, serving as a key component of the lightweight road inspection framework.

During data acquisition, image capture is controlled based on GNSS positioning information. The GNSS receiver obtains the vehicle's position at a frequency of 10 Hz, and the distance between adjacent positioning points d_{AB_i} is calculated using the Haversine formula:

$$d_{AB_i} = 2R \cdot \arcsin\sqrt{\sin^2\left(\frac{\phi_2-\phi_1}{2}\right) + \cos(\phi_1)\cos(\phi_2)\sin^2\left(\frac{\lambda_2-\lambda_1}{2}\right)} \qquad (1)$$

where R denotes the Earth's radius (approximately 6,371,000 m), and λ and ϕ represent longitude and latitude, respectively. All angular values are converted to radians:

$$\text{radians} = \text{degrees} \times \frac{\pi}{180} \qquad (2)$$

The distances between adjacent points are accumulated to obtain D_{AB}. When $D_{AB} > 20$, the camera is triggered to capture an image, which is stored in a designated local directory, and the distance counter is reset. This process is repeated continuously to achieve distance-based automatic image acquisition. In addition, a graphical user interface was developed using Qt Designer to display real-time pavement images and provide control of acquisition tasks.

For data communication, the system establishes a transmission channel based on the TCP/IP protocol. Captured images are compressed and packaged before being uploaded to the backend server through an asynchronous transmission mechanism. This approach enables parallel execution of data acquisition and data transmission, thereby reducing network latency and improving overall system efficiency. Through the integration of data acquisition and communication functions, the system ensures stable image collection and remote data transfer in embedded environments, providing reliable input for real-time road debris detection.

2.4 Improved Lightweight Detection Model: Dynamic-YOLOv8n

To accommodate the limited computational resources and strict power constraints of the inspection terminal, YOLOv8n—the most lightweight version in the YOLOv8 series—was selected as the baseline network. However, in the task of detecting small-scale road debris, challenges such as small object size, complex backgrounds, and high texture similarity lead to insufficient accuracy and a relatively high missed-detection rate in the original YOLOv8n. To address these issues, this study proposes an improved model, termed Dynamic-YOLOv8n, whose overall architecture is illustrated in Figure 3. While maintaining a lightweight structure, the model enhances detection performance by incorporating dynamic convolution and multi-scale attention mechanisms, achieving a balance between accuracy and computational efficiency.

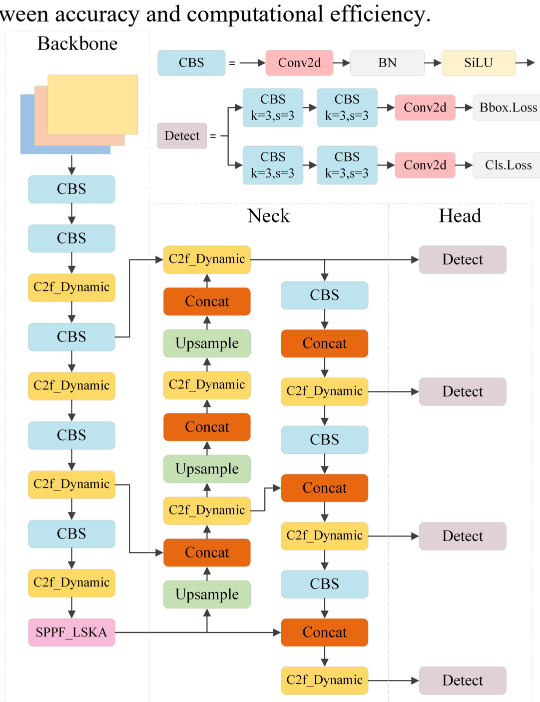

Figure 3. Improved YOLOv8n Network Architecture

2.4.1 C2f-Dynamic Module

To mitigate the limited feature representation capacity of lightweight networks, a Dynamic Convolution mechanism is introduced into the backbone of YOLOv8n, forming the C2f-Dynamic module. The DynamicConv layer adaptively generates convolution kernel weights based on input features, enabling dynamic multi-kernel aggregation and enhancing nonlinear representation capability. By replacing part of the standard convolutions in the original C2f module and integrating normalization operations with the SiLU activation function, the proposed structure improves training stability and feature resolution. This design effectively alleviates feature degradation in low-FLOPs models under complex scenarios. The architecture of the C2f-Dynamic module is shown in the corresponding Figure 4.

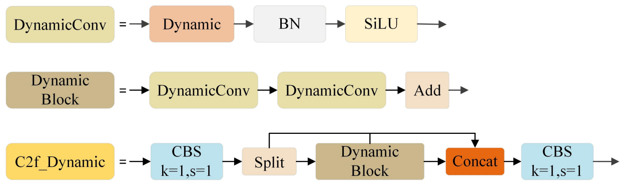

Figure 4. C2f-Dynamic Module

2.4.2 SPPF-LSKA Module

To enhance multi-scale feature fusion in complex pavement environments, a Large-Separable Kernel Attention (LSKA) mechanism is incorporated into the original SPPF structure, forming the SPPF-LSKA module. LSKA decomposes large-kernel convolutions into separable horizontal and vertical operations, enlarging the receptive field while controlling computational cost. Combined with dilated convolutions, the module generates attention weights to adaptively emphasize key regions. Without significantly increasing computational overhead, this design improves global perception and fine-grained feature representation. The architecture of the SPPF-LSKA module is illustrated in the corresponding Figure 5.

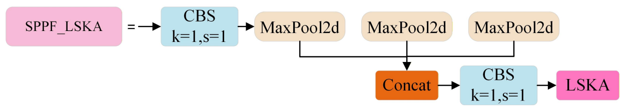

Figure 5. SPPF-LSKA Module

2.4.3 Fourfold Downsampling Module (P2)

To improve detection performance for small objects, an additional P2 detection layer is introduced in the neck network, generating high-resolution feature maps of 160 × 160 pixels. This layer is dedicated to small-scale object detection and is integrated with the FPN-PAN structure to achieve multi-scale collaborative detection. The proposed design effectively reduces the missed-detection rate for small targets.

Overall, the improved Dynamic-YOLOv8n model maintains a lightweight architecture while achieving a balance between detection accuracy and real-time performance, meeting the low-latency and low-power requirements of vehicle-mounted edge computing devices.

2.5 Functional Design of the Backend Management Platform

Within the intelligent detection framework for small-scale road debris, the backend system serves as the core support platform, undertaking key tasks including data reception, processing, analysis, and integrated management. It enables centralized management of images and spatiotemporal information uploaded from multiple terminals, such as inspection vehicles, fixed monitoring devices, and unmanned aerial vehicles, thereby providing support for road safety assessment and emergency decision-making.

The backend system consists of three layers: the data access layer, the information management layer, and the visualization layer. The data access layer aggregates front-end images and GNSS positioning data, parses detection results, and completes data registration to ensure integrity and transmission timeliness. It also supports coordinated interaction with the adaptive bandwidth transmission mechanism. The information management layer performs filtering, classification, and attribute extraction of detected debris based on the trained detection model, and conducts spatiotemporal correlation analysis by integrating vehicle speed, posture, and inspection route information, thereby generating structured safety datasets. The visualization layer utilizes map services for spatial representation and dynamic analysis, supporting multi-level visualization formats such as point markers, heat maps, and statistical charts, and providing managers with interactive tools for data querying and trend analysis. The backend structural system is illustrated in Figure 6.

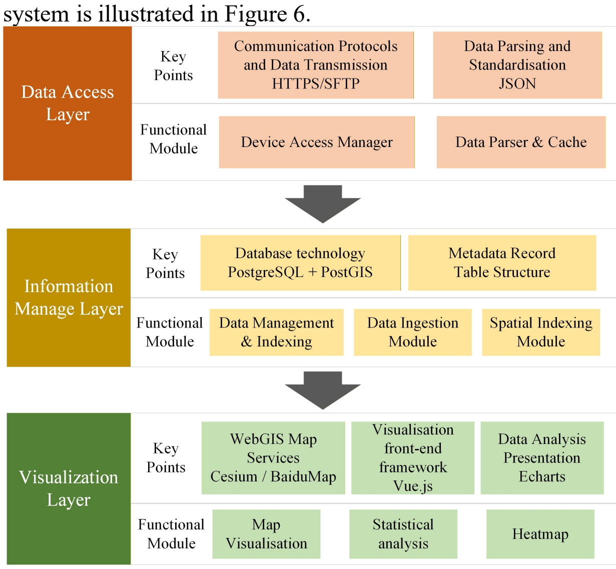

Figure 6. Technical Roadmap for Backend Development

3 Experiment

To validate the practicality and performance of the proposed system, this study conducted experimental evaluations focusing on the lightweight debris detection model. The objective was to assess real-time detection capability and recognition accuracy in an embedded environment, ensuring stable identification of small-scale debris and verifying the overall front-end performance and engineering feasibility of the system.

3.1 Experimental Environment and Test Scenario Configuration

To evaluate the feasibility of the lightweight debris acquisition and detection system in real road environments, an integrated experimental setup covering hardware, software, and data interaction processes was established. The experimental platform was based on Windows 11, equipped with an Intel i7-11700H CPU, an NVIDIA RTX 3060 GPU (12 GB VRAM), and 32 GB RAM, providing sufficient computational resources for model inference and image processing. The system was implemented using PyTorch 2.2.2 with CUDA 12.1 acceleration to enhance computational efficiency and real-time performance.

The backend server was deployed on an Alibaba Cloud ECS instance running Windows Server 2022, configured with a 1TB cloud storage disk for centralized storage of images and detection results. This environment simulates the complete workflow from front-end data acquisition to cloud-based analysis, offering stability and scalability for system performance validation.

3.2 Performance Evaluation of the Lightweight Detection Model

3.2.1 Dataset Construction and Model Evaluation

To enhance the adaptability and stability of the model under complex road conditions, a dedicated dataset of small-scale road debris was constructed based on self-collected images. Data acquisition was carried out using the proposed lightweight mobile monitoring system, which integrates a high-resolution industrial camera and a centimeter-level GNSS module to synchronously capture imagery and spatiotemporal information. The dataset covers multiple road types, including urban arterial roads, provincial highways, and branch roads, under diverse environmental conditions such as sunny, cloudy, nighttime, and rainy scenarios, and includes various representative debris categories.

All samples were manually annotated using rectangular bounding boxes to record object locations and category labels. The dataset was divided into training, validation, and testing sets at a ratio of 7:2:1, and an additional extended test subset was constructed to evaluate model robustness and generalization performance under complex conditions. Table 1 summarizes the dataset composition and diversity characteristics.

Classification	Subclass	Number of images
Road Type	Urban arterial roads, provincial highways, minor roads	About 1200/1000/1000
Weather Conditions	Sunny, Cloudy, Night-time, Rainy	About 900/800/700/800
Types of Lost Property	Metal fragments, plastic bags, fabric coverings, pieces of wood, tyres, etc.	Total about 3200
Data Augmentation	Flip, brightness perturbation, blur enhancement	—

Table 1. Overview of the Composition and Collection Conditions of the Abandoned Items Dataset

The model was trained using a supervised learning strategy based on the improved YOLOv8n framework. A combination of cross-entropy loss and IoU loss was employed for optimization, and the Adam optimizer was adopted, with key hyperparameters determined through experimental tuning. As publicly available datasets such as COCO and RDD2022 lack annotated samples of road debris, the model was trained and validated entirely on the self-constructed dataset to enhance its adaptability to real-world scenarios.
Experimental results indicate that the model achieved a mean Average Precision (mAP) of 93.2% on the test set, demonstrating high detection accuracy and stability across multiple debris categories. The dataset incorporates diverse road types, lighting conditions, and weather scenarios, contributing to improved environmental adaptability. Although a systematic generalization analysis was not conducted,

performance across multiple real-world scenarios suggests strong application potential in complex road environments.

3.2.2 Ablation Study

To validate the effectiveness of the proposed lightweight model improvements, ablation experiments were conducted using the original YOLOv8n network as the baseline model. The results of the ablation study are presented in Table 2.

Dynamic	LSKA	4×Downsampling	P	R	mAP50/%	FLOPs	FPS	Paras/M	Model Size/Mb
			82.8	64.6	70.9	8.1	549.9	3.01	5.96
√			81.3	63.3	71.6	5.8	348.7	5.85	11.3
	√		79.9	67.1	72.4	8.1	516.4	3.08	6.08
		√	81.2	66.5	74.2	12.4	436.9	2.93	5.90
	√	√	82.4	67.2	74.7	12.2	430.6	2.99	6.04

Table 2. Ablation Study

The ablation results demonstrate that each proposed module contributes positively to model performance. Specifically, incorporating the C2f-Dynamic module alone increases mAP50 by 0.7 while reducing computational cost by 2.3 GFLOPs. Adding the LSKA module alone improves mAP50 by 1.5 without increasing computational complexity. Introducing the fourfold downsampling (P2) module increases computational cost by 4.3 GFLOPs but significantly enhances mAP50 to 74.2.

When the LSKA attention mechanism is further integrated on top of the P2 module, mAP50 increases to 74.7 while model parameters decrease by 0.2 GFLOPs. With the additional incorporation of the dynamic convolution module, the overall model complexity is reduced to 9.4 GFLOPs, and mAP50 reaches 75.1, with an inference speed of 322.6 FPS, satisfying real-time detection requirements. Overall, the ablation experiments confirm the effectiveness of each component in the proposed Dynamic-YOLOv8n model.

3.2.3 Qualitative Comparison of Detection Results

A visual comparison was conducted between the improved Dynamic-YOLOv8n model and the baseline YOLOv8n model, as illustrated in Figure 7. The results indicate that the proposed model exhibits stronger feature learning capability for debris objects, achieving more accurate detection of small and distant targets. Moreover, false detections caused by shadows and pavement markings are significantly reduced compared to the baseline model.

(a) YOLOv8n model recognition results

(b) Dynamic-YOLOv8n recognition results

Figure 7. Comparison of Model Identification Results

4 Discussion

To evaluate the applicability and stability of the proposed system in real-world road environments and to compare its efficiency with manual inspection, field experiments were conducted in the main urban area of Gu'an County, Langfang City, Hebei Province. The selected area features diverse road types and representative traffic conditions, reflecting the distribution characteristics of debris across different road segments. The experimental routes covered major arterial roads, including Jinxiu Avenue and Kongque Avenue, with a total length of approximately 35.7km, providing sufficient data support for system performance evaluation. The vehicle-mounted experimental setup is shown in Figure 8.

Figure 8. Vehicle-mounted experimental setup

During the experiment, the inspection vehicle followed predefined routes, with driving speeds controlled between 40 and 70 km/h to balance image clarity and traffic safety. A total of 3,614 images were collected.

To assess the system ’ s effectiveness in reducing manual workload, two experienced road maintenance inspectors were invited to conduct offline annotation of the same image set and compile inspection records. Meanwhile, the proposed system transmitted images to the backend server in real time through a dynamic compression mechanism, automatically generating structured event lists with spatiotemporal information. The workflows of manual interpretation and automated detection are illustrated in Figure 9, and the comparison of processing time and performance is presented in Table 3.

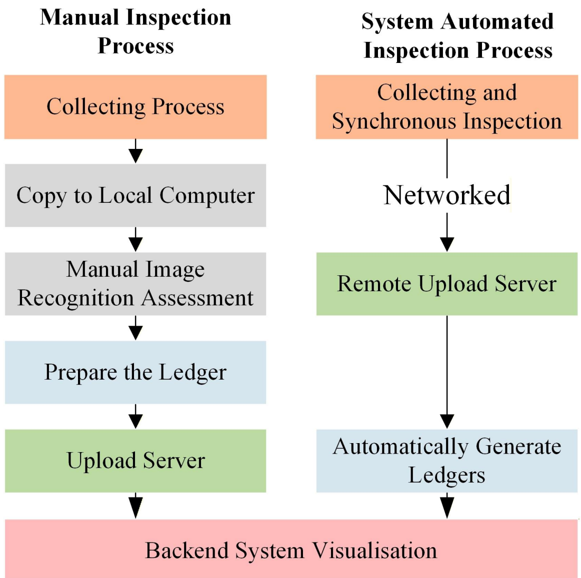

Figure 9. Manual Inspection and System Inspection Solution Process

Indicator	Manual (manual interpretation)	Our System (automatic)
Data transmission method	Hard Copy	Remote Transmission
Transmission time	10 Mins	12 Mins
Identification time	35 Mins	Real Time
Average number detected of items	394	422

Table 3. Comparison of Time and Performance Between Manual and Automated System Recognition

The results indicate that, compared with manual interpretation, the proposed system demonstrates a significant advantage in detection efficiency. In addition, the number of identified debris instances is more comprehensive and detailed, with small-scale objects that are often overlooked by human inspectors successfully detected. The vision-based recognition model trained on self-collected samples enables real-time detection of road debris during vehicle operation, achieving a transition from manual visual inspection to automated identification and substantially improving both inspection efficiency and detection accuracy. Representative detection results of common small-scale debris, such as gravel and litter, obtained using the improved lightweight model are shown in Figure 10.


Figure 10. Effectiveness of Recognition of Fine Debris

Through the developed visualization interface, the detected debris locations are marked and displayed in geographic coordinates, as illustrated in Figure 11. The system establishes a complete closed-loop workflow from front-end acquisition, dynamic transmission, and backend recognition to result visualization.

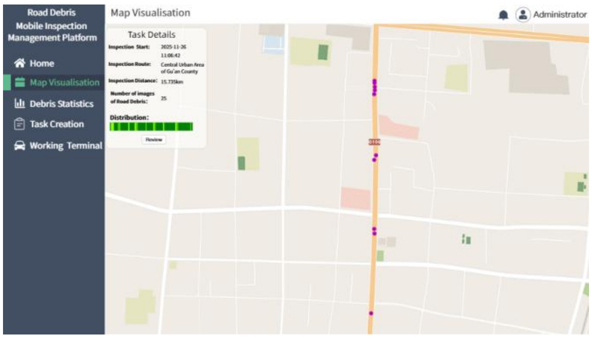

Figure 11. Interface demonstration of the backend system

The overall application results demonstrate that the system operates stably under dynamic traffic conditions, achieving real-time image acquisition, adaptive compression, and efficient transmission without significantly compromising detection accuracy. These findings validate the reliability and robustness of the proposed approach in complex road environments, laying a solid foundation for large-scale deployment in highway inspection and intelligent maintenance applications.

5 Conclusions

This study proposes a lightweight mobile monitoring system for road debris detection that integrates vehicle-mounted sensing, a lightweight object detection model, and a dynamic compression transmission mechanism. The system enables real-time image acquisition and automatic identification of small-scale debris while adapting data transmission to fluctuating network bandwidth. Field experiments demonstrate that the proposed approach operates reliably under complex road environments and significantly improves detection efficiency and timeliness compared with conventional manual inspection, while reducing labor and communication costs.

The results confirm the feasibility of combining lightweight vision-based detection with adaptive data transmission for practical road inspection applications. Future work will focus on enhancing feature extraction capability for small objects, improving detection performance under adverse weather and nighttime conditions, and exploring multi-source sensing fusion to support intelligent and large-scale road maintenance management.

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