



A Review of Road Defect Recognition Based on Unmanned Aerial Vehicles and Deep Learning

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Abstract: Real-time monitoring of transportation infrastructure is crucial for ensuring the safety and operational efficiency of road networks. Traditional manual inspections involve high risks and low efficiency, whereas unmanned aerial vehicles (UAVs), with their high maneuverability and broad coverage, have gradually become an important data collection platform in the field of pavement defect detection. However, the large-scale application of UAVs in complex environments still faces technical bottlenecks such as environmental interference, inconsistent data quality, and slow processing of massive images. This paper systematically reviews the frontier progress of UAV-based pavement defect monitoring technologies in recent years: First, it outlines the limitations and challenges during the UAV field data collection phase; Second, it deeply analyzes the algorithmic evolution in office data processing, from image preprocessing and 3D pavement reconstruction to deep learning and semantic segmentation; Building upon this, the paper constructs a multi-dimensional evaluation system ranging from apparent 2D defects to hidden 3D defects and summarizes multi-modal fusion recognition methods, including visible light, LiDAR, infrared thermal imaging, and ground-penetrating radar (GPR). Finally, the paper discusses the limitations of current technologies regarding hardware battery life, legal privacy, and complex background interference, and points out the development potential of edge computing, UAV swarm collaboration, and cyber-physical systems in future intelligent road maintenance.

Keywords: UAV inspection; Pavement defect detection; Deep learning; 3D reconstruction; Multi-source sensor fusion; Edge computing

1 INTRODUCTION

1.1 LIMITATIONS OF TRADITIONAL DETECTION METHODS AND THE RISE OF UAVS

Over the past decade, major countries around the world have successively incorporated the low-altitude economy into their national strategic development frameworks. In 2016, the US Federal Aviation Administration (FAA) issued the "Small Unmanned Aircraft Systems Regulations," providing a regulatory framework for commercial UAV operations for the first time; in 2019, the European Union Aviation Safety Agency (EASA) released the "General Aviation Regulations for UAVs," establishing a comprehensive UAV regulatory system covering Europe. Meanwhile, China's "Made in China 2025" plan in 2015 first integrated UAV industrialization into the national strategy, and relevant regulations in 2024 further clarified application scenarios for UAVs in transportation inspection and other fields.

UAVs have extensive applications in the transportation sector, such as traffic accident investigation [1], determination of traffic parameters [2], traffic flow analysis [3], bridge inspection [4],

and road distress monitoring [5]. Compared to manual inspections, UAVs avoid disrupting road traffic [6], offer higher efficiency [7], and yield more accurate detection results [8]. However, UAVs also have drawbacks. Technical limitations include short battery life [9], limited payload capacity [10], and high operational difficulty in adverse weather conditions [11]. Socio-economic challenges involve potential violations of personal privacy during operations [12], significant noise [13], and excessive reliance on policy guidelines [14]. Nevertheless, with continuous technological advancements in recent years, these shortcomings are gradually being overcome [15].

1.2 SCOPE OF THE REVIEW AND STRUCTURAL LOGIC

With the popularization of UAV hardware and the explosive growth of artificial intelligence computing power, the literature on UAV road inspections has surged. This review focuses on the application of UAVs in the identification of damage to asphalt pavements and surrounding highway infrastructure, systematically outlining breakthrough research achievements in computer vision, photogrammetry, and multi-modal non-destructive testing over the past decade. Non-pavement

engineering applications of UAVs, such as traffic flow monitoring and underside bridge flaw detection, are not the core subjects of this discussion.

Regarding structural logic, this paper innovatively adopts the engineering implementation process as its main thread, organized according to a progressive logic of "field data acquisition — in-office algorithm analysis — target object evaluation — future system deployment."

First, since the upper limit of algorithmic recognition is often determined by preliminary data quality, this paper initially explores the UAV field operation process, deeply analyzing how operational parameters like flight height and overlap rate affect data acquisition, as well as the challenges posed by extreme weather and spatial positioning errors. Subsequently, it systematically reviews the evolutionary history of in-office data processing algorithms, ranging from super-resolution images and 3D dense point cloud reconstruction used for recovering physical dimensions, to deep learning enabling high-level semantic understanding. After clarifying the development of underlying computing power, the paper projects cutting-edge

algorithms back onto specific traffic engineering objects, constructing a multi-dimensional evaluation system from surface cracks and volumetric rutting to hidden subgrade defects. It highlights how multi-modal sensor fusion—combining visible light, thermal imaging, and GPR—can overcome recognition interference caused by complex practical backgrounds. Finally, the article returns to engineering reality and the construction of smart city transportation networks. By analyzing restrictive factors for large-scale deployment, such as UAV battery life, legal regulations, and privacy protection, it proactively proposes the ultimate goals of achieving real-time edge-side detection via edge computing and driving multi-UAV swarm collaboration through modern communication technologies.

In summary, this paper aims to provide a clearly layered technological roadmap for interdisciplinary researchers in traffic engineering, computer vision, and geotechnical engineering, facilitating the research, development, and implementation of next-generation fully automated intelligent inspection systems for road networks.

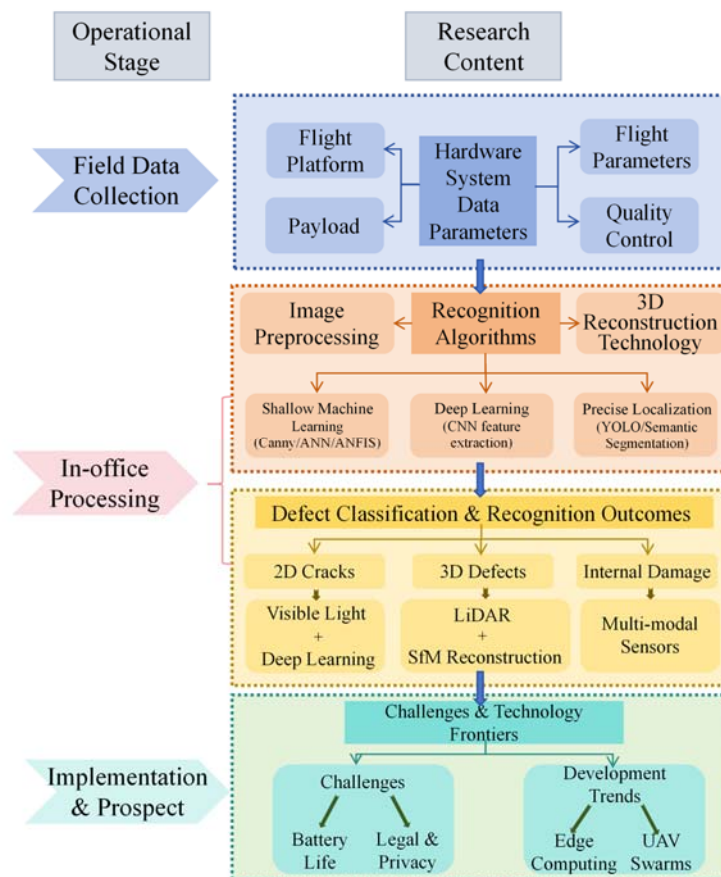


FIGURE 1 SYSTEM ARCHITECTURE OF THE PAPER

2 HARDWARE SYSTEM AND DATA PARAMETERS

2.1 SELECTION OF FLIGHT PLATFORMS AND SENSOR PAYLOADS

UAVs are classified into various types worldwide. Table 1 summarizes the classification of UAVs by different countries.



TABLE 1: CLASSIFICATION OF UAVS BY COUNTRY

Aviation Authority	Classification Name	Weight and Performance Standards	Regulatory Basis
Civil Aviation Administration of China (CAAC)	Micro	$M < 0.25\text{kg}$, $V_{\text{max}} \leq 40\text{km/h}$	Interim Regulations on the Flight Management of Unmanned Aerial Vehicles
	Light	$M < 7\text{kg}$, $V_{\text{max}} \leq 40\text{km/h}$	
	Small	$7\text{kg} \leq M < 25\text{kg}$, $V_{\text{max}} \leq 40\text{km/h}$	
	Medium	$25\text{kg} \leq M < 150\text{kg}$	
	Large	$M > 150\text{kg}$	
US Federal Aviation Administration (FAA)	Group 1	$< 20 \text{ lbs } (< 9\text{kg})$	Operations of Small Unmanned Aircraft Over People
	Group 2	$21 - 55 \text{ lbs } (9 - 25\text{kg})$	
	Group 3	$< 1320 \text{ lbs } (< 600\text{kg})$	
	Group 4/5	Large, long-endurance, high-altitude UAVs	
European Union Aviation Safety Agency (EASA)	C0	$< 250 \text{ g}$	Commission Delegated Regulation (EU) 2019/945
	C1	$< 900 \text{ g}$	
	C2	$< 4 \text{ kg}$	
	C3	$< 25 \text{ kg}$	
	C4	$< 25 \text{ kg}$	
	C5	$\leq 25 \text{ kg}$	
	C6	$\leq 25 \text{ kg}$	

UK Civil Aviation Authority (CAA)	UK0	$< 250 \text{ g}$	Unmanned Aircraft System Operations in UK Airspace - Policy and Guidance (2026)
	UK1	$< 900 \text{ g}$	
	UK2	$< 4 \text{ kg}$	
	UK3 / UK4	$< 25 \text{ kg}$	
	UK5 / UK6	Depends on specific design	

Based on wing structure, UAVs can be broadly categorized into four types: single-rotor, multi-rotor, fixed-wing, and hybrid fixed-wing UAVs. The single-rotor UAV features a helicopter-like design, with a main rotor providing lift and thrust, and a small tail rotor used to balance anti-torque. This type of UAV can take off and land vertically and hover, with a strong payload capacity suitable for carrying high-precision cameras or LiDAR equipment. However, due to its complex mechanical structure, high maintenance costs, and large rotor size, it is prone to airflow disturbances when flying at low altitudes close to the road, making it rarely used in road defect inspections. The multi-rotor UAV has multiple mechanical arms and a motor connected to each propeller. The number of engines determines its payload capacity and endurance—generally, more rotors mean heavier carrying capability, but increased power consumption leads to shorter flight times. Multi-rotor UAVs possess vertical take-off and landing (VTOL), hovering, and low-speed cruising capabilities, allowing them to capture close-range, high-resolution fixed-point images of road defects, making them the most commonly used type in current road inspections. Their main limitation is a short flight time, typically only 20 to 40 minutes, which restricts the mileage covered in a single operation. The fixed-wing UAV overcomes the flight time and speed limitations of multi-rotor UAVs, making it highly suitable for rapid, large-scale surveys of road networks, such as preliminary defect screening on highways or national and provincial trunk roads. However, fixed-wing UAVs require runways or catapults for take-off and landing, cannot hover, struggle to perform repeated or detailed lateral observations of defects, and have poor low-altitude maneuverability, complicating their application in complex road environments. The hybrid UAV is a compromise between multi-rotor and fixed-wing designs, combining vertical take-off and landing with efficient cruising capabilities: it relies on the rotor system for take-off and landing and switches to fixed-wing mode for cruising. In road defect detection, this UAV balances rapid, large-scale inspection with targeted local hovering reviews. However, the hybrid configuration results in a more complex structure, higher control difficulty, and payload and endurance capabilities that fall between the two traditional types, meaning it has not yet seen widespread adoption [16].

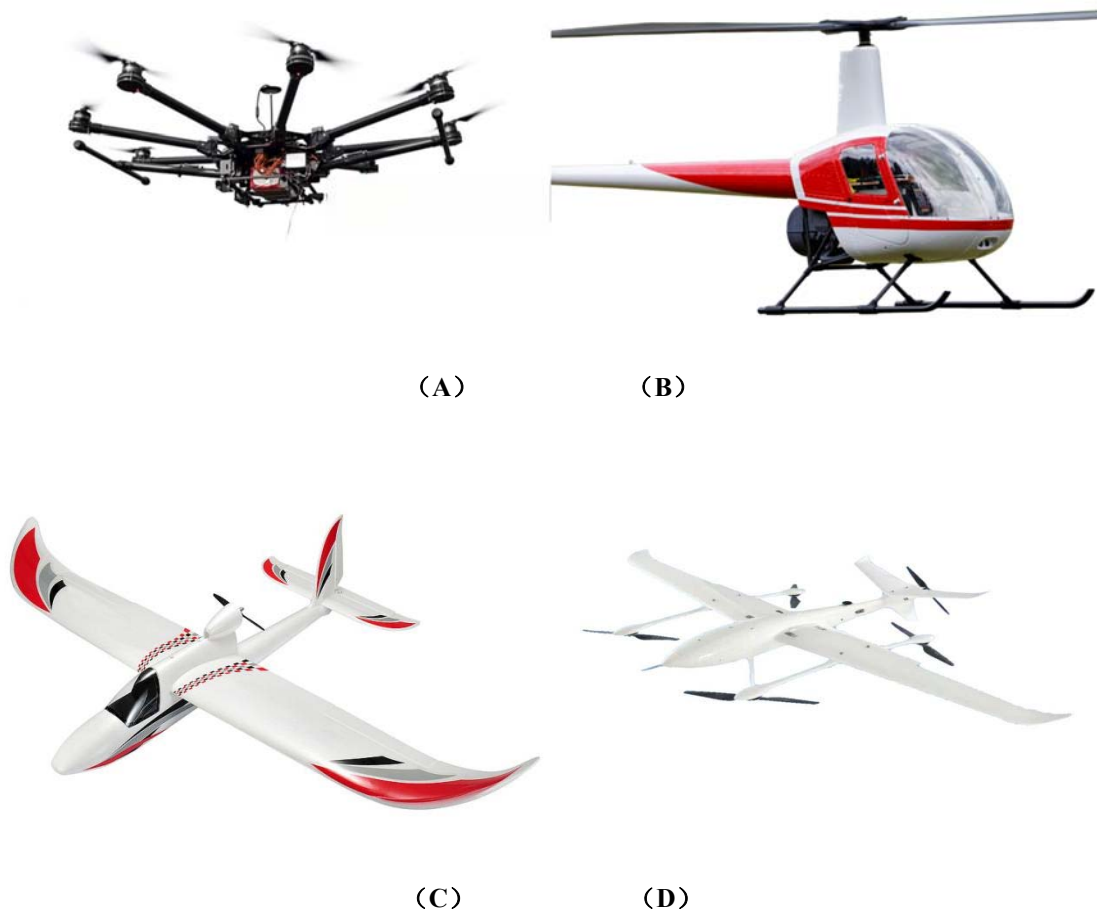


FIGURE 2 STRUCTURAL CLASSIFICATION OF UAVS

In UAV systems, components not strictly necessary for flight are collectively referred to as payloads. The type of payload depends on the specific application task, and its quantity and weight directly impact the UAV's endurance. Therefore, in task planning, a trade-off must be made between detection capability and flight duration [15].

Functionally, the payloads carried by UAVs are primarily divided into imaging equipment and specialized sensors, with imaging equipment being the most common type. Traditional UAVs are equipped with cameras by default, mainly including RGB cameras and infrared cameras: RGB cameras capture high-resolution visible light images suitable for visual interpretation and subsequent image processing; infrared cameras can be used to detect temperature anomalies, such as identifying subsurface voids or the thermal effects produced by early-stage defects [5]. In recent years, multispectral cameras capable of capturing multi-band data in a single flight have become increasingly popular, providing richer information for identifying road material properties and moisture content, though they generate larger data volumes and require more complex processing [17]. Besides imaging equipment, UAVs can also carry various specialized sensors, typically including biosensors, chemical sensors, and meteorological sensors. The parameters acquired

by these sensors serve as reference points for UAV flight stability and the environmental conditions contributing to defect formation [18].

This study focuses on the application of using RGB cameras as the primary payload for pavement defect monitoring. This is mainly because RGB cameras have low image acquisition costs, intuitive visual features, and good compatibility with existing computer vision algorithms, enabling effective identification of common road defects like cracks, potholes, and patches. Naturally, additional payloads can be installed on UAVs depending on actual detection needs to obtain more comprehensive road condition information.

2.2 KEY FLIGHT PARAMETERS AND DATA QUALITY CONTROL

The quality of images collected by UAVs determines the accuracy of subsequent defect identification, classification, and 3D pavement reconstruction algorithms. In pavement monitoring, the setting of flight parameters requires finding an optimal balance among detection resolution, flight efficiency, and data processing load [15].



2.2.1 OPTIMAL CONFIGURATION OF KEY FLIGHT PARAMETERS

The key parameters for UAV aerial photography mainly include Ground Sample Distance (GSD), flight altitude, overlap rate, and camera viewing angle. The synergistic setting of these parameters is crucial for capturing the geometric features of defects.

1. Ground Sample Distance (GSD) and Flight Altitude

GSD is the core metric for measuring UAV image resolution. It is used to define the resolution of digital images, representing the actual physical size mapped by a pixel on the terrain [19]. A higher GSD value indicates a lower spatial resolution of the image. Its calculation formula is as follows:

$$GSD = \frac{\text{Sensor Height} \times \text{Flight Altitude}}{\text{Focal Length} \times \text{Image Width}}$$

Regarding the setting of flight altitude, Romero-Chambi et al. suggested that the optimal height for detecting potholes is 10–15 meters [20], but given the complexity of actual sites, flight altitude must be determined on a case-by-case basis. Independent experiments by Atencio et al. and Congress et al. [21, 22] further explored the extensive impact of different flight altitudes on the final road defect recognition results. Furthermore, experiments by Congress and Puppala highlighted a trade-off relationship regarding computational cost: the higher the spatial resolution of the sensor, the larger and more numerous the images required per unit area, leading to a sharp increase in post-processing time [23]. Therefore, rationally selecting sensors and determining flight altitude are highly critical preparation steps when conducting UAV road defect inspections.

2. Image Overlap Rate

To generate high-quality 3D models using Structure from Motion (SfM) algorithms, a high degree of redundancy between images must be ensured. Engineering experience indicates that frontal overlap usually needs to exceed 75%, and side overlap needs to exceed 60%. Meanwhile, Goodbody et al. suggested that although side overlap significantly affects flight efficiency, its specific impact on 3D reconstruction lacks conclusive findings [24]. Regarding the optimization of this parameter, Congress et al. conducted a system-wide error analysis study for UAV transportation infrastructure monitoring [22]. By comparing different parameter combinations, they concluded that for areas without vegetation coverage, a combination of 80% frontal overlap and 60% side overlap yields the best results.

3. Camera Viewing Angle

Traditional UAV photogrammetry typically employs only a vertical (nadir) viewing angle. Research by James et al. indicates that integrating oblique photos into modern SfM and Multi-View Stereo (MVS) photogrammetry can reduce internal geometric system deformations caused by calculation inaccuracies [25, 26]. Furthermore, direct evidence from Nesbit et al. shows that incorporating oblique photos indeed helps improve the completeness of point cloud reconstruction, especially for pothole-type defects with depth [27].

2.2.2 DATA COLLECTION QUALITY CONTROL AND GEOREFERENCING

1. Lighting, Weather, and Environmental Interference

Environmental factors directly determine the signal-to-noise ratio of optical imaging. Micheletti provided recommendations for image acquisition, suggesting that static scene pictures should be captured using constant lighting to prevent feature color changes, and efforts should be made to avoid capturing overexposed or underexposed images, as well as transparent, reflective, or homogeneous surfaces [28]. Besides lighting, extreme temperatures can have a fatal impact on UAV battery life; the battery discharge life at 20°C is significantly shorter than at 25°C, requiring planners to leave sufficient power redundancy when mapping actual road networks.

Positioning Errors and Georeferencing

Relying solely on the UAV's built-in GPS cannot accurately map identified defects to a global coordinate system. Turner et al. and Tsai et al. proposed relying on differential GPS (dGPS) measurements and Inertial Measurement Units (IMU) to obtain known camera positions first, then executing preliminary georeferencing and scaling [29, 30]. However, Rippin et al. also emphasized that direct georeferencing is only a supplement to Ground Control Points (GCP), and external GCPs are still required subsequently to obtain a higher-precision final solution [31].

3.3. ALGORITHM EVOLUTION OF ROAD DEFECT RECOGNITION

3.1 IMAGE PREPROCESSING AND 3D RECONSTRUCTION TECHNOLOGIES

In the process of using UAVs for pavement defect detection, original images often suffer from low contrast, motion blur, or insufficient resolution due to extreme susceptibility to flight altitude, lighting changes, and airframe vibrations during operation. Therefore, image preprocessing and 3D reconstruction are necessary to ensure subsequent defect recognition accuracy.

Addressing the issue of limited UAV image quality, Inzerillo et al. pointed out that Super-Resolution Reconstruction (SSR) algorithms can resolve image motion blur and insufficient resolution, thereby improving the accuracy required for detecting surface defects like cracks [32]. In this field, Xiang et al. further proved that the Super-Resolution Convolutional Neural Network (SRCNN) exhibits outstanding performance in processing structural crack images [33]. However, this process also comes with challenges; research by Bae et al. noted that while SRR improves recall rates, it may lead to a decrease in detection precision in some cases [34].

Moreover, to address the lack of model generalization capabilities caused by small-sample datasets, Xu and Liu proposed using Generative Adversarial Networks (GANs) for image preprocessing and data augmentation [35]. Research by



Gao et al. demonstrated that using a depth-guided GAN model to augment structural images can significantly improve the training efficiency of subsequent Convolutional Neural Networks (CNN) [36]. Regarding feature extraction, Lin et al. introduced self-supervised learning and Transformer architectures, drawing on the Vision Transformer (ViT) concept proposed by Dosovitskiy et al., enabling the model to obtain richer global information about pavement textures during the preprocessing stage [37, 38].

Converting 2D aerial images into 3D models with spatial information is the foundation for achieving quantitative evaluation of defects. Eltner and Sofia proposed the SfM method, a photogrammetric technique that uses a series of 2D scenes to develop 3D objects [39]; Peddinti et al. detailed the evolution of SfM algorithms in pavement monitoring [15], a process usually paired with Multi-View Stereo (MVS) technology. Schonberger and Frahm pointed out that MVS can calculate 3D spatial positions based on the coordinates of identified homologous points, thereby generating high-density 3D point clouds [40]. Research by Tan and Li further refined the 3D modeling workflow based on oblique photogrammetry, proposing that post-processing software (e.g., Pix4D Mapper) can generate orthomosaic maps and Digital Surface Models (DSMs). The advantage of this method lies in its ability to achieve millimeter-level quantification of defects [5]. Regarding resolution selection, the experimental conclusions of Romero-Chambi et al. emphasized the decisive impact of overlap rate and GSD on pavement reconstruction quality [20].

After completing 3D dense point cloud reconstruction and spatial coordinate registration via SfM and MVS technologies, the next critical step is how to accurately extract the geometric parameters of defects from these high-dimensional spatial data. Traditional 2D images can only provide planar texture and grayscale information; 3D reconstruction technologies offer irreplaceable advantages in the quantitative evaluation of volumetric defects. Tan and Li emphasized that after reconstructing the DSM, it is equally important to use automated algorithms to separate the 3D pavement model from its surrounding environment (e.g., vegetation, vehicles). On this basis, algorithms can automatically calculate the length, width, and depth of road defect areas [5]. Additionally, for feature extraction of complex defects, research by Romero-Chambi et al. noted that Digital Elevation Models (DEMs) can be generated based on 3D point clouds, allowing researchers to directly obtain spatial mutation information of pavement depth [20]. Combined with region growing algorithms or specific edge detection operators, this enables the precise calculation of 3D physical indicators such as the perimeter, area, and volume of potholes. This transition from visual reconstruction to parameter quantification greatly enhances the application value of UAV pavement monitoring in actual road maintenance engineering.

3.2 FROM TRADITIONAL COMPUTER VISION TO DEEP LEARNING

In the field of UAV road inspections, recognition algorithms have shifted from relying on manually designed features to becoming more data-dependent through deep learning. This

evolutionary process has not only improved the automation level of road defect recognition but also resolved issues of complex background interference in UAV aerial photography environments.

Before the popularization of deep learning, pavement defect recognition mainly relied on digital image processing operators. Li et al. pointed out in their research that early algorithms focused on using threshold segmentation, Canny edge detection, or wavelet transforms to extract features; however, these methods are difficult to apply widely in real operational scenes because image noise and uneven lighting conditions significantly affect recognition results [41]. To enhance model robustness, researchers began introducing shallow machine learning models. Mokhtari et al. detailed the performance of Artificial Neural Networks (ANN), decision trees, k-Nearest Neighbors (kNN), and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) in their comparative study, concluding that ANN and ANFIS methods are more flexible and compatible in crack detection applications [42]. However, Hammer et al. also emphasized that such models rely on tedious preprocessing to design handcrafted features, resulting in severely limited generalization capabilities when dealing with large-scale, varying-texture images captured by UAVs [43].

In recent years, the rise of Convolutional Neural Networks (CNN) has broken the bottleneck of feature design. Li et al. explicitly pointed out that CNNs can automatically extract hierarchical features from raw pixels [41], avoiding blind manual modeling. Jingwei Liu et al. further proposed a two-stage architecture: the first stage locates the defect region, and the second stage performs pixel-level refinement. This broad-to-specific approach significantly improves recognition accuracy on complex pavements [44].

Addressing the problem of tiny defect targets caused by the "high-altitude perspective" of UAV inspections, Amieghemen and Sherif developed an ensemble model—DCNN ensemble—in their latest research. They pointed out that individual networks easily lose information when processing extremely small-scale cracks, while the ensemble model enhances the ability to capture subtle crack features in high-altitude UAV images [45]. Concurrently, work by Liu et al. on transfer learning also proved that pre-training models on large datasets followed by fine-tuning can effectively resolve the dilemma of scarce labeled samples for pavement defects [46].

Current algorithmic research has shifted from simple classification to more precise object localization and contour delineation. In the field of object detection, single-stage detectors are highly favored for their real-time performance. Cheng et al. proposed an enhanced RLD-Net (based on YOLOX) for complex crowded environments [47]. A case study conducted in Montreal by Zhang et al. also pointed out that traditional pavement defect detection methods often struggle to effectively capture small-scale or subtle damages in complex and crowded environments; by introducing a Location-Enhanced Attention Module (LEAM), road background noise interference can be effectively suppressed [48]. At the pixel-level semantic segmentation tier, Yue et al. proposed a TSPCS-net based on an encoder-decoder architecture [49], which, by



incorporating the multi-scale feature fusion theory proposed by Zhong et al., resolved the issue of fragmentation during the segmentation of subtle cracks [50].

TABLE 2: CORE ALGORITHM EVOLUTION AND COMPARISON

Evolutionary Stage	Representative Algorithms	Advantages	Limitations
Traditional Image Processing	Threshold segmentation, Canny edge detection, Wavelet transform	Low computing power requirements, transparent algorithm logic, no need for massive training datasets	Highly sensitive to abrupt lighting changes and shadow noise in the environment, difficult to handle complex pavements
Shallow Machine Learning	Artificial Neural Networks (ANN), Decision Trees, Support Vector Machines (SVM)	Stable performance on small sample datasets, good algorithm compatibility and flexibility	Highly dependent on manual design and extraction of defect features
Basic Deep Learning	Convolutional Neural Networks (CNN, Two-step CNN)	Automatically learns multi-scale features of defects	Difficult to provide precise locations and geometric contours of defects
Object Detection	YOLO series	Fast detection speed, effectively suppresses background	Single-stage detectors are prone to miss extreme minor or slender cracks under

		noise interference	UAV high-altitude perspectives
Pixel-level Semantic Segmentation	U-Net variants, Transformer (ViT), TSPCS-net	Achieves pixel-level detection of defects, meets high-fidelity restoration requirements of complex topological cracks	Massive model parameters, high computational cost, difficult to perform real-time inference directly on the UAV edge side

Synthesizing the above literature review, Table 2 systematically outlines the core characteristics, main advantages, and engineering limitations faced by UAV vision-based pavement defect recognition algorithms across different evolutionary stages. The shift from the traditional Canny operator to modern YOLOv12, RT-DETR, and various U-Net variants reflects a transition from pixel-level operations to global semantic understanding, establishing the algorithmic foundation for achieving real-time intelligent monitoring of road defects.

4 ROAD DEFECT TYPE CLASSIFICATION AND RECOGNITION PERFORMANCE

4.1 TYPICAL ROAD DEFECTS AND RECOGNITION METHODS

4.1.1 TYPICAL ROAD DEFECTS

Accurately classifying and extracting the physical features of road defects is a prerequisite for selecting underlying algorithms and sensor payloads [15]. Pavement monitoring involves regular damage detection and condition assessment of pavements to achieve efficient pavement management; clarifying the categories of target defects and their corresponding recognition methods constitutes the core of modern pavement monitoring systems.

Due to long-term exposure to natural environments and traffic loads, defects in asphalt pavements exhibit high complexity and diversity. Based on the "Standard Practice for Roads and Parking Lots Pavement Condition Index Surveys," this paper categorizes several core defect classes currently focused on by academia.

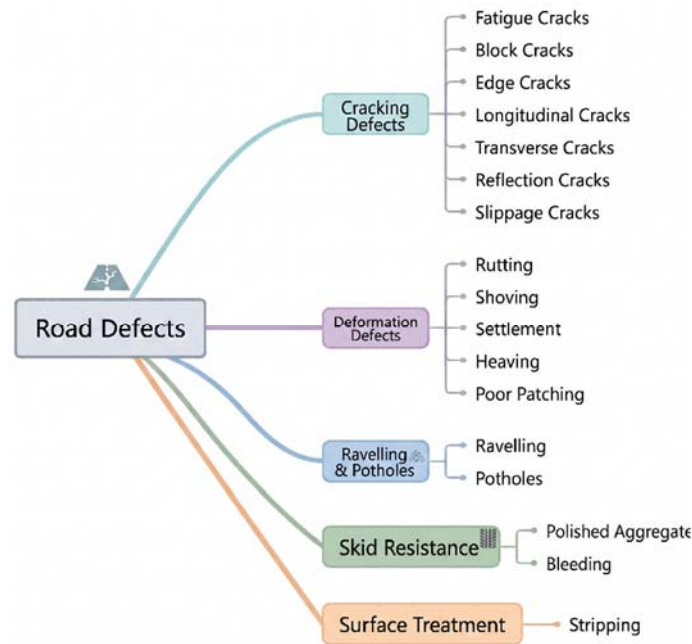


FIGURE 3 CLASSIFICATION OF COMMON PAVEMENT DISTRESSES

Cracking defects are the most common and widely studied road defects, typically including longitudinal cracks, transverse cracks, and fatigue cracks. Because of their variable morphology, recognizing these defects poses extremely high requirements on algorithms. He et al. explicitly pointed out that the difficulties of UAV crack detection lie in complex crack morphology, color similarity to the pavement, and small crack areas [51]. Currently, much research remains at the binary classification level of "whether a crack is detected or not," while in actual maintenance engineering, determining the severity of a defect is more valuable for decision-making than mere location extraction. To this end, research by Liu et al. constructed an asphalt pavement crack classification dataset, refining it into four levels: no cracks, low-severity cracks, medium-severity cracks, and high-severity cracks, pointing out that precisely dividing severity is the basis for making road network maintenance decisions [52].

Deformation defects include rutting, shoving, and settlement. Rutting is a permanent longitudinal banded depression produced by wheel action on asphalt pavements. As it manifests as an elevation change in 3D space, conventional 2D images struggle to capture it accurately. Famili et al. emphasized that regularly measuring and identifying the presence and severity of pavement rutting is crucial for pavement management programs conducted by transportation agencies [53].

Ravelling and potholes primarily involve the dislodgement of aggregates and binders in the asphalt mixture. When this occurs, the pavement exhibits ravelling, which can deteriorate into potholes—a typical 3D volume loss. Manjusha and Sunitha highlighted pothole detection as one of the core applications of UAV pavement evaluation in their article [16]. Romero-Chambi et al., in their study on 3D reconstruction of potholes, noted that using only 2D images cannot assess the severity of ravelling and pothole defects; 3D modeling must be relied upon to calculate

their volume [20]. Ravelling and potholes are the result of the combined effects of crack deterioration and moisture damage. Future monitoring algorithms should not only measure the existing volume of potholes but also establish a prediction model for the remaining service life of the road based on the expansion rate of ravelled areas.

Driving safety on roads heavily depends on the skid resistance provided by the micro-texture of the road surface. Polished aggregates and bleeding are the primary causes of a precipitous drop in skid resistance. Wang et al., in their early research, emphasized the massive potential of using high-precision 3D image data to measure pavement surface texture [54]. Li et al. proposed that insufficient skid resistance represents millimeter-level or even micrometer-level surface feature degradation [41]. Due to the high-altitude flying characteristics of UAVs, directly utilizing conventional UAV-captured images to assess skid resistance still faces significant technical barriers, prompting academia to explore air-ground collaborative detection modes combining "UAVs + ground robots."

In actual highway and urban road networks, pavements often undergo multiple preventive maintenance treatments, which spawn surface treatment defects and other anomalies. Liu et al., citing the internationally recognized ASTM D6433 standard in their research, explicitly listed "patching" and "surface defects" as independent deduct items in Pavement Condition Index (PCI) calculations [55]. UAV images exhibit a very high detection recall rate in recognizing such large-area color anomalies and texture unevenness.

4.1.2 DEFECT RECOGNITION METHODS

Aiming at the multi-dimensional road defects mentioned above, academia has shifted from initial single-vision perception recognition to multi-source sensor fusion recognition. Current

defect recognition methods can be categorized into the following major technical paths:

1.2D Recognition Based on Visible Light Images and Deep Learning: For surface cracks and potholes, UAVs equipped with high-definition RGB cameras combined with deep learning are currently the most mainstream solution. Besides the CNN and object detection algorithms discussed in Section 3.2, some scholars are also exploring comprehensive evaluation methods based on image grayscale features. For instance, Zuo et al. used UAVs to collect pavement images, extracted texture features through Gray-Level Co-occurrence Matrices (GLCM), and, combined with Yang et al.'s research on entropy weight method optimization, established a defect classification and pavement condition comprehensive assessment model integrating an improved Analytic Hierarchy Process (AHP) [56, 57]. Additionally, Akbar et al. proposed combining apparent defects captured by UAVs with in-situ subgrade investigations, achieving a transition from surface recognition to subgrade bearing capacity calculation [58].

2.3D Recognition Based on LiDAR and Spatial Features: For deformation defects like rutting and settlement, depth information must be acquired for accurate recognition. In addition to the UAV oblique photogrammetry (SfM) technology mentioned in Section 3.1, Famili et al. evaluated the application of Mobile Terrestrial LiDAR Scanning (MTLS) systems in rutting recognition [53]. By introducing mathematical algorithms like local curve mapping and Fréchet distance, this

study successfully quantified rutting depth and area automatically from 3D profiles. Early work by Fu et al. also emphasized the critical role of 3D transverse profiles in distinguishing complex pavement defects [59].

3. Recognition Based on Multi-modal Sensors: To overcome the shortcomings of visible light under restricted lighting conditions and to identify internal road defects, multi-modal non-destructive testing technologies are currently becoming a frontier hotspot.

(1) **Infrared Thermal Imaging Method:** Liu et al. noted that due to the difference in specific heat capacity between the air inside cracks and the surrounding asphalt medium, infrared images can significantly highlight defect contours [55]. Therefore, fusing visible light images with infrared images and incorporating transfer learning can drastically improve the robustness of crack severity classification models.

(2) **Ground Penetrating Radar (GPR) Method:** Addressing the aforementioned internal stripping and voids in roads, Li et al. proposed that GPR can non-destructively provide high-resolution profiles of roads [60]. Todkar et al. suggested introducing wavelet transforms and signal gain algorithms into machine learning methods, enabling deep learning models to automatically parse hidden defect features in radar echo signals [61].

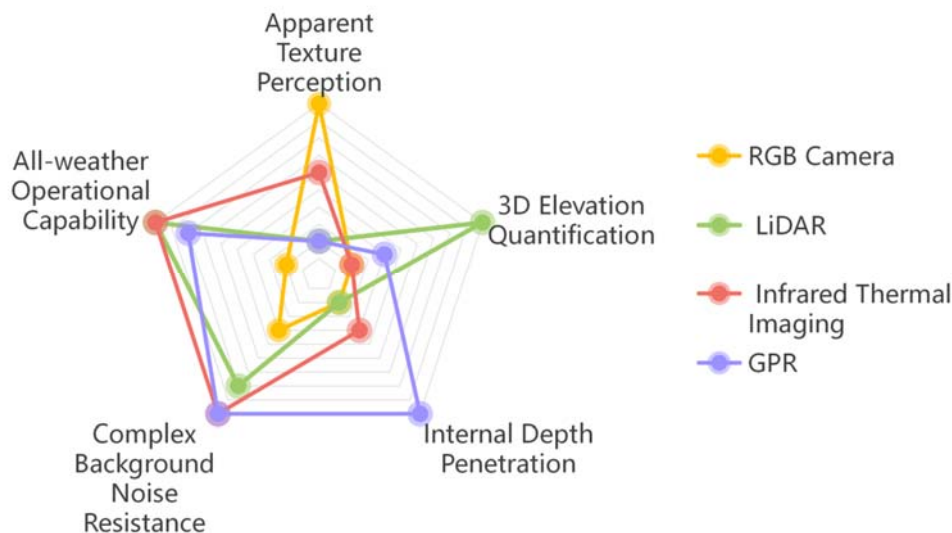


FIGURE 4 RADAR CHART OF SENSOR CAPABILITY

In summary, modern pavement defect recognition has broken through the limitations of single vision, evolving into a comprehensive recognition method based on visible light sensing the road surface, LiDAR measuring elevation, thermal infrared assisting in denoising, and GPR penetrating the interior. As a single sensor cannot meet all-around requirements

simultaneously—for instance, while visible light cameras excel in apparent texture perception, they are easily disturbed by ambient lighting—it is precisely the complementarity of multiple sensors that drives modern detection systems towards multi-source data fusion.

4.2 RECOGNITION CHALLENGES AND

INFRASTRUCTURE SYNERGY

The key to the implementation of road defect detection technologies lies in how to cope with interference factors in real road environments. With the deepening of smart transportation research, modern transportation infrastructure monitoring is no longer limited to flat, ideal pavement surface layers but is expanding towards complex background interference resistance and comprehensive geological disaster early warning, such as subgrade and slope synergy.

1. Complex Background Interference and Lightweight Algorithms

In actual UAV inspection tasks, road cracks and potholes are often highly integrated with complex natural backgrounds (e.g., dappled tree shadows, irregular water stains, worn road markings). Addressing this engineering pain point, Zhang et al. proposed a lightweight pavement defect detection method for UAV remote sensing images applicable under complex backgrounds with cross-scale fusion [62]. To enhance model generalization capabilities in real field environments, Arya et al. deeply discussed the importance of data-driven approaches, emphasizing the necessity of cross-regional, multi-scenario data sources for suppressing background noise [63].

There is a significant gap between the laboratory accuracy of detection algorithms and their actual engineering application. The future development trend in the field of road defect detection will inevitably abandon the pursuit of high-precision networks with massive parameter counts, turning instead to the development of lightweight models that can run in real-time on the UAV edge. Only by achieving real-time background filtering on computationally constrained devices can these algorithms move toward large-scale application.

2. Multi-Data Fusion

Besides complex background interference, sudden changes in environmental lighting also severely restrict the robustness of pure vision algorithms. To break through operational limitations at night or under extreme shadow conditions, many scholars adopt multi-data fusion to resolve this issue. Meier et al. explored pothole segmentation and area estimation methods

based on deep neural networks and UAV thermal imaging, pointing out that there are significant differences in heat absorption and dissipation rates between pothole areas and normal pavements; introducing thermal infrared data can greatly overcome lighting interference [64].

To accurately translate features in thermal infrared images into area quantification in physical dimensions, early research on Mask R-CNN instance segmentation by He and Gkioxari et al. proved that after obtaining a rough bounding box for a pothole, pixel-level masks must be relied upon to precisely calculate the true affected area of irregular volumetric defects [65].

3. Expanding the Detection Scope

The health condition of highway infrastructure depends not only on the integrity of the asphalt pavement layer but is also closely related to the stability of the underlying subgrade structure and surrounding high and steep slopes. As Outay et al. emphasized, the development of low-altitude UAVs is crucial for integrating airspace to advance transportation systems [66], and their core applications have expanded to overall highway infrastructure management. Zhang et al. also demonstrated the irreplaceability of UAVs in achieving fully automated dynamic monitoring on low-volume roads and in harsh geographical environments [67].

When the root cause of road defects lies in deep geological movements, mere superficial pavement patching only addresses the symptoms, not the underlying problem. Therefore, Araujo et al. extended convolutional neural networks to the field of geotechnical damage detection, noting that most natural disasters stem from geodynamic events like landslides and slope collapses [68]. Concurrently, Zhang et al., in a review of deep learning applications in geotechnical engineering, pointed out that machine vision should take on the task of slope sliding early warning in harsh environments [69]. Building on this, Chen et al. further proposed combining terrestrial laser scanning with UAV photogrammetry to perform a 3D joint assessment of shallow block stability on high and steep slopes [70]. Progress in remote sensing landslide investigations by Xu et al. also proved the accuracy of extracting rock mass discontinuity features through multi-source spatial data fusion [71].

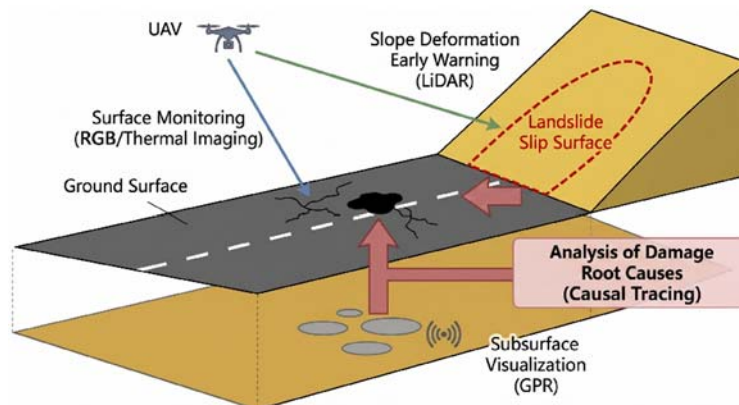


FIGURE 5 THREE-DIMENSIONAL COORDINATION DIAGRAM OF PAVEMENT AND SLOPE



Traditional research often discusses pavement monitoring separately from geological slope disasters, focusing solely on the asphalt surface layer. However, large-area alligator cracking and settlement appearing on pavements are highly likely the result of displacement in surrounding high and steep slopes or subgrade soil and water loss. Through a multi-modal UAV platform, modern systems can not only extract surface defects but also monitor slope deformation using LiDAR and visualize internal moisture damage using GPR, simultaneously accomplishing the joint monitoring of road defect recognition and slope displacement mapping.

5 CHALLENGES AND TECHNOLOGY FRONTIERS

Although deep learning and 3D pavement reconstruction technologies have achieved remarkable results in laboratories or tests, pushing UAV pavement monitoring systems from concept validation to large-scale deployment on national highway networks still faces severe physical limitations, regulatory barriers, and computing power bottlenecks.

5.1 HARDWARE LIMITATIONS AND LEGAL PRIVACY CHALLENGES

As current UAV monitoring systems move toward practical engineering applications, the primary obstacles come from the physical limitations of the flight platforms themselves and the complex social attributes of their operating environments.

The greatest pain point restricting multi-rotor UAVs from improving maneuverability is their extremely limited payload and battery energy density. Mozaffari et al. clearly pointed out this inherent flaw in their research on UAV communication and hover time optimization [72]. This flight time limitation directly prevents a single UAV sortie from completing the mapping of long, continuous road sections, increasing the monitoring costs for major repair segments. Additionally, Peddinti et al. emphasized that UAVs are extremely sensitive to extreme weather conditions such as wind shear and rainfall [15]. Adverse weather can not only induce high-frequency vibrations in the airframe, leading to severe image blurring, but can also cause drone crashes. This makes all-weather pavement condition monitoring an engineering vision that remains difficult to realize at the current stage.

When monitoring scenarios transition from remote highways to core urban road networks, technical problems evolve into social and legal issues. Outay et al. deeply discussed the obstacles to the widespread deployment of UAVs in highway infrastructure management, pointing out that currently, civil aviation authorities in various countries (such as the FAA in the US or EASA in Europe) have extremely strict bans on beyond-visual-line-of-sight (BVLOS) flights and flying over densely populated areas [66]. Furthermore, because UAVs must carry high-resolution visual sensors, they inevitably record vehicle license plates, pedestrian faces, and even private residences around the roads. Nikitas et al., when discussing smart cities and AI in transportation, emphasized the core status of public acceptance

[73]. Hengstler et al., in sociological research on "AI and Trust," also pointed out that artificial intelligence, if used responsibly, has significant potential to bring positive changes to society [74].

Hardware endurance can be alleviated by replacing batteries or deploying UAV relay stations, but privacy and legal barriers cannot be bypassed purely through engineering means. Future road network monitoring UAVs must forcefully embed privacy-masking algorithms in their underlying hardware; that is, before images are saved to disk, sensitive information unrelated to road defects must be blurred in real-time. This is a necessary condition for achieving city-scale deployment of UAVs.

5.2 FUTURE TECHNOLOGY FRONTIERS

To break through the aforementioned limitations, UAV road defect monitoring is undergoing a revolution driven by communication technology and chip computing power. Liu et al. pointed out that the future development direction of UAVs will inevitably be stronger temporal responsiveness and broader spatial coverage [55].

Current UAV monitoring workflows employ an offline post-processing mode—where the UAV first collects massive amounts of images and then copies them to high-performance workstations for 3D reconstruction or CNN computation. This mode suffers from huge time lags. Consequently, research frontiers are rapidly shifting toward edge-side real-time detection. Du et al. proposed a lightweight framework called LEE-YOLO based on cyber-physical systems; they provided a real-time cyber-physical system solution for UAVs used in road crack detection, improving pavement evaluation to achieve efficient highway maintenance [75]. To enable the extremely weak airborne chips on UAVs to run complex models smoothly, Xiang et al. further developed the GC-YOLOv5s lightweight detector. By introducing group convolution and linear operations, this study drastically slashed model parameters [76]. This means that future UAVs will no longer just be "flying cameras," but rather "flying edge computing nodes." UAVs will be able to complete defect recognition and localization during flight, transmitting back to the command center only minimal text data containing defect coordinates and severity levels, completely freeing themselves from the reliance of massive raw video transmission on bandwidth.

Facing large-scale highway networks, the endurance limit of single-UAV operations has become a bottleneck. Outay et al. pointed out that transitioning from single UAVs to multi-UAV swarm collaboration is an inevitable trend in infrastructure management [66]. At the scheduling and collaborative algorithm level, Chow proposed a stochastic arc-inventory routing policy to solve dynamic UAV traffic monitoring problems under uncertainty [77]; early research by Wu et al. also emphasized the importance of adaptive data processing and dissemination for UAV swarms in urban sensing [78]. To support this swarm collaboration, 5G and future 6G communication technologies will play extremely critical roles. They can not only provide ultra-low-latency vehicle-to-vehicle (V2V) inter-drone communication but also guarantee collision-free safe flying of multiple UAVs under complex weather conditions.

In the next-generation smart highway inspection architecture based on edge computing and UAV swarms, the UAV swarm is no longer merely a data collection terminal, but an edge node equipped with lightweight inference capabilities. Concurrently, leveraging 5G/6G communication achieves efficient, low-latency backhaul, ultimately completing decision-making in the cloud and automatically dispatching tasks to local transportation departments for road maintenance.

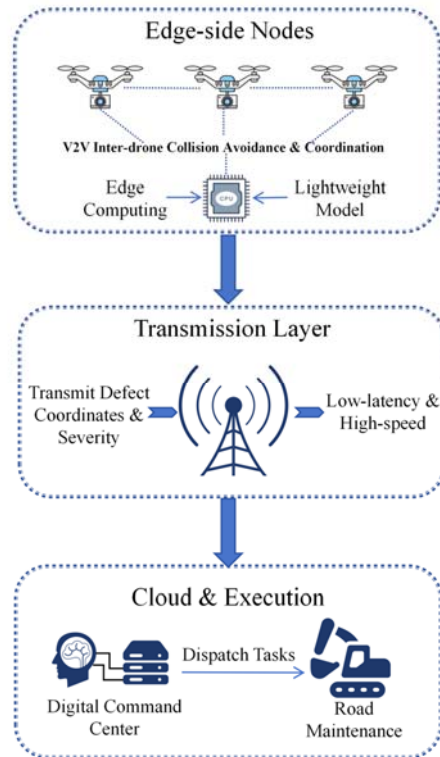


FIGURE 6 ARCHITECTURE DIAGRAM OF INTELLIGENT INSPECTION SYSTEM

In summary, edge computing allows UAVs to diagnose road defects independently, while swarm collaboration and high-speed communication networks enable UAV fleets to conduct coordinated operations. The deep integration of these two demonstrates the development prospect of unmanned monitoring for future smart highway networks.

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