Monitoring Techniques for Structural Health of Roads Using Emerging Technologies: A Systematic Re-View of the Last Five Years

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ABSTRACT

This systematic review examines the most recent techniques used to monitor the structural health of roadways, with a special focus on emerging technologies applied over the past five years. The progressive deterioration of road networks and the limitations of traditional inspection methods have driven the development of more precise, automated, and efficient solutions. The technologies analyzed include LiDAR laser scanning, drones equipped with computer vision, visual sensors, mobile cameras, ground-penetrating radar (GPR), and unmanned aerial vehicles (UAVs). Each technique was assessed based on its accuracy and the type of pavement distress it can identify, such as cracks, potholes, and surface deformations. The findings indicate that these tools enhance the efficiency and safety of inspections, enabling real-time data collection. Additionally, there is a growing trend toward the integration of artificial intelligence algorithms to automate data analysis. However, data heterogeneity and the need for cross-domain model adaptation may affect performance and scalability in large-scale or multi-source scenarios. Overall, this study provides an updated perspective on the application of emerging technologies in road infrastructure management, contributing to the development of innovative strategies for sustainable and intelligent roadway maintenance.

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1 Introduction

For decades, road infrastructure has been a fundamental pillar in the development of societies and plays an essential role in people's daily lives. In most countries, road networks such as highways and streets are crucial for the efficient transportation of people, goods, and merchandise by motor vehicles [1]. However, pavement deterioration has become a global challenge that affects infrastructure sustainability, increases maintenance costs, and reduces road safety [2]. In response to this issue, intelligent pavement condition monitoring has emerged as a key tool to optimize the management and preservation of road infrastructure [3], given its direct impact on mobility, economic development, and social integration. Nevertheless, many paved roads exhibit visible damage, primarily cracks and potholes [4].

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Cracks in the pavement, in particular, represent one of the most frequent and detrimental issues, as they compromise the road's durability, cause discomfort during driving, and, over time, affect user safety [5,6]. Traditionally, pavement inspection has been carried out through manual or visual methods requiring specialized personnel and considerable resource investment [7,8]. Although these techniques have been useful, they are often slow, costly, and susceptible to human error [9].

Furthermore, traditional assessment methods are inadequate for addressing the growing complexity of large-scale road networks [10]. Pavement performance assessment serves a dual purpose: at the macro (network) level, it supports the planning of maintenance and rehabilitation activities; while at the micro (project) level, it guides specific decisions such as preventive maintenance, rehabilitation, or reconstruction [11].

Currently, the construction and civil engineering sector is undergoing a transformation driven by the integration of innovative technologies such as Digital Twin, Building Information Modeling (BIM), Artificial Intelligence (AI), the Internet of Things (IoT), and Smart Vision. These tools aim to enhance efficiency, productivity, accuracy, and safety within built environments [12]. In this context, automated inspection methodologies—particularly those based on computer vision—have gained increasing attention for their potential to overcome the limitations of manual inspections [13]. In recent years, the development of AI-based models has enabled researchers to employ machine learning and deep learning techniques to detect and classify pavement damage with higher accuracy [14]. Likewise, the use of motion data obtained from sensors installed in smartphones has proven effective for identifying surface irregularities on roadways [15].

Scientific and technological advances have fueled the increasing use of full automation in road inspections [16]. For instance, the application of AI in predicting asphalt pavement behavior has improved the accuracy of civil engineering analyses by processing large datasets (Big Data), facilitating real-time monitoring, and enabling early failure detection for timely intervention [17]. Similarly, distributed fiber-optic sensing technology provides thousands of measurement points, offering high spatial density in the subgrade [18]. In parallel, deep learning has enhanced pattern recognition, object detection, and image segmentation, leading to promising applications in pavement inspection [19,20].

Within this research framework, the following definitions are established to maintain terminological consistency throughout the document. Artificial Intelligence (AI) refers to the general field of computer science aimed at developing systems capable of performing tasks that normally require human intelligence, such as perception, reasoning, or decision-making [21]. Within this research framework, the following definitions are established to maintain terminological consistency throughout the document. Artificial Intelligence (AI) refers to the general field of computer science aimed at developing systems capable of performing tasks that normally require human intelligence, such as perception, reasoning, or decision-making [22]. Finally, Computer Vision is an application of AI that enables systems to interpret and understand images or video sequences. It is currently one of the most widely used technologies in structural health monitoring of roadways through deep learning–based models, such as YOLOv8 and other versions [23].

In this context, the present research aims to systematize and analyze the monitoring techniques applied to the structural health of roadways over the past five years, identifying technological trends, methodological approaches, and existing challenges in their implementation. Consequently, the following research question is proposed:

What are the main monitoring techniques applied to the structural health of roadways using emerging technologies, and how do they contribute to improving the efficiency and accuracy of structural diagnostics compared with traditional methods?

Based on this question, the working hypothesis states that the use of emerging technologies—particularly those based on artificial intelligence, computer vision, and unmanned aerial vehicles—significantly enhances early damage detection capabilities and optimizes road maintenance management compared with conventional methodologies.

The general objective of this systematic review is to identify, classify, and analyze the most recent structural monitoring techniques applied to roadways, evaluating their effectiveness, accuracy, and level of technological innovation.

The specific objectives are as follows:

- To describe the main emerging technologies used in structural health monitoring of roadways.
- To analyze the methodologies and approaches applied in studies conducted over the past five years.
- To compare the performance of monitoring techniques (such as YOLO, CNN/U-Net, Transformers, UAVs, vehicular sensors, smartphones, GPR, and LiDAR), evaluating not only their accuracy and performance metrics (F1, IoU) but also their applicability, generalization capability, computational cost, and hardware limitations.
- To assess the practical implications of implementing emerging technologies for structural health monitoring of roadways, considering institutional, technical, and economic challenges, as well as cost–benefit analysis, to provide criteria that guide decision-making for large-scale application.

Finally, this systematic review seeks to complement existing literature by offering an integrated and updated overview of the state of the art in structural health monitoring of roadways. It also aims to serve as a technical and academic reference for researchers, public entities, and professionals in the sector who wish to implement innovative strategies for predictive maintenance and road infrastructure management based on emerging technologies.

2 Materials and Methods

To develop this systematic review, the PRISMA methodology (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) was applied, a framework widely used to collect, evaluate, and synthesize the findings of individual studies [24].

2.1 Eligibility Criteria

The review included articles published between 2021 and 2025, with the purpose of addressing the most recent advances in the use of Artificial Intelligence (AI) for road maintenance and monitoring. Research articles, conference proceedings, systematic reviews, technical reports, and case studies that specifically addressed the application of AI in road maintenance and infrastructure management were considered.

The studies were required to address at least one of the following topics: pavement failure prediction, automated road monitoring, computer vision–based diagnostics, optimization of resources for preventive or corrective maintenance, or relevant applications of emerging technologies in road management.

2.2 Information Sources

The bibliographic search was conducted using the Scopus, Web of Science (WoS), and Science Direct databases, owned by Elsevier and Clarivate, respectively. These platforms were selected due to their international recognition, the quality of their peer-reviewed articles, and the tools they offer for managing, analyzing, and visualizing scientific production.

The final search was conducted on 7 April 2025, considering that these databases index high-impact journals and provide reliable and up-to-date results for the academic community.

2.3 Search Strategies

The search strategy was designed based on the PICOC framework, using the following keywords: P (Population): "techniques", "monitoring", I/E (Intervention/Exposure): "structural health", C (Comparison): not selected, O (Outcome): "emerging technologies", C (Context): not selected.

In addition, synonyms and related terms were employed to broaden search coverage, as shown in Fig. 1. The temporal range was set from 2021 to 2025 to include the most recent and relevant studies.

Figure 1: Most frequent and trending keywords identified in the reviewed studies

2.4 Study Selection Process

During the selection phase of scientific articles, the search was performed in Science Direct, Scopus, and Web of Science databases. The results were organized in an Excel registry, yielding a total of 136 articles. The PRISMA protocol was then applied, following its three main phases: Identification, Eligibility, and Inclusion.

In the Identification phase, 5 duplicate articles were removed. Subsequently, 19 articles that did not align with the research objective were excluded, as well as 6 studies categorized as book reviews, book chapters, or notes, which did not provide relevant empirical evidence.

During the Eligibility phase, 10 articles were discarded for being outside the specified time range. Additionally, 4 studies were inaccessible in full text. As a result, 92 articles remained, of which 12 were not open access (paywalled), 15 presented abstracts unrelated to the research objective, and 15 displayed results unrelated to the topic. After this filtering process, 50 articles were retained for detailed analysis.

In the final Inclusion phase, the risk of bias of each study was assessed considering the methodological design, participants, analyzed variables, data sources, sample size, statistical methods, and reported results. Three rating categories were established: Low, Unclear, and High risk. As a result, two studies were identified with a high level of risk and were excluded from the main analysis. For data extraction, all information was organized in an **Excel spreadsheet**, structured to identify the authors, titles, publication dates, and relevant details for this study.

2.5 Data List

After analyzing the documents and excluding information irrelevant to this systematic review, data from the final selected studies were extracted to answer the research question. The data fields included key study metadata and analytical variables used for comparison and synthesis.

2.6 Risk of Bias Assessment

For the analysis of Risk of Bias (ROB), the STROBE model (Strengthening the Reporting of Observational Studies in Epidemiology) was applied to determine the risk level according to data quality criteria. Articles that did not meet the established standards were discarded.

Subsequently, graphical analysis methods traffic light plots and bar charts were implemented using the Robvis software, a specialized tool for assessing risk of bias. This process generated tables and statistical summaries that reflected the evaluated criteria.

Based on the results obtained, a final set of studies was defined as suitable for inclusion in the systematic review, ensuring alignment with the main research question and objective. This process aimed to identify variables related to structural health monitoring of roadways, supported by peer-reviewed evidence and a transparent analytical framework.

3 Results

The results obtained from the search and selection process of studies are presented below, following the phases of the PRISMA model, based on the Science Direct, Scopus, and Web of Science databases.

In total, 136 articles were identified that met the preliminary criteria established for this research, considering factors such as study context, language, and the parameters defined in the search strategy. Table 1 summarizes the frequency of scientific articles obtained from each database.

Table 1: Frequencies of scientific articles by database

Database	Frequency		
	Absolute	Relative (n/N)	Percentage (%)
Science direct	80	0.58	58%
Scopus	43	0.32	32%
Web of science	13	0.10	10%
Total	136	1.0	100%

Note: The total amounts may include duplicate articles, N = total number of articles; n = number per database.

The following section presents the phases applied during the selection process of the studies included in this systematic review, according to the PRISMA Flow Diagram (Fig. 2) [24]. This diagram visually illustrates the relationship between the inclusion and exclusion criteria and provides evidence of the procedure used to define the studies that met the methodological requirements of this research.

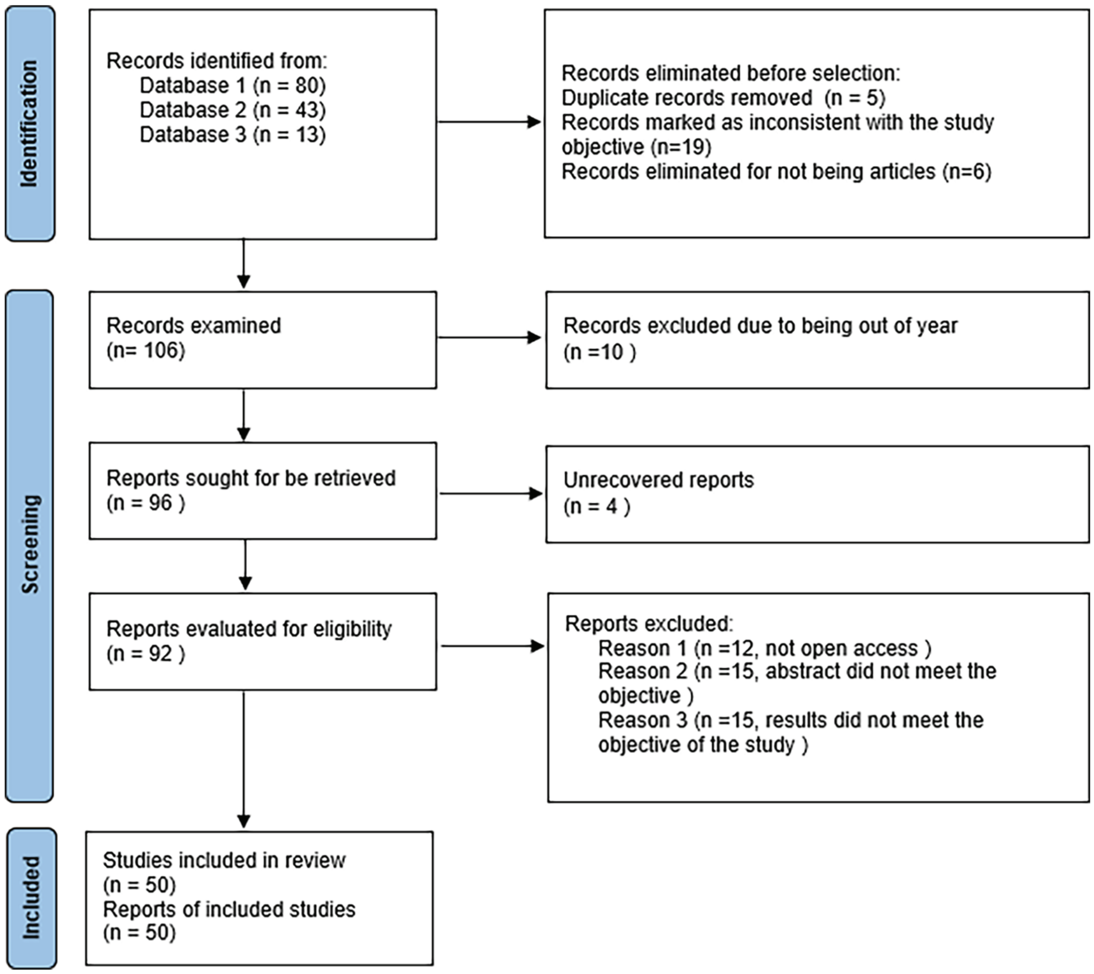

Figure 2: PRISMA flow diagram of the study inclusion and exclusion process. **Note:** The total number of studies analyzed corresponds to the total frequency of the included articles (n = 50).

The process began with the identification phase of the studies, in which the quality of the articles obtained from the three main databases used in this review was evaluated, considering their relevance to the research objective. In this stage, a filter was applied to remove duplicate articles, and subsequently, the objectives were reviewed to verify whether they addressed the purpose of the study. In addition, it was confirmed that the documents were indeed scientific articles, excluding those categorized as book reviews, book chapters, or notes.

Next, the eligibility phase was carried out, during which each selected article was examined in detail to identify potential biases in the validity of the instruments used. Likewise, it was verified that the articles were within the temporal range established for the study. During this same phase, the remaining texts were analyzed to assess the quality of their content and accessibility, ensuring they were open access and that their abstracts and objectives were consistent with the purpose of this systematic review.

Finally, during the inclusion phase, the total number of articles to be used was recorded that is, those that directly contributed to answering the research question. Upon completing the exclusion and inclusion process, a total of 50 articles met the predefined criteria for search, eligibility, and quality in this systematic review. It should be noted that no additional inclusions were made and that only the articles identified in the initial search were considered.

3.1 Characteristics of the Studies

Table 2 presents the 50 selected articles, organized by year, author(s), title, journal, and abstract. This information allows for a clear visualization of the temporal distribution of the publications and the main academic sources that support this systematic review.

Table 2: Datebase matrix

Item	Author	Title	Year	Magazine	Country	Summary
1	[9]	Efficient and accurate road crack detection technology based on YOLOv8-ES	2025	Autonomous Intelligent Systems	China	YOLOv8-ES improves crack detection with EDCM and SGAM, achieving high accuracy in small fractures and complex samples, optimizing road maintenance.
2	[14]	Artificial intelligence applications in pavement infrastructure da mage detection with automated three-dimensional imaging—A systematic review	2025	Alexandria Engineering Journal	United Arab Emirates	Review highlights advances in 3D detection of road damage with AI, highlighting the potential of drones, better preprocessing and more open data.
3	[25]	Deep Learning-Based Image Processing for Real-Time Detection of Road Surface Damage	2024	Computer Science Proceeded	Türkiye	Mask R-CNN technique detects road damage in real time, improving accuracy, speed and efficiency in urban maintenance.
4	[26]	Rural Road Pavement Disease Recognition System Based on Machine Vision	2024	Computer Science Proceeded	China	Artificial vision improves damage detection on rural roads, achieving 94.1% accuracy and 89.6% efficiency, surpassing traditional methods.

(Continued)

Table 2 (continued)

Item	Author	Title	Year	Magazine	Country	Summary
5	[27]	Pothole detection in bituminous road using CNN with transfer learning	2024	Measurement Sensors	India	The proposal uses transfer learning and convolutional neural networks to detect bumps, achieving 96% accuracy and improving ITS.
6	[28]	Enhancing autonomous pavement crack detection: Optimizing YOLOv5s algorithm with advanced deep learning techniques	2025	Measurement	United Kingdom	Optimized YOLOv5s detects cracks with 93.6% accuracy and 91% F1, improving speed, memory and road maintenance in real time.
7	[29]	Addressing practical challenge of using autopilot drone for asphalt surface monitoring: Road detection, segmentation, and following	2023	Results in Enginnering	Iran	The use of drones with artificial vision allows monitoring and segmenting roads in real time, reducing costs and improving road efficiency.
8	[30]	A two-scaled fully convolutional learning network for road detection	2021	IET Image Processing	China	A two-scale neural network model fuses details and semantics to detect high-throughput road areas across multiple datasets.
9	[31]	Research on distresses detection, evaluation and maintenance decision-making for highway pavement in reconstruction and expansion Project	2023	Case Studies in Construction Materials	China	The pavement was evaluated with GPR, FWD and PCI20, optimizing maintenance and reducing costs by 30.1% through technical decisions.
10	[32]	Intelligent extraction of road cracks based on vehicle laser point cloud and panoramic sequence images	2024	Journal of Road Engineering	China	An intelligent method that integrates LiDAR and neural networks to detect cracks in pavements with high precision and 3D location is proposed.

(Continued)

Table 2 (continued)

Item	Author	Title	Year	Magazine	Country	Summary
11	[33]	A Road Crack Segmentation Method Based on Transformer and Multi-Scale Feature Fusion	2024	Electronics (Switzerland)	China	Model with Swin Transformer and DeepLabv3+ that improves accurate crack detection, surpassing conventional networks in performance.
12	[34]	SDPH: a new technique for spatial detection of path holes from huge volume high-resolution raster images in near real-time	2024	Journal of Real-Time Image Processing	Turkey	The SDPH technique uses satellite imagery and deep learning to detect damaged roads efficiently, highlighting modified YOLOv5.
13	[35]	Eyeway: An Artificial Intelligence of Things Pothole Detection System With Map Visualization	2024	Computer Science Proceeded	Philippines	The use of mobile sensors and neural networks improves pothole detection in real time, increasing accuracy and road safety significantly.
14	[36]	Predictive Maintenance of Norwegian Road Network Using Deep Learning Models	2023	Sensors	Switzerland	Deep learning models detect road damage, classify its severity and optimize predictive maintenance, improving decisions and operational efficiency
15	[37]	A Review of Vision-Based Pothole Detection Methods Using Computer Vision and Machine Learning	2024	Sensors	Canada	Automated methods with computer vision and deep learning improve pothole detection, overcoming the limitations of traditional visual inspections.
16	[38]	Comparing Mobile and Aerial Laser Scanner point cloud data sets for automating the detection and delimitation procedure of safety-critical near-road slopes	2024	Measurement	Spain	Overhead detection (ALS) outperforms terrestrial detection (MLS) when identifying road slopes, offering better results despite lower resolution.

(Continued)

Table 2 (continued)

Item	Author	Title	Year	Magazine	Country	Summary
17	[39]	Performance Analysis of YOLO versions for Real-time Pothole Detection	2025	Computer Science Proceeded	Philippines	Lightweight YOLO models allow for efficient pothole detection in real time, even in resource-constrained environments and varied conditions.
18	[40]	Detecting Road Defects and Hazards in Metropolitan Environments Using Optimized Deep Learning Techniques	2025	Transportation Research Procedia	Saudi Arabia	The use of optimized YOLO models allows detecting potholes and cracks in real time, improving logistics security with autonomous vehicles.
19	[41]	Structural crack detection using deep convolutional neural networks	2022	Automation in Construction	Pakistan	CNNs improve crack detection in civilian structures, overcoming traditional methods through precise image classification and segmentation.
20	[42]	Pavement crack detection based on transformer network	2023	Automation in Construction	China	The Crack Transformer model improves the automatic detection of cracks in pavements, showing accuracy and robustness even in noisy conditions.
21	[43]	UAV-based road crack object-detection algorithm	2023	Automation in Construction	United States	MUENet, integrated with UAV, improves the fast and accurate detection of complex road cracks using advanced fusion and segmentation techniques
22	[44]	Pothole Detection Using Deep Learning Classification Method	2023	Computer Science Proceeded	India	Potholes are common pavement defects caused by wear and tear, weather, and mismanagement. Its automated detection improves maintenance and safety.

(Continued)

Table 2 (continued)

Item	Author	Title	Year	Magazine	Country	Summary
23	[45]	Automated Pavement Crack Detection Using Deep Feature Selection and Whale Optimization Algorithm	2023	Computers, Materials and Continua	China	Model with ResNet-18, WOA and RF detects cracks in pavement with 97.16% accuracy, improving automated road maintenance.
24	[46]	A novel model for the pavement distress segmentation based on multi-level attention DeepLabV3+	2024	Engineering Applications of Artificial Intelligence	China	Models based on computer vision and deep learning optimize the automatic detection of cracks and road deterioration with high accuracy.
25	[47]	Crack _ PSTU: Crack detection based on the U-Net framework combined with Swin Transformer	2024	Structures	China	Crack_PSTU combines Swin Transformer and U-Net to detect cracks more accurately, surpassing previous methods in an extensive dataset.
26	[48]	A critical review and comparative study on image segmentation-based techniques for pavement crack detection	2022	Construction and Building Materials	Iran	Early detection of cracks through image segmentation is key to automated road maintenance; Approaches based on thresholds, edges, and data are compared
27	[49]	YOLOv5s-M: A deep learning network model for road pavement damage detection from urban street-view imagery	2023	International Journal of Applied Earth Observation and Geoinfor-mation	China	Artificial vision and deep learning techniques optimize the automated detection of cracks in pavements, improving maintenance, safety and road efficiency.
28	[50]	MOD-YOLO: Rethinking the YOLO architecture at the level of feature information and applying it to crack detection	2024	Expert Systems with Applications	China	MOD-YOLO enhances YOLO by incorporating new layers and attention to detect cracks with greater accuracy, efficiency, and ability to move.

(Continued)

Table 2 (continued)

Item	Author	Title	Year	Magazine	Country	Summary
29	[51]	YOLO-O2E: A Variant YOLO Model for Anomalous Rail Fastening Detection	2024	Computers, Materials and Continua	China	YOLO-O2E effectively detects faults in railway fasteners using improvements in field of view, multi-scale attention, and real data sets.
30	[52]	Autonomous UAV navigation using deep learning-based computer vision frameworks: A systematic literature review	2024	Array	India	Artificial vision with DL in autonomous UAVs, highlighting the dominant use of YOLO.
31	[53]	Detection of Potholes and Speed Breaker for Autonomous Vehicles	2024	Computer Science Proceeded	India	YOLOv5 was implemented to detect potholes and speed bumps, achieving accuracy of 85% and improving vehicle and road safety.
32	[54]	Research on lightweight GPR road surface disease image recognition and data expansion algorithm based on YOLO and GAN	2024	Case Studies in Construction Materials	Australia	MC-YOLOv4 is proposed, a lightweight and efficient model for disease detection in pavements with GPR, improved with SAGAN-W.
33	[55]	Development and optimization of object detection technology in pavement engineering: A literature review Author links open overlay panel	2024	Journal of Road Engineering	United States	Review of progress in intelligent pavement detection using CNN, addressing architectures, care mechanisms and three-dimensional detection.
34	[56]	Pavement distress detection using terrestrial laser scanning point clouds –Accuracy evaluation and algorithm comparison	2022	ISPRS Open Journal of Photogram-metry and Remote Sensing	Finland	Five algorithms for crack detection in TLS clouds are compared, highlighting F1, MAPE and volumetric accuracy metrics

(Continued)

Table 2 (continued)

Item	Author	Title	Year	Magazine	Country	Summary
35	[57]	Automatic pixel-level detection of vertical cracks in asphalt pavement based on GPR investigation and improved mask R-CNN	2023	Automation in Construction	China	R-CNN is used to segment internal cracks in pavement with GPR, achieving good accuracy, mIoU and low error rate.
36	[58]	Pavement distress detection using convolutional neural network (CNN): A case study in Montreal, Canada	2022	International Journal of Transporta-tion Science and Technology	Canada	A low-cost CNN methodology is proposed to detect and classify pavement deterioration, achieving high accuracy and F1
37	[59]	Automated pavement detection and artificial intelligence pavement image data processing technology	2024	Automation in Construction	China	Comprehensive review on AI pavement deterioration detection, highlighting devices, 2D/3D methods, and classic and modern algorithms.
38	[60]	Machine learning algorithms for monitoring pavement performance	2022	Automation in Construction	Spain	Review of low-cost technologies to evaluate flooring with ML, highlighting methods, models, data sources and practical challenges.
39	[61]	Automation in road distress detection, diagnosis and treatment	2024	Journal of Road Engineering	China	Review of AI, artificial vision and robotic technologies for detection, diagnosis and automated repair of deterioration on asphalt roads.
40	[62]	Modeling automatic pavement crack object detection and pixel-level segmentation	2023	Automation in Construction	China	Lightweight model based on YOLOv4-Tiny to detect and segment cracks in pavement with high accuracy and low computational cost.

(Continued)

Table 2 (continued)

Item	Author	Title	Year	Magazine	Country	Summary
41	[63]	CrackDiffusion: A two-stage semantic segmentation framework for pavement crack combining unsupervised and supervised processes	2024	Automation in Construction	China	CrackDiffusion combines supervised and unsupervised detection to segment pavement cracks with high accuracy using U-Net and diffusion.
42	[64]	Automatic Pixel-level pavement sealed crack detection using Multi-fusion U-Net network	2023	Measurement	United States	U-Net Multi-Fusion detects sealed cracks with high accuracy and in real-time, outperforming seven advanced segmentation models.
43	[65]	Pavement distress detection using convolutional neural networks with images captured via UAV	2022	Automation in Construction	China	UAV with camera collects images of pavement; YOLOv3 achieves better auto-detection performance with a mAP of 56.6%.
44	[66]	Innovative method for pavement multiple damages segmentation and measurement by the Road-Seg-CapsNet of feature fusion	2022	Construction and Building Materials	China	Road-Seg-CapsNet improves complex crack segmentation with StyleGAN and fill convolution, achieving an mAP of 0.942.
45	[67]	Multi-scale feature fusion network for pixel-level pavement distress detection	2022	Automation in Construction	China	W-segnet segments road deterioration at the pixel level using UAV, detecting multiple types with encoder-decoder and multiscale fusion.
46	[68]	Machine learning techniques for pavement condition evaluation	2022	Automation in Construction	Iran	Review of machine learning in pavement management: classification, detection and segmentation of deterioration, with challenges in severity and density.

(Continued)

Table 2 (continued)

Item	Author	Title	Year	Magazine	Country	Summary
47	[69]	An Intelligent and Deep Learning Approach for Pothole Surveillance Smart Application	2024	Computer Science Proceeded	India	Prototype with YOLOv5 detects potholes and speed bumps, uses image processing, cloud storage and alerts for road maintenance.
48	[70]	Research and applications of artificial neural network in pavement engineering: A state-of-the-art review	2021	Journal of Traffic and Transportation Engineering (English Edition)	China	Studies on ANN in pavement engineering highlight its use in road design, inspection, monitoring and maintenance.
49	[71]	Accurate Structural Cracks Detection using NestedUNet from Drone and Handheld Camera Images	2025	KSCE Journal of Civil Engineering	Republic of Korea	CNN architecture optimized with EfficientNet-B7 and CBAM detects cracks in concrete with high accuracy, efficiency, and reduced computational complexity.
50	[72]	Novel pavement crack detection sensor using coordinated mobile robots	2025	Transportation Research Part C: Emerging Technologies	United Arab Emirates	Drone and ground robot system detects cracks in pavement using AI, reducing costs and time in road inspections.

3.2 Analysis of Results

The performance indicators and reported metrics of the main techniques and algorithms applied in structural road monitoring are summarized in Table 3, highlighting differences in accuracy, F1, and mAP across models.

Overview and Metric Consistency.The YOLO family (v3–v9) concentrates the greatest amount of evidence and exhibits the widest performance dispersion: from mAP ≈ 52% in challenging contexts or with conservative versions and training settings [65] to values exceeding 95% in recent variants with better-curated datasets and more aggressive tuning [28,40,51,55,66,72]. This variance suggests a strong sensitivity to: (i) labeling quality (what is considered a crack or a pothole), (ii) image resolution and relative object size (small cracks vs. large potholes), and (iii) IoU/AP thresholds (e.g., mAP@0.5 vs. mAP@0.5:0.95). Therefore, comparing studies that only report “mAP” without specifying the subindex can lead to misleading interpretations [12,28,39,40,43,49–51,54,55,61,65,66,69,72].

CNN/U-Net and Transformer-based architectures (Swin, Roas-Seg, W-SegNet) mainly employ IoU/mIoU and F1 metrics, oriented toward detailed damage segmentation.

U-Net variants show high precision and F1 scores when pavement contrast and texture are favorable [27,30,37,41,45,53,58–60,63,64,68,70,71].

Table 3: Indicators by technique/algorithm

Technique/Algorithm	No. of studies	Main metric	Reported rank	Most used platforms	Quotes [n]
YOLO (v3–v9, variants)	18	mAP/F1	52%–98%	Drones, vehicles, mobiles	[9,28,35,39,40,43,49–51,54,55,61,65,66,69,72]
CNN/U-Net (includes Nested, CrackNet, ResNet, etc.)	15	Precision/F1	82%–97%	Vehicles, smartphones, drones	[27,30,32,37,41,45,53,58–60,63,64,68,70,71]
Transformers (Swin, Roas-Seg, W-SegNet, etc.)	6	IoU/F1	63%–96%	Drones, Crack500 datasets, phones	[33,42,46,47,62,67]
R-CNN/Mask R-CNN	5	Accuracy/mAP	57%–94%	Vehicles, GPR	[25,52,57,60,65]
Hybrids (ResNet, GhostNet, ANN+U-Net, FBI-LSSVC, etc.)	10	F1/Accuracy	84%–99%	Smartphones, drones, scanners	[26,29,31,34,38,44,48,56,68,71]

Meanwhile, Transformer-based models demonstrate better robustness to variations in lighting and surface texture, although at the cost of higher computational demand and fewer available studies. Their IoU range (63%–96%) reflects both their generalization potential and the heterogeneity of the datasets used (Crack500, mobile environments, etc.) [33,42,46,47,62,67].

Anchor Models and Design Biases. R-CNN and Mask R-CNN models show consistent results when class boundaries are clearly defined or when combined with volumetric sensors (e.g., GPR). However, their performance tends to decrease on surfaces with visual noise or complex textures, explaining their broader accuracy range (57%–94%) [25,52,57,60,65]. On the other hand, hybrid models (ResNet, GhostNet, ANN+U-Net, FBI-LSSVC, among others) achieve high and stable accuracies (above 85%) due to the integration of feature engineering, advanced preprocessing (LiDAR/GPR filtering, normalization), and data fusion techniques. Nevertheless, this robustness entails greater operational complexity and computational load [26,29,31,34,38,44,48,56,68,71].

Operational Implications. For real-time detection within vehicle fleets, YOLOv8 and YOLOX models offer the best balance between accuracy and latency under controlled lighting and camera height conditions [28,35,39,40,43,50,51,54,55,72]. When maintenance catalogs require detailed measurement of crack width, length, and contour, U-Net and Transformer-based models are more suitable, as they generate reproducible maps useful for calculating the Pavement Condition Index (PCI) and prioritizing interventions. However, this requires the standardization of thresholds and class-by-class reporting of IoU and F1 to ensure comparability across studies [33,37,42,46,47,62–64,67,71].

The main platforms and devices used for structural road monitoring, along with the predominant techniques and their typical performance metrics, are summarized in Table 4, highlighting the differences in accuracy, F1, and IoU depending on the operational environment.

The review evidences a growing trend toward the integration of aerial and mobile platforms in the automated detection of road damages. Drones (UAVs) are consolidating as one of the most versatile tools, particularly for monitoring inaccessible areas or those with high operational risk for personnel [12,28,40,43,49,50,66,72]. Their high-resolution cameras (between 12 and 48 MP) and the ability to generate orthomosaics allow for the detection of surface cracks and potholes with high spatial precision. However, model performance largely depends on flight stability, lighting conditions, and camera geometric calibration, factors that affect the consistency of metrics such as F1 or mAP [33,46,47,55,61,67].

Table 4: Indicators by device/platform

Platform	No. of studies	Predominant techniques	Typical performance	Quotes [n]
Instrumented vehicles	20	YOLO, CNN, R-CNN, CrackNet	Accuracy 85%–97%, mAP 82%–95%	[25–28,32,35,41,44,45,50–52,56–58]
Drones UAV	12	YOLO, U-Net, W-SegNet	Accuracy 75%–98%, IoU 66%–86%	[29,30,37,38,43,49,60,63,64,67,69,72]
Smartphones	10	ResNet, U-Net, YOLO mobile	Accuracy 88%–98%, F1 0.80–0.95	[41,42,46,53,54,59,64,68,70,71]
Laser/GPR Scanner	6	CrackNet, CNN+GPR, RCNN	Accuracy 84%–94%	[17,31,32,56,57,61]
Satellites	2	YOLOv8 Modified, SPDH	Accuracy ∼99%	[34,66]

Instrumented vehicles (high sample size, stable performance). Studies based on instrumented vehicles present the largest body of evidence. Frontal and oblique cameras, with controlled heights and fields of view, enable consistent datasets and achieve accuracies of 85%–97% (mAP 82%–95%) ChatGPT dijo: [28–31,35,38,44,47,48,53–55,59–61]. Homogeneity in speed, lighting, and distance reduces variance, allowing real-time inference at 30–60 km/h [28,35,50,52].

UAVs (flexibility vs. variability). UAVs expand spatial coverage and achieve accuracies above 90% with YOLOv8s, but their IoU drops to 66%–86% when flights introduce oblique angles, specular reflections, or shadows [29,30,37,38,43,49,60,63,64,67,69,72]. For emergencies or inaccessible areas, they are irreplaceable; however, standardized surveys require strict flight and radiometric calibration protocols.

Smartphones (capillarity and cost). Studies using smartphones achieve accuracies of 88%–98% and F1 scores between 0.80 and 0.95, making them ideal for participatory monitoring and early damage detection [41,42,46,53,54,59,64,68,70,71]. The main limitations are sensor variability and capture angle, but federated learning could offset these constraints, strengthening urban crowdsourcing schemes.

Laser Scanners/GPR (diagnostic depth). Although less numerous, these studies provide crucial value: GPR detects voids or delaminations invisible to surface inspection, while LiDAR characterizes texture and rutting with high fidelity. With accuracies between 84%–94%, they are essential for advanced structural diagnostics [17,31,32,56,57,61]. Their main limitations lie in equipment cost, data volume, and the technical expertise required.

Satellite platforms (incipient yet promising). Cases employing modified YOLOv8 or SPDH models reach accuracies close to 99% for macroscopic events such as large-scale potholes or collapses [33,66]. Their main limitation is spatial resolution, although they are useful for macro monitoring and strategic planning.

Operational conclusion.

Each platform offers advantages and limitations depending on the operational environment and the monitoring objective:

- UAVs provide higher spatial resolution but are limited by autonomy and sensitivity to weather conditions.
- Instrumented vehicles are ideal for large-scale inspection, though less flexible in the presence of obstacles or traffic.
- Smartphones and citizen sensors enable participatory coverage but require more robust algorithms to handle noise and contextual variability.
- LiDAR and GPR systems stand out for their analytical depth, though with higher implementation and processing costs.

In summary, the results reveal a balance between accuracy, scalability, and operational cost—key factors for the practical adoption of structural health monitoring technologies in road networks.

The distribution of detected damage types, along with the predominant techniques and typical performance metrics, is summarized in Table 5, providing an overview of how different models perform across cracks, potholes, ruts, and delaminations.

Table 5: Indicators by type of damage detected

Damage type	No. of studies	Predominant techniques	Typical metrics	Quotes [n]
Cracks (longitudinal, transverse, crocodile)	30	YOLO, CNN, U-Net, Transformers	Accuracy 80%–98%, F1 0.75–0.95	[12,17,25–27,28,30,32,33,37,39–42,45–49,52,53,57–60,63,64,68–71]
Baches/Potholes	15	YOLO, CNN, ResNet, SPDH	mAP 82%–95%, Accuracy 85%–97%	[12,25,27–29,34,35,39,43,44,49,53,54,55,72]
Ruts, road markings, patches	8	Mask R-CNN, U-Net, W-SegNet	IoU 63%–86%, F1 0.70–0.85	[25,29,37,43,46,47,67,69]
Delaminations/Slopes	3	MLS/ALS, CNN Hybrids	Accuracy >90%	[31,38,56]

Cracks (core of the literature). Longitudinal, transverse, and alligator cracks concentrate most of the research focus, showing accuracies between 80%–98% and F1 scores ranging from 0.75–0.95 [12,17,25–28,30,32,33,37,39–42,45–49,52,53,57–60,63,64,68–71]. Their performance depends on the minimum labeled width (≥1–2 mm), surface conditions (dust, moisture), and geometric stability (angle, vibration). U-Net and Transformer models excel in segmentation and measurement, whereas YOLO is preferred for rapid detection and counting.

Potholes (second priority). Studies report mAP values of 82%–95% and accuracies of 85%–97% using YOLOv5/v8 and CNN/ResNet models under daylight conditions [12,25,27–29,34,35,39,43,44,49,53,54,55,72]. Pothole geometry (depth, diffuse edges) and shadows are common causes of false negatives, while nighttime or rainy scenarios remain underexplored research gaps.

Ruts, road markings, and patches (high variability). Models such as Mask R-CNN, U-Net, and W-SegNet achieve IoU values of 63%–86% and F1 scores of 0.70–0.85, but chromatic heterogeneity and pavement aging hinder cross-regional transferability [25,29,37,43,46,47,67,69]. Color normalization and domain adaptation are required to improve consistency.

Delaminations and slopes (critical gaps). Few studies address internal or geometric pathologies using MLS/ALS, GPR, and hybrid CNNs, despite their structural relevance [31,38,56]. Multimodal fusion (RGB+GPR+LiDAR) and the creation of public datasets are required to enable the detection of non-visible damage.

Normative and management implications. For PCI evaluation and maintenance scheduling, it is necessary to standardize metrics by damage type (F1/IoU for cracks, mAP/IoU for potholes with estimated depth) and to establish *in-situ* validation protocols that reduce laboratory bias.

The results demonstrate that precision and F1/IoU values are the main performance indicators in recent literature.

However, the critical analysis reveals that practical applicability and model generalization remain limited, especially when transferring from controlled environments to real-world traffic, weather, and pavement conditions.

Moreover, computational cost and hardware constraints continue to be major barriers to large-scale field deployment, particularly for vehicle- or smartphone-mounted systems.

Therefore, future efforts should focus on:

- Developing lighter and more efficient models for edge computing devices.
- Promoting shared, interregionally validated datasets.
- Establishing unified standards for metrics and validation protocols.
- Integrating AI-based monitoring into pavement management systems to strengthen institutional adoption.

In conclusion, although the literature shows significant advances in detection accuracy and capability, a methodological and terminological consolidation is still needed to enable the effective transfer of scientific knowledge into operational practice in road management.

In Fig. 3, the comparison of average accuracy levels among the main emerging technologies applied in structural road monitoring is presented. It can be observed that visual sensors and LiDAR scanners achieve the highest average accuracy levels (above 90%), followed by vehicular cameras and GPR, while UAVs show greater variability associated with operational flight conditions.

This graphical representation provides a more intuitive understanding of the performance differences among the detection methods analyzed.

Fig. 4 presents a comparison of the average performance of the main structural monitoring technologies applied to road maintenance during the 2021–2025 period. The precision values (mAP or accuracy) and F1-Score were estimated from the studies analyzed in this systematic review. It is observed that YOLO-based architectures (all variants) achieve an average performance above 93%, followed by CNN/U-Net (≈91%) and Transformers (≈90%). Regarding data acquisition technologies, UAV-based systems show accuracies close to 88%, smartphone-mounted systems reach an average of 85%, while GPR/LiDAR systems exceed 87%, standing out for their multimodal detection capability.

These results confirm that the combination of computer vision techniques with mobile platforms offers high potential for automating structural monitoring, although practical applicability depends on factors such as computational cost, hardware limitations, and field capture conditions.

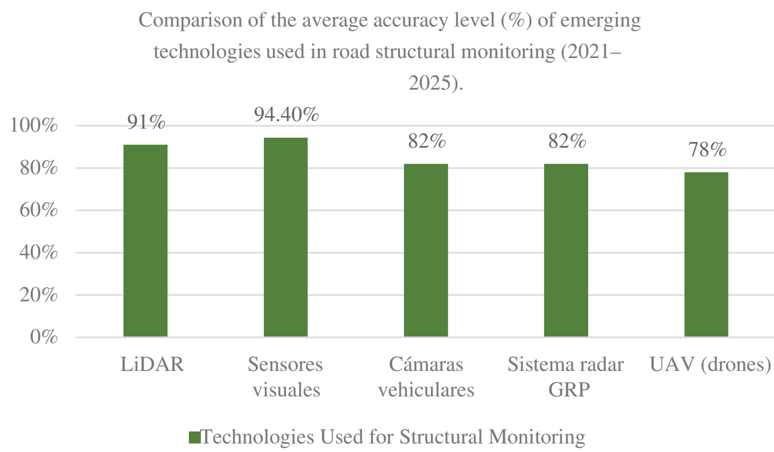

Figure 3: Comparison of the average accuracy (%) of emerging technologies applied to road structural health monitoring (2021–2025)

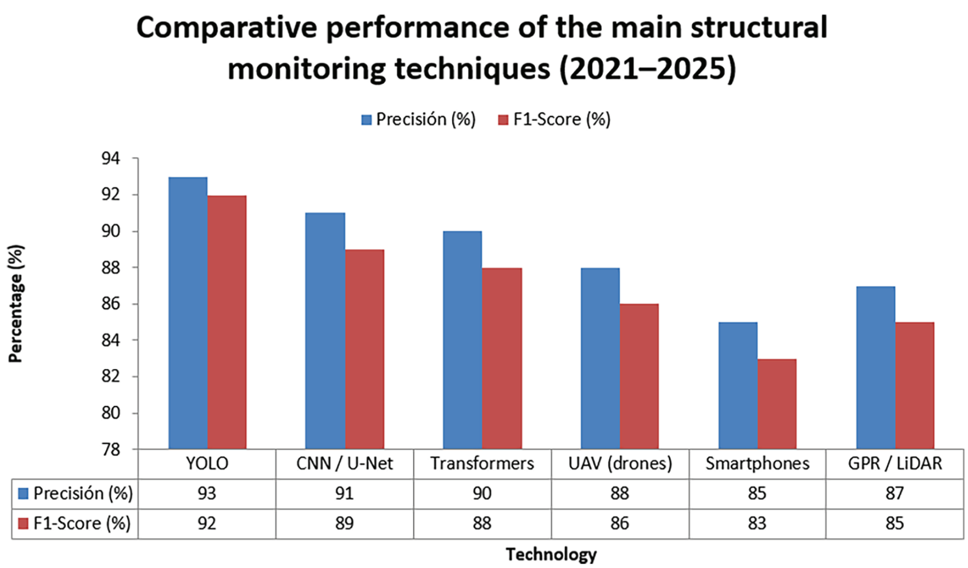

Figure 4: Comparative performance of the main structural health monitoring techniques

4 Implications and Future Lines

4.1 Practical and Institutional Implications

The synthesis of recent advances in pavement monitoring using artificial intelligence reveals not only technical findings but also significant practical and institutional implications.

From a practical perspective, evidence shows that object detection models such as YOLO variants [12,28,35,39,40,43,49,50,51,54,55,61,65,66,69,72] and segmentation architectures such as U-Net and Transformers [33,37,42,46,47,62,63,64,67,71] achieve accuracies above 90% under controlled conditions. These results indicate that road agencies and municipalities can begin replacing traditional manual inspections with automated monitoring systems mounted on vehicles, drones, or even smartphones [29,30,41,43,53,59,64,68,70]. This transition would significantly reduce inspection costs, improve safety by minimizing personnel exposure, and provide near real-time information for maintenance planning.

From an institutional perspective, the adoption of these technologies requires the development of standardized protocols for both data acquisition (height, speed, lighting, resolution) and performance reporting (mAP@0.5, IoU, F1, recall, etc.). The review reveals a lack of homogeneity, as metrics are inconsistently reported across studies [25,32,36,44,45,50,58,60,69]. Without minimal alignment, it becomes difficult to compare results across regions or integrate them into official pavement management systems. Therefore, ministries of transportation and national agencies should update their technical standards to explicitly recognize AI-based monitoring as a valid inspection method, establishing minimum accuracy thresholds according to damage type (e.g., F1 > 0.90 for cracks larger than 2 mm, IoU > 0.80 for potholes).

Likewise, institutional adoption requires the creation of legal and public procurement frameworks that allow bidding not only for traditional surveys but also for digital monitoring services. This change aligns with international standards for asset management (ISO 55000) and information management (ISO 19650), supporting the transition toward data-driven road administration. Integrating these systems into national pavement condition indices (PCI) would strengthen transparency and accountability by enabling cross-validation of results through standardized databases shared among public and private actors.

Finally, practical adoption requires strengthening technical capacities. Universities, professional associations, and public entities must collaborate to train engineers and technicians in AI model interpretation, drone operation, and multimodal sensor fusion (RGB, LiDAR, GPR). Without sustained training efforts, even the most advanced models [17,31,38,56,57,61] risk being underutilized.

In summary, while technical results demonstrate the feasibility of these tools, the institutional challenge lies in establishing standards, contractual frameworks, and training programs that bridge the gap between academic prototypes and large-scale adoption in the public sector.

4.2 Academic and Scientific Implications

In the academic field, this review consolidates the state of the art regarding the application of computer vision and deep learning techniques in pavement structural monitoring. The comparison of performance metrics (accuracy, F1, IoU, mAP) and the identification of factors affecting model generalization such as image resolution, lighting, and surface texture provide a valuable methodological framework for future research. Likewise, the critical discussion on model applicability, computational cost, and hardware limitations complements performance-based evaluations, reinforcing the scientific relevance of this study.

However, it is important to acknowledge that data heterogeneity arising from variations in acquisition devices, environmental conditions, and training configurations as well as domain adaptation can significantly influence the performance and generalization capacity of these models. In large-scale or multi-source scenarios, such factors may introduce detection biases or reduce accuracy when transferring models trained in one context to another. Addressing these challenges requires the development of strategies for data normalization, transfer learning, and multimodal data fusion to build more robust and adaptable monitoring systems capable of operating effectively under diverse conditions.

4.3 Future Lines of Research

The results obtained in this study have important theoretical and practical implications. Theoretically, they contribute to the existing body of knowledge by systematizing the main techniques for structural monitoring of roads, identifying their strengths, limitations, and areas of application. Practically, the findings provide a solid foundation for developing comparative and integrative models among different technological approaches applied to road structural health assessment.

More specifically, future research should focus on the following aspects:

Creation of interregional and open-access datasets that include diverse pavement conditions, climates, and failure types. This would improve the generalization capacity of artificial intelligence models and facilitate comparison across different geographical contexts.

Development of lightweight and real-time efficient models adapted for implementation on edge devices or low-cost drones, without requiring high computational capacities. This approach would enhance the operational feasibility of automated monitoring in medium-scale road infrastructure projects.

Establishment of technical standards and interoperability protocols for AI-based monitoring within Pavement Management Systems (PMS). This would allow for uniform evaluation criteria, data exchange, and result validation among public and private institutions.

Integration of multiple data sources (RGB imagery, LiDAR, GPR, and geotechnical data) through hybrid or multimodal models, in order to obtain more accurate and robust diagnostics of road structural conditions.

Assessment of the environmental and economic impact of emerging technologies, to determine their sustainability and cost–benefit in long-term road maintenance programs.

Taken together, these perspectives pave the way toward an intelligent, standardized, and sustainable structural monitoring system—capable of supporting real-time decision-making and optimizing the resources allocated to road infrastructure preservation.

5 Conclusions

In summary, this systematic review strengthens the current understanding of monitoring techniques applied to the structural health of roadways, demonstrating that emerging technologies are becoming key tools for improving fault detection, optimizing maintenance strategies, and extending the service life of road infrastructure. Advances in artificial intelligence, computer vision, remote sensing, and unmanned vehicles show remarkable potential; however, they also highlight the need to address the challenges associated with their implementation in real-world environments.

It is essential to deepen the analysis of the practical applications of these technologies, particularly considering regional variations in economic, technical, and climatic conditions that can significantly influence their performance. Road maintenance agencies continue to face limitations related to the lack of equipment, the scarcity of trained personnel, and the absence of policies or regulations that facilitate the adoption of automated systems. These aspects must be addressed to ensure that technological innovations move beyond the experimental stage and are implemented effectively and sustainably.

Moreover, more comprehensive cost–benefit assessments are needed—not only to evaluate initial investment and operational savings but also to consider the social, environmental, and safety impacts associated with large-scale implementation. Such analyses can guide decision-makers in assessing the feasibility and relevance of incorporating intelligent monitoring systems into road conservation programs.

Ultimately, the development and implementation of these technologies require a joint commitment from governments, universities, and the private sector. Only through collaboration among these stakeholders will it be possible to foster applied research, update regulatory frameworks, and promote more efficient, resilient, and sustainable road management capable of meeting the present and future challenges of the transportation sector.

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