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Review Article

AI-Powered Revolution in Concrete Crack Analysis: An In-Depth Review on Detection and Classification Methods

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ABSTRACT

Concrete crack detection and classification are pivotal for structural health monitoring and civil infrastructure maintenance. However, traditional manual inspections are labour-intensive, inconsistent, and often hazardous in complex environments. Conventional manual inspections are time-consuming and could turn out ineffective, leading to risks in challenging circumstances. To address these limitations, a systematic literature review (SLR) of 68 peer-reviewed studies published between 2021 and 2025 was conducted, examining the evolution of concrete crack detection and classification methods over the past decade. This systematic review organises recent concrete crack detection and classification studies based on the crack analysis pipeline (data acquisition, preprocessing, model development, and performance evaluation) and identifies the key techniques employed at each stage. This review evaluates the accuracy, practical usefulness, limitations, and implementation challenges of recent concrete crack detection and classification methods, as well as their practical problems and ongoing problems, such as limited training datasets, variable environmental conditions, real-time deployment constraints, and limited model interpretability. To fill these gaps, the review suggests future research directions like creating standard crack datasets and making lightweight, easy-to-understand AI models that can be directly implemented in field applications. The review shows a clear shift from traditional image processing and classical machine learning methods to more advanced deep-learning models, which have improved automated crack

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detection capability. Convolutional neural networks and transformer-based architectures have reported strong performance in selected studies, although these values should be interpreted within the context of different datasets, validation protocols, and evaluation metrics. This greatly improves the safety and efficiency of inspections. Consequently, deep learning has emerged as one of the most widely adopted and promising approaches for concrete crack detection and classification during the reviewed period.

Keywords: Concrete crack, crack classification, crack detection

INTRODUCTION

Concrete cracks in civil engineering compromise the stability and serviceability of buildings, bridges, and road infrastructure. Structural cracks from excessive loading or foundation settlement may indicate potential structural failure. Even small cracks can allow moisture to penetrate the concrete and reach the steel reinforcement, which speeds up corrosion and degradation (Cui & Qin, 2024; Yu et al., 2021). If left untreated, repetitive stress can increase crack propagation, reduce load-bearing capacity, and create safety risks (Golding et al., 2022). For structural health monitoring, it is important to detect and repair cracks at an early stage (Ali et al., 2021).

Concrete may crack due to temperature variation, excessive loading, material defects, or construction-related deficiencies (Cui & Qin, 2024). Cracks are commonly categorised based on origin, appearance, age, orientation, and structural significance. For example, they can be structural or non-structural, such as shrinkage cracks, early-age plastic or later-age hardened cracks, and vertical or diagonal cracks. Crack classifications can indicate possible structural problems (Cui & Qin, 2024; Golding et al., 2022). Industry standards provide acceptable crack-width limits for durability assessment. Cracks that are less than 0.2 mm wide are generally considered less critical, but cracks that are more than 0.5 mm wide may indicate reduced structural or material performance (Nyathi et al., 2024). To prevent further deterioration, cracks that exceed these limits usually require repair or remedial intervention (Yu et al., 2021).

Although maintenance guidelines provide acceptable crack-width limits, they do not prevent the initial development of cracks. Manual visual inspection remains time-consuming, labour-intensive, and susceptible to subjective judgement (Ali et al., 2021; Golding et al., 2022). In large structures such as bridges and building systems, inspection may require several weeks, delay repair decisions, and expose inspectors to safety risks (Golding et al., 2022). In addition, fatigue, limited accessibility, and environmental conditions may cause small or hidden cracks to be overlooked. These limitations highlight the need for automated crack detection systems that are more objective, scalable, and reliable (Cui & Qin, 2024; Wang et al., 2024).

The 1990s and 2000s witnessed the development of semi-automated crack detection and identification systems through the combination of inexpensive digital cameras and basic computer vision technology. Engineers employed edge detection and thresholding filters to display cracks and shadowed regions in concrete surface photographs (Ali et al., 2021). The initial image-based methods provided rapid results and improved inspection consistency compared with manual surveying. Basic filtering and morphological procedures can detect cracks with 70-80% accuracy under optimal illumination and surface conditions (Ali et al., 2021). However, these values should be interpreted within the context of controlled image conditions, because early image processing methods were highly sensitive to lighting, stains, shadows, and surface texture.

The performance of basic image analysis methods declined under challenging environmental conditions. The algorithms often failed to recognise irregular surfaces, where shadows, stains, or rough textures caused false positive detections or missed cracks on complex backgrounds. The software required separate algorithm adjustments because it lacked adaptive intelligence for different field conditions. Basic image processing could assist human inspectors, but it was unreliable for independent use by the late 2000s. These limitations encouraged the development of artificial intelligence systems dedicated to more robust crack detection.

Traditional machine learning models detected cracks with 75-85% accuracy, outperforming earlier image processing methods in several reported studies (Fan, 2021; Yu et al., 2021). However, these performance values should not be interpreted as direct evidence of superiority because studies used different datasets, validation protocols, and testing conditions. These models had several drawbacks, such as dependence on hand-crafted features. If these features could not accurately represent a crack under different lighting or material conditions, model performance declined. Most studies trained models using limited image datasets, which restricted generalisation (Yu et al., 2021). Sliding window scanning was also impractical for inspecting large surface areas because each image required considerable processing time. By the end of the 2010s, conventional machine learning had become too limited in terms of scalability and robustness. Consequently, deep learning approaches were increasingly adopted for crack analysis.

Crack detection and classification are complementary but distinct concrete structure evaluation processes. Crack detection algorithms locate and quantify cracks in images (Ali et al., 2021). Crack classification categorises cracks by type, such as structural or non-structural, and by severity, such as minor or major (Nyathi et al., 2024). In practice, crack detection addresses where the crack is located, while classification addresses the nature and severity of the crack, which is crucial for maintenance planning.

Inspectors or algorithms first identify cracks, then classify each crack according to type and severity (Pu et al., 2022; Taj et al., 2024). Crack classification is important for maintenance because different crack types require different levels of intervention (Mazni et al., 2024). A minor surface hairline crack may require only periodic monitoring, but a large structural crack may need immediate repair (Ye et al., 2024). Engineers can prioritise repairs based on safety and structural risk by accurately classifying crack severity and type (Golding et al., 2022).

The latest developments enable unified AI models to perform crack detection and classification through integrated systems. Current deep learning algorithms can detect and classify cracks simultaneously (Diniz et al., 2024; Li et al., 2022). The integrated approach allows cracks to be analysed in real time by reducing separate detection and classification procedures (Abubakr et al., 2024; Ye et al., 2024). However, the implementation of integrated techniques still encounters several practical challenges. These include limited training data, model generalisation problems, unpredictable field conditions, and difficulty in interpreting AI outputs (Kolappan Geetha et al., 2023). Researchers are developing solutions to enhance the reliability of AI-based crack analysis systems for practical implementation.

This review contributes by providing a structured synthesis of AI-based concrete crack detection and classification. Beyond summarising previous studies, it proposes a conceptual understanding of the crack analysis workflow, from data acquisition and preprocessing to AI model development, crack detection or classification output, and structural health monitoring decision-making. It also organises the reviewed methods into a taxonomy of AI approaches and identifies maturity levels, research gaps, and future directions. This contribution helps clarify which AI methods are closer to practical field adoption and which areas still require further validation, standardisation, and integration with engineering decision-making.

Detection algorithms require greater computational resources and depend on pixel- or region-based outputs, which can create difficulties for users when compared with classification algorithms. Classification methods usually operate at higher speed and produce binary outputs or category labels. Different applications exist for each approach. Crack detection produces maps, masks, or bounding boxes that enable further examination and measurement. Classification enables rapid evaluation of crack images and provides essential information about crack type or severity. The methods typically work together as a combined system, where detection or segmentation creates a map of the detected crack, while classification provides interpretation of the detected damage.

In summary, crack detection focuses on locating damage through masks, bounding boxes, or segmented crack regions, whereas crack classification assigns crack presence, type, or severity category. Figure 1 shows the main differences between crack detection and crack classification.

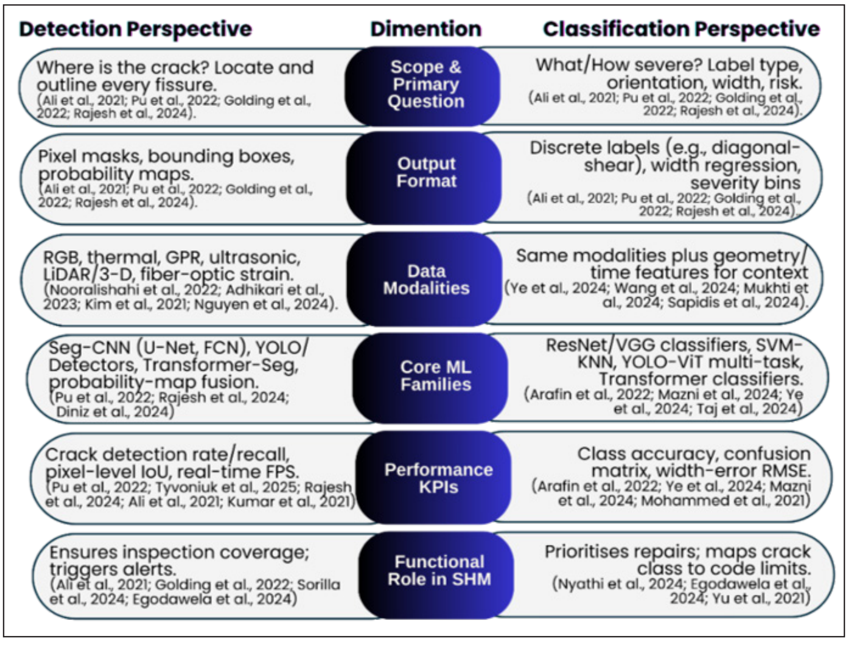

Figure 1. Key differences between crack detection and crack classification

METHODOLOGY

Systematic Literature Review Process

This study adopted a systematic literature review approach guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework (Kitchenham et al., 2009). The review aimed to identify, screen, evaluate, and synthesise recent studies related to artificial intelligence-based concrete crack detection and classification (Khallaf et al., 2018). The focus was limited to studies published between 2021 and 2025 to ensure that the analysis reflected recent developments in computer vision, machine learning, deep learning, transformer-based models, and structural health monitoring applications.

The Scopus database was selected as the primary source because it provides broad coverage of engineering, computer science, and multidisciplinary peer-reviewed journals. The search was limited to English-language journal articles published between 2021 and 2025. The database search was conducted using the Boolean search string "concrete crack" AND ("crack detection" OR "crack classification") AND ("deep learning" OR "CNN" OR "transformer") AND "structural health monitoring". This search strategy was designed to retrieve studies that applied AI-based techniques to concrete crack detection, crack classification, crack segmentation, or crack severity assessment within structural health monitoring applications. The identified records were then screened using predefined inclusion and exclusion criteria, as shown in Table 1.

Table 1
Inclusion and exclusion criteria for article selection

Criterion	Inclusion criteria	Exclusion Criteria
Publication year	Articles published from 2021 to 2025	Articles published before 2021
Database/source	Scopus-indexed peer-reviewed journal articles	Non-indexed, non-peer-reviewed, or unreliable sources
Publication type	Journal articles	Conference papers, thesis, reports, book chapters, editorials, and review notes
Language	Articles written in English	Non-English articles
Research focus	Studies related to concrete crack detection, crack detection, crack classification, or crack severity assessment	Studies not related to concrete crack analysis, such as cracks or defects in asphalt, steel, soil, masonry, or non-structural materials.
Method used	Studies applying AI, machine learning, deep learning, CNN, transformer, computer vision, UAV, LiDAR, thermal imaging, or acoustic emission methods	Studies based only on manual inspection or studies that recommended AI without applying it
Accessibility	Full-text articles accessible for review	Articles without accessible full text
Data and findings	Studies reporting methodology, dataset, findings, performance metrics, or challenges	Conceptual studies without clear methodology, dataset, or performance evaluation

The screening process followed the PRISMA-guided stages of identification, screening, eligibility assessment, and inclusion. The initial database search produced 1,050 records, which were checked for duplication. After duplicate removal, 870 records were retained for title and abstract screening. At this stage, 730 records were excluded because they were not related to concrete crack detection, did not apply AI-based techniques, or were outside the scope of structural health monitoring. The remaining 140 articles were assessed in full text based on the predefined inclusion and exclusion criteria. Articles were excluded if they lacked sufficient methodological information, did not report relevant performance results, focused on non-concrete materials, or discussed AI only conceptually without actual application. Finally, 68 articles met the criteria and were included in the final analysis.

Two reviewers independently screened the titles, abstracts, and full texts. Any disagreement was resolved through discussion and consensus to minimise selection bias and improve the reliability of the review process. The quality of the included studies was assessed based on relevance to concrete crack analysis, clarity of methodology, dataset description, reported performance metrics, and discussion of limitations or practical implications. Each criterion was rated as fulfilled, partially fulfilled, or not fulfilled, and studies with insufficient methodological detail, unclear dataset information, or no relevant performance reporting were excluded.

Data extraction was conducted using a standardised form covering author, publication year, country, crack analysis category, AI method, dataset characteristics, performance indicators, major findings, contributions, limitations, and reported challenges. The extracted data were organised thematically according to detection method, classification method, reported impact, and research limitations. Descriptive and narrative synthesis was then used to analyse the distribution of studies by country, summarise crack detection and classification methods, compare reported impacts, and identify major challenges such as dataset limitations, annotation bottlenecks, generalisation issues, real-time deployment constraints, and integration into structural health monitoring systems. The complete selection and refinement process is summarised in Figure 2.

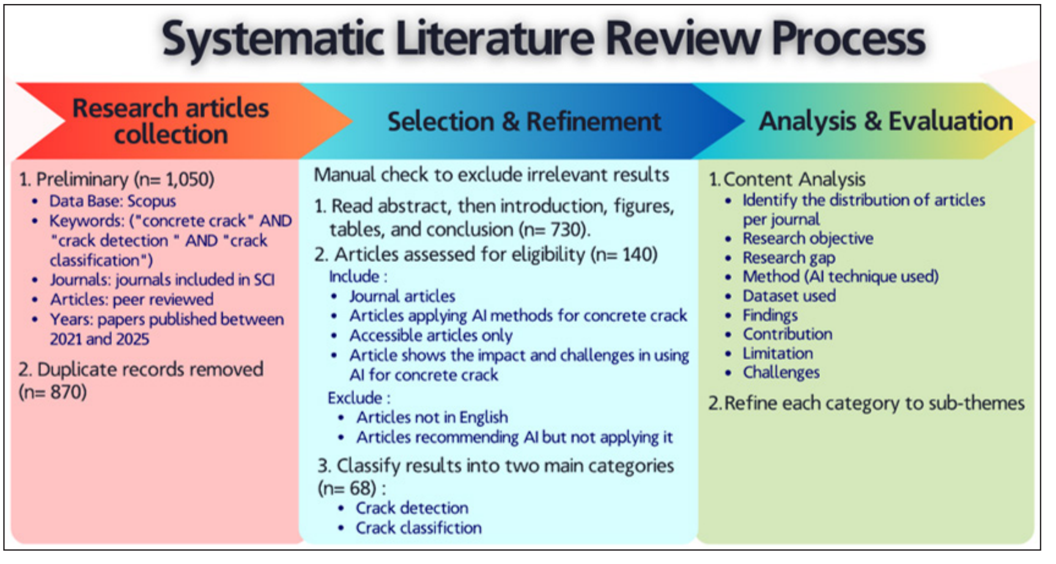

Figure 2. Summary of the systematic literature review process (search strategy, selection criteria, and quality control) used in this research

RESULT AND DISCUSSIONS

Descriptive information

The 68 reviewed articles were sourced from 21 countries, as shown in Figure 3. China accounted for the largest proportion with 22 articles (32.40%), followed by South Korea with 7 (10.29%) and India with 6 articles (8.82%). Australia and the UK both provided 5 articles (7.35%), while the USA offered 4 articles (5.88%), and Canada and Greece each contributed 3 articles (4.41%). The remaining publications were distributed across 13 countries, each providing one article (1.47% per country; 19.1% collectively), signifying a long-tail distribution of contributions beyond the main publishing countries.

Table 2 presents the crack detection and crack classification methods used in the reviewed studies. Overall, the evidence indicates that recent studies are mainly concentrated on computer vision and deep learning methods for concrete crack detection. Computer

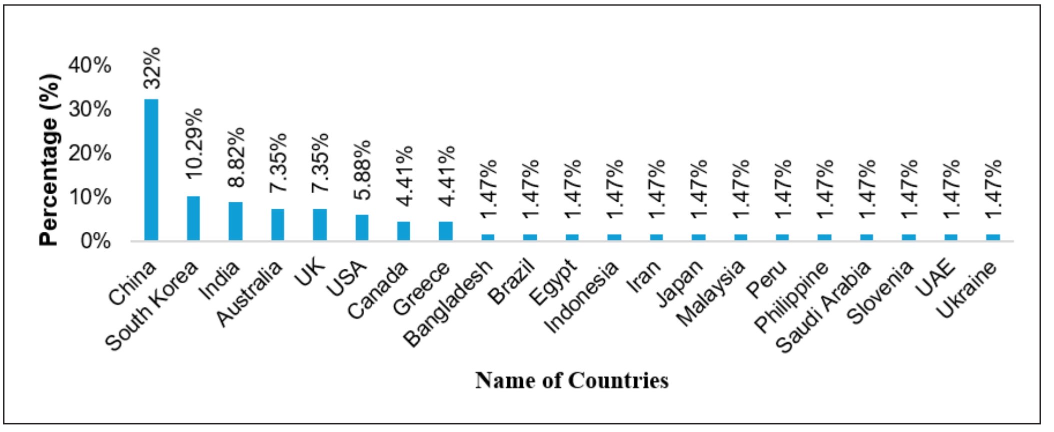

Figure 3. Distribution of research based on origin

vision and image preprocessing are commonly used for image enhancement, crack localisation, and early-stage detection, while deep learning methods are increasingly applied to improve automated feature extraction and detection accuracy (Ali et al., 2021; Pu et al., 2022; Yadav et al., 2024).

However, the distribution of methods also shows an imbalance between crack detection and crack classification. Most studies focus on detecting or segmenting cracks, whereas fewer studies classify crack type, crack severity, or maintenance priority. This suggests that automated crack detection has progressed more strongly than automated crack interpretation and severity assessment (Mazni et al., 2024; Nyathi et al., 2024). Therefore, Table 2 should be interpreted as a distribution of reported methods rather than a direct comparison of method performance.

Following the method distribution in Table 2, the reviewed approaches were further organised into a taxonomy to clarify their main functions, outputs, maturity levels, and limitations. The maturity level was qualitatively interpreted using four indicators: frequency of use, field application, deployment readiness, and main limitations. "High" indicates approaches that are frequently reported and closer to practical use, "Moderate" indicates approaches that are established but still limited, "Emerging to high" indicates approaches with growing potential but requiring further validation, and "Emerging" indicates approaches with limited use or complex validation needs. This taxonomy helps show the original contribution of this review by moving beyond a list of individual studies towards a structured interpretation of how different AI approaches support concrete crack detection, classification, and structural health monitoring.

Table 2
Crack detection and crack classification methods for concrete structures

No.	Author's Year	Country	Crack Detection							Crack Classification						
			CVIP	ML	DL	TI	LiDAR/3D	UAV	AE	CVIP	ML	DL	TI	LiDAR/3D	UAV	AE
1	Shahin et al., 2024	USA	✓		✓											
2	Pu et al., 2022	China	✓		✓											
3	Mazni et al., 2024	Malaysia	✓							✓		✓				
4	Nogueira Diniz et al., 2023	Brazil	✓		✓											
5	Lin et al., 2025	China	✓		✓											
6	Nguyen et al., 2024	Australia	✓		✓											
7	Arafin et al., 2024	Canada	✓		✓					✓		✓				
8	Tyvoniuk et al., 2025	Ukraine	✓	✓												
9	Yadav et al., 2024	India	✓		✓											
10	Adhikari et al., 2023	South Korea					✓									
11	Kang et al., 2022	South Korea	✓		✓											
12	Alkannad et al., 2025	China	✓		✓											
13	Mukhti et al., 2024	USA									✓					✓
14	Sapidis et al., 2024	Greece	✓		✓											
15	Rajesh et al., 2024	India	✓		✓											
16	Gaur et al., 2023	India	✓		✓											
17	Arafin et al., 2022	Canada								✓		✓				
18	Fan et al., 2021	China	✓	✓												
19	Wang, 2023	China	✓		✓											
20	Kun et al., 2022	China	✓		✓											
21	Mohammed et al., 2021	China	✓		✓											
23	Nugraheni et al., 2023	Indonesia	✓		✓					✓		✓				
24	Kumar et al., 2021	India	✓		✓											
25	Hong et al., 2022	South Korea	✓	✓												
26	Kim et al., 2021	South Korea	✓			✓										
27	Rajadurai et al., 2021	South Korea	✓		✓											
28	Mir et al., 2022	Japan	✓	✓												
29	Meng et al., 2023	China	✓		✓											
30	Mayya et al., 2024	Greece								✓		✓				

Table 2 *(Continued)*

No.	Author's Year	Country	Crack Detection							Crack Classification						
			CVIP	ML	DL	TI	LiDAR/3D	UAV	AE	CVIP	ML	DL	TI	LiDAR/3D	UAV	AE
31	Dow et al., 2023	UK	✓													
32	Ali et al., 2021	UAE	✓		✓											
33	Yu et al., 2021	Australia	✓	✓						✓	✓					
34	Golding et al., 2022	Australia	✓		✓											
35	Pennada et al., 2023	UK	✓		✓											
36	Gradišar et al., 2023	Slovenia	✓	✓												
37	Fang et al., 2025	China	✓		✓											
38	Alkayem et al., 2024	Greece	✓		✓											
39	Taj et al., 2024	Saudi Arabia	✓	✓	✓											
40	Nooralishahi et al., 2022	Canada	✓			✓		✓								
41	Cui et al., 2022	China	✓		✓											
42	Gharehbaghi et al., 2022	Australia	✓	✓												
43	Shang et al., 2023	USA	✓		✓											
44	Li et al., 2022	China	✓	✓												
45	Zhou et al., 2024	China			✓				✓							
46	Miele et al., 2025	USA	✓		✓											
47	Li et al., 2022	China	✓		✓					✓		✓				
48	Swarna et al., 2024	Bangladesh	✓		✓											
49	Cui et al., 2024	China	✓													
50	Nyathi et al., 2024	UK	✓		✓											
51	Del Savio et al., 2023	Peru	✓													
52	Wang et al., 2024	China	✓		✓											
53	Chen et al., 2021	China	✓		✓											
54	Li et al., 2024	China					✓									
55	Diniz et al., 2024	UK	✓		✓											
56	Ye et al., 2024	China								✓		✓				
57	Abubakr et al., 2024	Egypt								✓		✓				
58	Lee et al., 2024	South Korea	✓													
59	Ghafari et al., 2024	Iran	✓		✓											
60	Liu et al., 2025	China	✓		✓											
61	He et al., 2024	China	✓													
62	Lin et al., 2025	China	✓	✓												

Table 2 *(Continued)*

No.	Author's Year	Country	Crack Detection							Crack Classification						
			CVIP	ML	DL	TI	LiDAR/3D	UAV	AE	CVIP	ML	DL	TI	LiDAR/3D	UAV	AE
63	Egodawela et al., 2024	Australia	✓		✓			✓		✓		✓			✓	
64	Kolappan Geetha et al., 2023	South Korea	✓							✓		✓				
65	Qiao et al., 2021	China	✓		✓											
66	Philip et al., 2023	India	✓		✓											
67	McAlorum et al., 2023	UK	✓		✓											
68	Naser et al., 2021	India	✓		✓					✓		✓				
		Total	60	10	42	2	2	3	1	12	2	11	-	-	1	1

Note. CVIP= Computer Vision and Image Preprocessing; ML= Machine Learning; DL= Deep Learning; TI= Thermal Imaging; LiDAR/3D Scanning; UAV= Unmanned Aerial Vehicle; AE= Acoustic Emission. Reported methods are presented as a distribution summary and should not be interpreted as direct performance comparisons

As shown in Table 3, computer vision and image preprocessing, machine learning, and deep learning represent more established approaches because they were more frequently reported in Table 2, especially for crack detection. In contrast, thermal imaging, LiDAR/3D scanning, unmanned aerial vehicle-based inspection, and acoustic emission remain less mature or emerging because their use was reported less frequently and still involves field, equipment, or data-processing limitations. Therefore, the maturity classification suggests that future AI-based crack analysis should focus on field reliability, severity interpretation, and integration with structural health monitoring decisions.

Table 3.
Taxonomy and maturity of AI approaches in concrete crack analysis

AI Approach	Main Function	Typical Output	Maturity Level	Main Limitation
Computer vision and image preprocessing	Image enhancement and crack localisation	Enhanced image or crack map	High for basic detection	Sensitive to lighting, stains, shadows, and texture (Ali et al., 2021; Rajadurai & Kang, 2021)
Machine learning	Crack or non-crack classification using handcrafted features	Crack class or defect category	Moderate	Depends on feature selection and dataset quality (Fan, 2021; Yu et al., 2021)

Table 3 *(Continued)*

AI Approach	Main Function	Typical Output	Maturity Level	Main Limitation
Deep learning	Automated crack detection, segmentation, and classification	Crack mask, location, or class label	High for detection and classification	Requires large, labelled datasets and may suffer domain shift (Golding et al., 2022; Pu et al., 2022)
Thermal Imaging (TI)	Crack or damage detection using temperature variation and thermal patterns	Thermal crack indication or heat-based damage region	Emerging	Affected by temperature variation, environmental conditions, and interpretation of thermal signals (Kim et al., 2021; Nooralishahi et al., 2022)
LiDAR / 3D Scanning	Geometric crack or surface damage measurement using 3D data	Point-cloud damage features or 3D surface profile	Emerging	Higher cost, complex data processing, and limited routine use (Adhikari et al., 2023; Li et al., 2024)
Unmanned Aerial Vehicle (UAV)	Large-scale and hard-to-reach crack inspection using aerial image acquisition combined with AI analysis	Inspection images, crack maps, or detected crack regions	Emerging too high	Affected by camera angle, flight stability, image resolution, lighting, and operating regulations (Egodawela et al., 2024; Kumar et al., 2021; Sorilla et al., 2024)
Acoustic Emission (AE)	Internal damage detection and source localisation using acoustic signals	Damage signal pattern, source location, or internal fracture indication	Emerging	Depends on sensor placement, calibration, signal noise, and interpretation of acoustic data (Mukhti et al., 2024; Zhou et al., 2024)

A Decade of Methodological Evolution in AI-Based Concrete Crack Detection and Classification (2016-2025)

Evolution of Crack Detection Methods

Concrete crack detection was initially performed through manual visual inspection by engineers, which was laborious, subjective, and highly dependent on inspector expertise (Ali et al., 2021; Golding et al., 2022). Large-scale structures, such as bridges, may require long inspection periods, which can delay repair decisions and increase safety risks when damage progresses (Golding et al., 2022). Inspector fatigue, limited accessibility, and inconsistent judgement may also lead to missed minor cracks or variable assessment outcomes. These limitations highlight the need for a more objective, scalable, and reliable crack detection approach (Cui & Qin, 2024).

The 1990s and 2000s saw the development of semi-automated crack detection through digital imaging and computer vision technology. Edge detection, thresholding, and morphological processing were commonly applied to concrete surface images to enhance crack visibility and separate cracks from the background. These methods improved inspection speed and consistency compared with manual inspection, and basic filtering approaches achieved approximately 70-80% accuracy under controlled lighting and uniform surface conditions (Ali et al., 2021). However, their performance declined in the presence of shadows, stains, rough textures, and complex backgrounds, which often caused false detections or missed cracks. This shows that early computer vision methods were useful but highly dependent on image quality and environmental conditions.

Machine learning methods emerged in the early 2010s as researchers moved from fixed image filters to trainable classifiers such as Support Vector Machines. These models improved crack detection accuracy to approximately 75-85%, exceeding many rule-based image processing methods (Fan, 2021; Yu et al., 2021). However, classical machine learning still relied heavily on handcrafted features, which limited its robustness across different lighting conditions, materials, and crack patterns. Models trained on limited datasets were also prone to overfitting and had restricted generalisation to real field environments (Yu et al., 2021). These limitations encouraged the transition towards deep learning approaches.

Deep learning marked a major methodological shift because crack features could be learned automatically from images without manual feature design. CNN-based models improved crack detection by capturing hierarchical image features and became more effective than traditional computer vision and classical machine learning methods (Golding et al., 2022; Pu et al., 2022). In the early 2020s, deep learning models were increasingly used for crack localisation, segmentation, and real-time video analysis (Kumar et al., 2021; Kumar et al., 2021; Pu et al., 2022). Compared with earlier methods, CNN-based models were less affected by surface texture and background noise, allowing them to distinguish cracks from non-crack artefacts more effectively (Yadav et al., 2024). However, their performance still depends on large, labelled datasets, diverse training images, and suitable validation under field conditions.

Recent studies indicate a further shift towards transformer-based models, hybrid CNN-transformer architectures, sensor fusion, and edge-AI deployment. Transformer-based models can capture wider contextual information and improve crack detection in complex backgrounds, while hybrid models combine local feature extraction from CNNs with global attention mechanisms from transformers (Shahin et al., 2024; Yadav et al., 2024). At the same time, UAV-based and edge-device models have improved the feasibility of real-time on-site inspection (Nguyen et al., 2024). Collectively, the evidence suggests that crack detection has progressed from subjective manual assessment to automated AI-based monitoring. Nevertheless, field generalisation, dataset diversity, computational efficiency, and integration with structural assessment standards remain unresolved challenges.

Evolution of Crack Classification Methods

Crack classification by type and severity was traditionally performed through manual assessment, guided by engineering judgement and code-based recommendations. Cracks are commonly classified according to their origin, form, timing, orientation, width, and potential structural implications (Cui & Qin, 2024; Golding et al., 2022). For example, hairline cracks below 0.2 mm are generally considered less critical, whereas cracks exceeding 0.5 mm may require repair or structural intervention (Nyathi et al., 2024; Yu et al., 2021). However, manual classification is subjective and may vary depending on inspector experience, site conditions, and interpretation of severity criteria.

Earlier automated systems commonly separated crack detection and crack classification into two stages. In this approach, the first stage identified the presence or location of cracks, while the second stage used extracted crack properties to determine crack type or severity (Ali et al., 2021; Nyathi et al., 2024). This two-stage approach was widely used because it provided a structured workflow for image-based crack analysis (Pu et al., 2022; Taj et al., 2024). However, it was prone to error propagation, as missed or incorrect detection in the first stage could affect the accuracy of subsequent classification.

Compared with crack detection, crack classification remains less mature in the reviewed literature. Most studies focus on identifying crack presence, location, or segmentation, while fewer studies classify crack type, severity, or maintenance urgency. This is a key limitation because structural maintenance requires more than crack localisation. Engineers also need information about crack severity, possible cause, and structural implications before deciding whether monitoring, repair, or urgent intervention is required (Mazni et al., 2024; Ye et al., 2024).

Recent AI models show potential for integrated crack detection and classification. Deep learning systems can perform multiple tasks within a single workflow, including crack localisation, segmentation, and severity estimation (Li et al., 2022; Diniz et al., 2024). This integrated approach reduces duplicated processing, improves inspection speed, and limits the risk of error propagation between detection and classification stages (Abubakr et al., 2024; Ye et al., 2024). Therefore, the methodological trend is moving from separate detection-classification pipelines towards unified AI-based crack assessment systems.

Nevertheless, contradictory findings remain in crack classification research. Some studies report high classification accuracy using CNN, transformer-based, or hybrid models, but these results are often based on controlled datasets, limited crack categories, or predefined severity labels (Abubakr et al., 2024; Ye et al., 2024). In real field conditions, severity classification is more complex because crack width, length, orientation, location, pattern, and structural context must be considered together (Nyathi et al., 2024; Nugraheni et al., 2023). Models may also perform less reliably when field images differ from training data due to lighting variation, surface texture, background clutter, or subtle crack patterns (Kolappan Geetha et al., 2023).

Collectively, the evidence suggests that crack classification has progressed from subjective manual judgement to automated AI-based severity assessment. However, classification remains less developed than detection, especially for engineering-based maintenance decision-making. Future crack classification systems should therefore combine detection, segmentation, measurement, severity classification, and maintenance recommendation within a single structural health monitoring workflow. The crack detection and classification methods from 2021 until now are summarised in Figure 4.

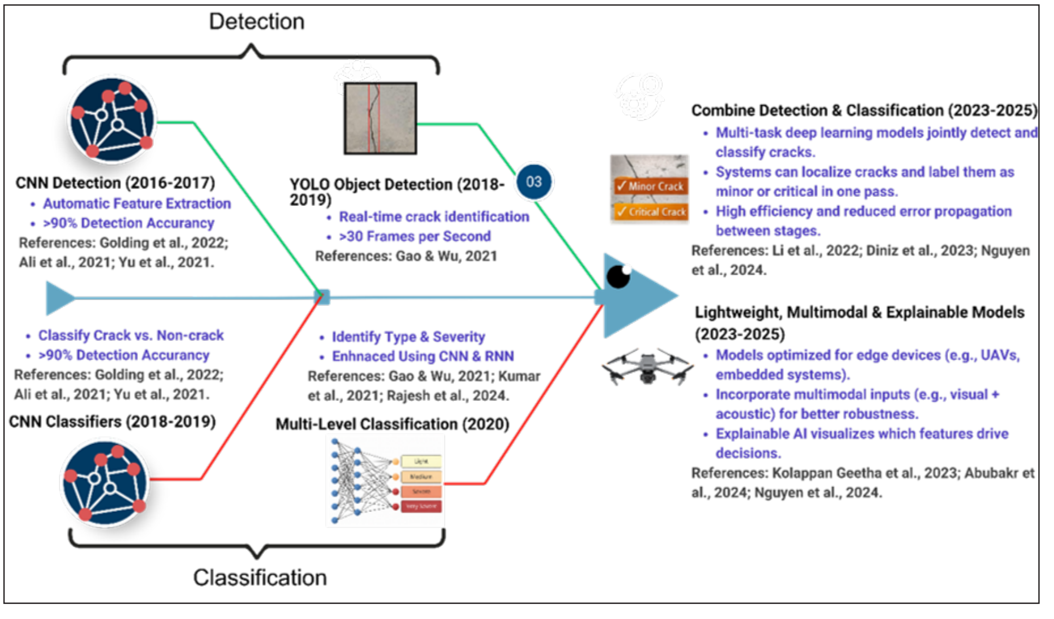

Figure 4. Summary evolution of crack detection and classification methods from pre-2000 to recent

Impact of AI on Concrete Crack Detection and Classification

Accuracy and Robustness Across AI-Based Methods

Across the reviewed studies, AI-based methods generally reported improved crack detection performance compared with manual inspection, traditional image processing, and classical machine learning (Ali et al., 2021; Golding et al., 2022). Deep learning models are effective because they can automatically learn crack features from images and identify complex crack patterns. However, reported performance values should be interpreted cautiously because the reviewed studies used different datasets, validation protocols, image acquisition conditions, environmental settings, crack characteristics, and evaluation metrics (Arafin et al., 2024; Shahin et al., 2024). Therefore, accuracy, precision, recall, F1-score, Intersection over Union, and mean average precision are presented as study-specific indicators rather than direct evidence that one method is universally superior to another.

Transformer-based and hybrid CNN-transformer models have shown strong potential for crack detection under complex backgrounds because their attention mechanisms can capture wider contextual information and focus on relevant crack regions (Shahin et al., 2024; Yadav et al., 2024). In contrast, YOLO-based and edge-AI models are often more suitable for real-time inspection because they support faster inference and field deployment (Diniz et al., 2024; Nguyen et al., 2024). Nevertheless, these methods should not be directly ranked based only on isolated accuracy values because their reported performance depends on dataset diversity, image resolution, annotation quality, crack morphology, validation strategy, and field conditions. Thus, the collective evidence is more useful for identifying broad methodological trends rather than determining absolute superiority between models.

Segmentation-based deep learning models, including U-Net and its variants, provide detailed crack localisation because they analyse images at the pixel level. For example, a U-Net-based model reported a mean Intersection over Union above 0.91 for crack boundary detection in the tested images (Pu et al., 2022). This value indicates strong performance within that specific study setting, but it should not be directly compared with studies using different image datasets, segmentation labels, or evaluation procedures. Across segmentation studies, the improvement in robustness appears to be linked to pixel-level localisation, multi-scale feature extraction, attention mechanisms, and data augmentation, which help models detect cracks with different sizes, shapes, and orientations (Kang et al., 2022; Li & Zhao, 2022).

Lightweight AI models also show practical value for real-time crack inspection. YOLOv4-Tiny, for example, reported 87% mean average precision for real-time crack detection in a specific experimental setting (Ali et al., 2021), while recent YOLOv8-based studies have shown promising crack mask generation and recall performance (Diniz et al., 2024). However, lightweight models also involve a practical trade-off because faster inference may reduce reliability when detecting very fine cracks, low-contrast cracks, or cracks in noisy field images. Therefore, model selection should consider not only reported accuracy, but also robustness, computational demand, deployment platform, and field usability.

To further strengthen the comparative contribution of this review, Table 4 presents a benchmark-style performance matrix of AI-based concrete crack analysis methods. The matrix synthesises reported performance indicators together with methodological context and limitations. It is intended to show broad evidence patterns rather than directly rank the methods, because the reviewed studies used different datasets, validation protocols, environmental conditions, crack characteristics, and evaluation metrics.

Table 4
Benchmark-style performance matrix of AI-based concrete crack analysis methods

Method	Reported Performance Indicators	Context and Limitations
Computer vision and image preprocessing	Accuracy up to 96.6% was reported in selected studies	Effective under controlled image conditions, but sensitive to lighting, stains, shadows, noise, and surface texture (Mohammed et al., 2021; Rajesh et al., 2024; Rajadurai & Kang, 2021).
Machine learning	SVM-based methods reported up to 99.50% precision for orientation-related tasks	Depends on handcrafted features, dataset quality, and validation conditions; generalisation may be limited (Arafin et al., 2022; Fan, 2021; Taj et al., 2024).
Deep learning / CNN	Accuracy values approaching 99% were reported in selected datasets	Strong for detection and segmentation, but requires large, labelled datasets and may suffer laboratory-to-field domain shift (Golding et al., 2022; Lin et al., 2025; Pu et al., 2022).
Transformer-based models	Accuracy, mAP, and IoU were commonly reported	Captures wider contextual features but is computationally demanding and needs diverse datasets (Shahin et al., 2024; Yadav et al., 2024).
YOLO / real-time detectors	YOLOv4-Tiny reported 87% mAP in a specific setting	Suitable for real-time and UAV inspection, but may miss fine, low-contrast, or noisy cracks (Ali et al., 2021; Diniz et al., 2024; Nguyen et al., 2024).
UAV-based AI inspection	Detection, localisation, and segmentation performance were reported	Useful for bridges, roads, buildings, and high-rise structures; affected by flight stability, camera angle, resolution, and lighting (Egodawela et al., 2024; Kumar et al., 2021; Sorilla et al., 2024).
LiDAR / 3D scanning	Geometric measurement and point-cloud damage representation were reported	Supports 3D damage assessment, but has higher cost, complex processing, and limited routine accessibility (Adhikari et al., 2023; Li et al., 2024).
Acoustic emission / sensor-based methods	Source localisation and internal fracture detection were reported	Useful for internal damage monitoring, but depends on sensor placement, calibration, and signal-to-noise interpretation (Mukhti et al., 2024; Zhou et al., 2024).
Multimodal AI	Combined detection, classification, or damage assessment was reported	Improves damage coverage using multiple sensors, but data fusion, calibration, cost, and standardisation remain challenging (Liu et al., 2025; Nooralishahi et al., 2022).

Note. Reported values are study-specific and should not be interpreted as direct method rankings

Cost and Labour Efficiency

AI-driven crack examination reduces costs and labour while improving inspection efficiency. Large structures previously required large inspection teams, scaffolding, and lifting equipment. In contrast, AI-based systems reduce manual workload by automating crack identification, measurement, and documentation**.** Small CNN models on NVIDIA Jetson modules enable on-site crack analysis without cloud computation (Nguyen et al., 2024). This reduces the need for specialised hardware and supports field-based inspection (Kolappan, 2023; Meng et al., 2023).

AI-enabled drones have improved inspection efficiency, especially for bridges, high-rise buildings, and difficult-to-access structures (Kumar & Batchu, 2021). UAV-based crack detection can inspect large structures faster than manual inspection, with some studies reporting up to an 80% reduction in inspection time (Egodawela et al., 2024). Collectively, the evidence suggests that AI provides the strongest cost and labour benefit in large-scale, repetitive, and hazardous inspection tasks. However, the actual cost benefit still depends on equipment cost, operator training, software maintenance, and scale of deployment (Sorilla et al., 2024).

AI also supports preventive maintenance. Continuous crack monitoring allows early repair before small cracks develop into severe defects (Nyathi et al., 2024). Automated measurement and documentation allow inspectors to focus more on analysis and decision-making rather than data collection (Nooralishahi et al., 2022). Thus, AI contributes not only to short-term inspection efficiency, but also to long-term asset management.

Impact on Safety

AI inspections have improved worker safety. Drones can inspect high-rise buildings and bridge undersides, reducing the need for workers to climb scaffolding or enter traffic-risk areas (Egodawela et al., 2024; Kumar & Batchu, 2021; Kumar, 2021). This shows that AI shifts hazardous inspection tasks from humans to remote or automated platforms.

Field studies show that drone inspections reduce falls and accidents by 40% compared with conventional methods (Egodawela et al., 2024). Remote AI crack analysis also protects inspectors in disaster-affected or fire-damaged structures (Andrushia et al., 2022). The collective evidence suggests that AI improves safety most clearly in high-risk inspection environments, including bridges, high-rise structures, post-fire structures, and disaster-affected areas.

After earthquakes, AI crack detection can rapidly identify severely damaged areas and reduce emergency inspection team “hours at risk” (Naser et al., 2021). However, safety benefits depend on system reliability, false-alarm control, and human verification before safety-critical decisions are made.

Real-Time Inspection Capability

Artificial intelligence detects cracks quickly and supports faster inspection. YOLOv4-Tiny can detect cracks in real-time video streams at over 60 frames per second on standard hardware (Rajadurai & Kang, 2021). CNNs optimised for embedded devices can reach 30 frames per second, while earlier detectors such as Faster R-CNN operate below 10 frames per second (Ali et al., 2021; Kumar et al., 2021).

Further optimisation, such as pruning, transfer learning, and GPU acceleration, has improved real-time performance (Nguyen et al., 2024; Yadav et al., 2024). This indicates a clear methodological trend towards lightweight, optimised, and hardware-compatible AI models for field inspection. However, real-time capability often involves a trade-off between speed, image resolution, model complexity, and detection accuracy. Therefore, real-time inspection systems must balance computational efficiency with reliable crack detection performance.

Automated Severity Assessment

AI can now quantify crack severity from images in addition to detecting cracks. Segmentation models combined with geometric algorithms can measure crack width, length, and affected area. U-Net-based crack width measurement achieved an average error of 0.16 mm, which is close to manual calliper measurement (Nyathi et al., 2024). This shows that AI is moving from simple crack detection towards quantitative damage assessment.

AI models can classify crack severity using crack width and related features. Minor cracks are usually below 0.2 mm, while severe cracks above 0.5 mm may require repair (Nugraheni et al., 2023). Some AI models classify crack severity with 85–90% accuracy (Abubakr et al., 2024; Nugraheni, 2023). However, severity assessment remains more complex than binary detection because it requires interpretation of crack width, length, orientation, location, propagation pattern, and structural context.

AI can also support damage prioritisation by analysing crack patterns, cracked area ratio, water leakage risk, and load-bearing implications (Li et al., 2022; Mir, 2022; Swarna, 2024; Taj et al., 2024). Collectively, the evidence suggests that automated severity assessment has strong potential, but its reliability depends on accurate measurement, clear severity thresholds, and alignment with engineering standards.

Continuous Monitoring and Multimodal Integration

Permanent AI-based monitoring systems can track crack formation and growth beyond scheduled inspections. Smart cameras and embedded sensors can continuously monitor structures and detect new cracks or crack expansion (Nguyen et al., 2024). This suggests that continuous monitoring is a key advantage of AI because it supports earlier detection and preventive maintenance. However, false alarms from lighting, debris, and environmental changes remain a practical limitation.

Multimodal systems combine visual, thermal, acoustic, radar, or LiDAR data to detect cracks that one sensor may miss. Regular cameras may fail to detect hidden or low-visibility cracks, while thermal imaging and ground-penetrating radar can support deeper damage identification (He et al., 2024; Liu et al., 2025; Nooralishahi et al., 2022). The evidence suggests that multimodal integration improves detection coverage, but it also increases cost, calibration difficulty, and data interpretation complexity.

Digital twin and Building Information Modelling integration can further support predictive maintenance by linking crack data with structural performance models (Lee et al., 2024). Overall, continuous monitoring, multimodal sensing, and digital twin integration represent an emerging direction in AI-based crack analysis. However, unresolved issues remain in data standardisation, sensor calibration, system interoperability, and translation of AI outputs into engineering decisions. Table 5 summarises the reported benefits and limitations of AI-based crack inspection.

Table 5
Summary of reported benefits and limitations of AI-based crack inspection

Dimension	Reported Benefits	Reported Limitations
Accuracy & Robustness	CNN models ~90-93% accurate; transformer-based models ~95-99%, greatly reducing false detections under complex conditions (Mohammed et al., 2021; Yadav et al., 2024)	Performance drops in unfamiliar environments without extensive diverse training data (Shahin et al., 2024)
Cost Efficiency	~30-50% lower inspection costs reported with UAV/AI methods (e.g., replacing scaffolding and manual labour) (Sorilla et al., 2024)	High initial cost for drones and equipment; cost benefits realised only at larger-scale deployments
Labour Efficiency	Automation covers more area with fewer staff – e.g., ~50% reduction in manual image annotation effort using transfer learning (Gradišar & Dolenc, 2023)	Requires skilled operators for drones/ AI systems and ongoing training; human oversight still needed for verification
Safety	Dangerous tasks shifted to robots (e.g., drones inspect high places); some studies reported reduced inspection-related safety risk (Egodawela et al., 2024; Kumar et al., 2021)	Relies on technology reliability (battery, communication); regulatory limits on drone use can constrain deployment
Real-time Capability	Immediate crack alerts during inspections – lightweight models run 30-60 FPS (vs. <10 FPS for older methods), enabling on-the-spot decisions (Ali et al., 2021)	Achieving high FPS may require powerful hardware or lower image resolution; trade-off between speed and maximum accuracy

Table 5. *(continued)*

Dimension	Reported Benefits	Reported Limitations
Automated System Assessment	AI measures crack width to ~0.1-0.2 mm precision and reported severity classification performance of approximately 85-90% in selected studies (Nyathi et al., 2024; Nugraheni et al., 2023)	Calibration needed for each structure (e.g., scaling in images); very fine cracks near resolution limits may still be missed
Other Impact: Continuous 24/7 Monitoring	Always-on monitoring catches crack formation and growth between scheduled inspections, enabling instant maintenance alerts (McAlorum et al., 2023)	Potential false alarms from lighting or dirt require careful system calibration (McAlorum et al., 2023); constant power and data management are needed
Other impact: Multimodal Integration	Combined sensors (visual + thermal, radar, etc.) detect hidden or nighttime cracks, improving overall detection coverage (Liu et al., 2025; Nooralishahi et al., 2022)	Additional sensors increase complexity and cost; requires precise sensor alignment and can be difficult to interpret multi-source data (Nooralishahi et al., 2022)

Key Challenges and Methodological Limitations in AI-Based Crack Analysis

Dataset Limitations and Annotation Bottlenecks

Crack image collections have accelerated AI research but are limited (Arafin et al., 2024). SDNET2018 has over 56,000 labelled images of cracked and uncracked concrete bridges, walls, and pavements, with crack widths ranging from 0.06 to 25 mm (Shahin et al., 2024). However, even large databases cannot capture all real-world diversity (Arafin et al., 2024). Many datasets do not fully represent actual field conditions, such as lighting variation, surface stains, shadows, moisture, debris, rough textures, and different camera angles. Models trained on a single dataset often struggle with unfamiliar textures, lighting conditions, or damage types (Lin et al., 2025). This dataset bias limits real-world generalisation (Adhikari et al., 2023).

Data annotation is time-consuming and may introduce inconsistency (Mazni et al., 2024). Manual crack annotations may contain ground truth errors, labelling discrepancies, or selection bias, especially for thin or irregular cracks (Arafin et al., 2024; Shahin et al., 2024). Therefore, dataset size alone is not sufficient; dataset diversity, annotation consistency, and benchmark quality are also required for reliable model development.

Crack datasets often have significant asymmetry. Photos of unblemished concrete may outnumber cracked surfaces, or certain crack forms may predominate. Training on uneven data can skew model predictions (Arafin et al., 2024). Without data augmentation or balanced sampling, models may predict “no crack” and fail to identify rarer crack types (Shahin et al., 2024). This is particularly important for crack classification because severity categories must be well represented to support maintenance decision-making.

Generalisation Challenges and Lab-to-Field Performance Decline

AI crack detection models often perform well on laboratory or benchmark datasets, but their practicality may be limited (Arafin et al., 2024). Deep learning models often detect cracks with over 95% accuracy in controlled tests, and specialised architectures can achieve almost 99% accuracy under ideal conditions (Lin et al., 2025; Yadav et al., 2024). However, field conditions affect these results (Arafin et al., 2024). This shows a contradiction in the literature: high accuracy in controlled datasets does not always translate into reliable field performance.

The domain shift between training data and real-world infrastructure scenarios degrades performance (Shahin et al., 2024). Many datasets fail to represent environmental changes such as lighting, weather, surface textures, and noise (Shahin et al., 2024). Cracks in an old bridge, indoor parking structure, or wet road may appear differently (Arafin et al., 2024). Therefore, future models should be tested using external datasets, cross-dataset validation, and real field images to confirm their robustness.

Generalisation is also affected by the balance between missed detections and false positives. False negatives are dangerous because missed cracks may continue to grow and compromise structural integrity (Adhikari et al., 2023). However, aiming for very high recall may increase false positives when stains, shadows, or surface marks are classified as cracks (Kang & Cha, 2022). Thus, future studies should balance sensitivity and precision rather than focusing only on overall accuracy.

Real-Time Processing and Deployment Constraints

Deploying AI crack detection models from laboratory settings to field environments remains challenging due to computational demands and processing-speed constraints (Nguyen et al., 2024). Many deep learning models require GPUs for real-time processing because of their complex CNN or transformer-based architectures (Shahin et al., 2024). In many field applications, high-resolution images are collected on-site but processed offline using advanced computers, which can delay inspection results and slow maintenance decision-making (Mazni et al., 2024). This indicates that high detection performance alone is insufficient if the model cannot operate efficiently under real field conditions.

For practical deployment, recent studies have shifted towards lightweight, optimised, and edge-compatible AI models (Nguyen et al., 2024). Real-time object detection frameworks such as YOLO support rapid inference and allow drone or video-based inspections to be conducted more efficiently (Kumar & Batchu, 2021; Nguyen et al., 2024). CNN- and YOLO-based crack detection systems on UAVs can support faster inspection of large or difficult-to-access areas (Mazni et al., 2024). In addition, lightweight and attention-based architectures have been explored to improve mobile or embedded deployment while maintaining crack detection performance (Kang & Cha, 2022). However, their effectiveness still depends on hardware capability, image resolution, model complexity, camera stability, and field image quality.

There is an inherent trade-off between inference speed, model complexity, and detection accuracy (Mazni et al., 2024). Although enhanced YOLO-based models and efficient encoder-decoder CNNs have shown promising real-time potential, these findings remain dependent on specific datasets, hardware settings, and testing environments (Nguyen et al., 2024; Pu et al., 2022). Higher inference speed may require lower image resolution, model compression, or simplified detection tasks, which can reduce sensitivity to fine cracks, low-contrast cracks, or cracks in noisy backgrounds (Mazni et al., 2024). In UAV and robotic inspection, additional constraints such as battery life, camera movement, communication stability, and data storage also affect real-time performance (Nguyen et al., 2024). Therefore, future real-time crack detection systems should balance computational efficiency with reliable detection performance under variable lighting, surface texture, camera movement, and environmental conditions.

Integration into Structural Health Monitoring and Reliability Concerns

AI detection results are not always directly connected to safety or maintenance decisions (Arafin et al., 2024). Although algorithms can identify cracks and severity indices, repair scheduling, load limits, and maintenance priority still require engineering judgment (Arafin et al., 2024). This creates a gap between AI-based image analysis and practical structural health monitoring.

AI systems must work in a closed-loop process to identify cracks, assess severity, and support appropriate maintenance actions (Arafin et al., 2024). Most AI models provide static evaluations and do not fully monitor crack propagation or damage patterns over time (Adhikari et al., 2023). Future systems should therefore connect crack detection, severity assessment, crack progression, and maintenance priority within the same structural health monitoring workflow.

Implementation is also hindered by trust and interpretability. Deep learning models often operate as black-box systems, identifying cracks without clearly explaining the model rationale (Kang & Cha, 2022; Tyvoniuk et al., 2025). Explainable AI methods, such as saliency maps, may help users understand which image regions influenced the prediction (Lin et al., 2025). Therefore, explainability is important not only for model interpretation, but also for user trust and engineering acceptance.

Reliability remains a major concern because false negatives may allow major cracks to grow, while false positives may reduce user confidence and increase unnecessary inspection costs (Adhikari et al., 2023; Kang & Cha, 2022). The industry also lacks a standard approach for testing and applying AI systems for crack detection (Arafin et al., 2024). Therefore, future AI-based crack analysis requires benchmark datasets, standardised reporting metrics, external validation, and closer alignment with civil engineering assessment standards.

Research Gaps and Future Directions

The synthesis of the reviewed studies highlights several important research gaps. First, AI-based crack detection performs well in controlled datasets, but its generalisation to real infrastructure remains insufficiently validated (Arafin et al., 2024; Shahin et al., 2024). Second, crack classification and severity assessment are less developed than crack detection, especially for engineering-based decision-making (Mazni et al., 2024; Nyathi et al., 2024). Third, AI outputs are not yet fully integrated with structural health monitoring decisions, such as repair priority, safety risk, and maintenance strategy (Adhikari et al., 2023; Arafin et al., 2024). Fourth, explainability remains limited because many deep learning models provide accurate outputs without clearly explaining the basis of their decisions (Kang & Cha, 2022; Swarna et al., 2024).

Overall, the collective evidence suggests that AI-based methods have improved the speed, consistency, and accuracy of concrete crack analysis. However, unresolved issues remain in field robustness, standardised evaluation, explainability, and integration with engineering decision-making (Nguyen et al., 2024; Yadav et al., 2024). Therefore, the future research agenda should prioritise benchmark dataset development, external field validation, automated severity assessment, explainable AI, lightweight real-time deployment, standardised evaluation metrics, and stronger integration with structural health monitoring decisions.

CONCLUSION

AI-based methods have significantly advanced concrete crack detection and classification by improving inspection speed, consistency, automation, and accessibility in structural health monitoring. Deep learning models, YOLO-based detectors, vision transformer approaches, UAV-assisted inspection, and multimodal sensing have expanded the capability of crack analysis from simple detection towards segmentation, classification, severity assessment, and maintenance support. However, reported performance values should be interpreted cautiously because the reviewed studies used different datasets, validation protocols, environmental conditions, crack characteristics, and evaluation metrics. Therefore, the findings should be understood as broad methodological trends rather than direct rankings of model superiority.

Despite these advances, several limitations remain before AI-based crack inspection can be fully implemented in field practice. Current systems still face challenges related to dataset diversity, annotation quality, field generalisation, computational demand, explainability, and integration with engineering decision-making. Crack classification and severity assessment are also less mature than crack detection, particularly in real infrastructure conditions where crack width, length, orientation, location, propagation pattern, and structural significance must be considered together.

Future research should prioritise benchmark dataset development, external field validation, standardised evaluation metrics, explainable AI, lightweight edge deployment, and stronger integration with structural health monitoring systems. Greater attention should also be given to automated severity assessment and maintenance decision support so that AI-based crack inspection can move beyond detection towards practical asset management. With these improvements, AI-based crack analysis can become a more reliable and field-ready tool for preventive maintenance, infrastructure safety, and long-term structural monitoring.

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