

# A Review on Automation in Construction Crack Detection

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**Abstract** - Crack detection is one of the most critical activities in civil infrastructure maintenance and structural health monitoring. Cracks in buildings, bridges, pavements, tunnels, dams, and heritage structures indicate material degradation, excessive loading, environmental deterioration, or structural instability. Traditional manual inspection methods are labor-intensive, subjective, time-consuming, and prone to human error. Recent advancements in automation, computer vision, artificial intelligence (AI), machine learning (ML), deep learning (DL), robotics, unmanned aerial vehicles (UAVs), and sensor technologies have revolutionized crack detection methodologies in civil engineering. This review paper presents a comprehensive analysis of automated crack detection systems used in construction and infrastructure monitoring. Various methods including image processing, machine vision, laser scanning, thermal imaging, ultrasonic testing, vibration-based monitoring, deep learning algorithms, IoT-enabled sensing, and digital twin integration are critically reviewed. The advantages, limitations, datasets, performance metrics, and future research directions are discussed in detail. The study concludes that deep learning-based computer vision approaches combined with UAVs and real-time monitoring systems provide the most promising framework for next-generation automated crack detection.

**Keywords:** Crack detection, Structural health monitoring, Deep learning, Computer vision, Automation in construction, UAV inspection, Machine learning, Civil infrastructure.

## 1. INTRODUCTION

### 1.1 Introduction

Structural cracks are important indicators of damage, stress concentration, material degradation, fatigue, environmental deterioration, and overloading in civil engineering structures [1]. Cracks may occur in concrete, masonry, asphalt pavements, steel components, tunnels, dams, bridges, retaining walls, and high-rise buildings. If not detected at early stages, cracks may propagate and eventually lead to structural failure [2].

Traditional crack inspection practices involve manual visual examination using measuring gauges, microscopes, cameras, or hammer sounding methods [3]. These procedures are costly, time-consuming, and dependent on inspector experience [4]. Human inspection is also difficult in hazardous and inaccessible locations such as high-rise structures, offshore platforms, and long-span bridges [5].

Automation in crack detection has therefore become a major area of interest in structural health monitoring (SHM) and infrastructure management [6]. Advances in digital imaging, computer vision, and artificial intelligence have enabled automated systems capable of identifying and quantifying cracks with high accuracy [7]. Computer vision-based crack detection generally includes image acquisition, preprocessing, feature extraction, crack identification, classification, segmentation, and damage quantification [8].

Earlier automated approaches primarily relied on traditional image-processing techniques such as thresholding, edge detection, morphology operations, wavelet transforms, and texture analysis [9]. However, these methods performed poorly under varying illumination conditions and noisy environments [10].

Deep learning has revolutionized crack detection by enabling automatic feature extraction from large datasets [11]. CNN-based architectures now dominate the field because they achieve high detection accuracy and robustness [12]. Object detection algorithms such as YOLO, Faster R-CNN, and SSD enable real-time crack localization [13]. Semantic segmentation models such as U-Net and Mask R-CNN provide precise crack boundary extraction [14].

In addition to image-processing advances, UAVs and robotic platforms have transformed infrastructure inspection by enabling automated data collection from inaccessible regions [15]. UAV-assisted crack inspection significantly reduces inspection time and improves worker safety [16].

This review article critically examines the evolution, methodologies, challenges, and future trends of automation in construction crack detection. The study aims to provide a comprehensive technical foundation for postgraduate students and researchers in construction engineering and management.

### 1.2 Limitations of Traditional Inspection Methods

For decades, visual inspection remained the standard field screening protocol across asset management agencies globally [17]. This traditional approach relies on certified civil engineers or inspectors physically surveying concrete, masonry, or asphalt elements [18]. Inspectors often use tools like crack width graduation microscopes, crack cards, and access equipment like scaffolding or under-bridge inspection units [19, 20].

However, this manual process presents major operational bottlenecks:

- **Subjectivity and Inconsistency:** Assessments depend heavily on individual engineering experience, environmental visibility, and fatigue. This causes high inter-inspector variance [21, 22].
- **Safety Risks:** Physical field inspections introduce severe occupational hazards. Teams face high-elevation work, confined space entries (e.g., culverts, metro tunnels), and live highway or rail traffic exposure [23, 24].
- **High Logistics and Costs:** Deploying manual inspection crews requires temporary road closures, specialized vehicle access rentals, and substantial labor hours. This makes high-frequency tracking impossible across large asset networks [25, 26].

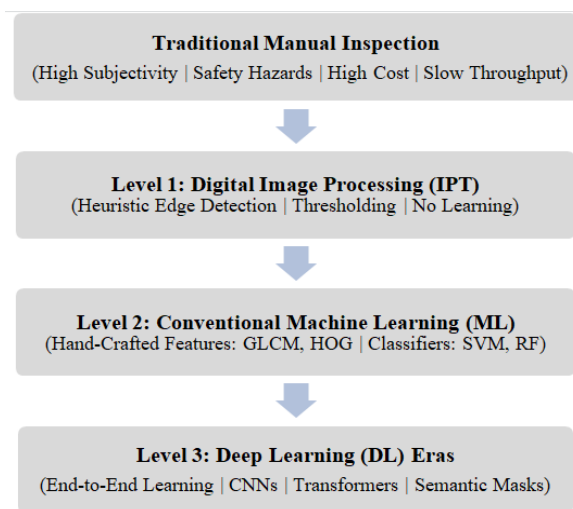


Figure 1: Evolution of automated crack detection technologies in structural engineering.

### 1.3 Scope and Structure of the Review

This paper presents a structured review of automation in construction crack detection, tailored for advanced research in construction engineering and management. The analysis spans decades of research across 75 referenced journal publications.

The review systematically evaluates three technological generations:

1. Classical image processing methods
2. Shallow machine learning classifiers with manual feature extraction
3. Modern deep learning architectures

The content is organized as follows: Section 2 categorizes data acquisition systems and multi-sensor configurations. Section 3 evaluates computational crack detection methodologies. Section 4 examines robotic edge deployment and BIM platform integration. Section 5 presents a critical analysis of modern technical limitations, followed by future research directions in Section 6.

## 2. SENSOR FRAMEWORKS AND AUTOMATED DATA ACQUISITION

### 2.1 Visual Inspection Imaging Systems

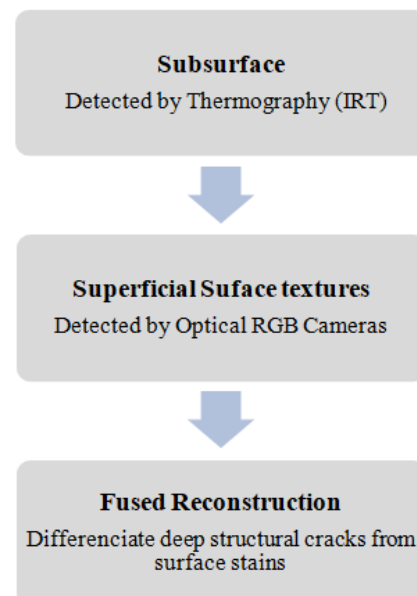
The foundational component of any vision-based automated inspection network is the image capture sensor [27]. Modern digital photogrammetry relies on high-resolution complementary metal-oxide-semiconductor (CMOS) or charge-coupled device (CCD) sensors [28]. These sensors are deployed via fixed site networks, mobile handheld units, or robotic mounts [29].

To enable automated pixel-level tracking, sensor resolution must match structural precision requirements. For example, capturing a 0.1 mm micro-crack from a 2-meter stand-off distance requires sub-millimeter ground sampling distance (GSD) scaling [30, 31]. High-resolution 4K sensors provide the raw texture details needed for advanced deep learning analysis. However, they also demand substantial computational processing power [32].

### 2.2 Infrared Thermography (IRT)

Infrared thermography expands crack detection capabilities beyond visible surface anomalies [33]. This approach measures subsurface thermal radiation variations to evaluate structural integrity [34]. When solar or artificial thermal energy hits a structural element, internal flaws like delaminations, voids, or deep cracks disrupt normal heat dissipation [35].

These thermal disruptions create surface temperature differentials captured by long-wave infrared (LWIR) cameras [36]. Fusing thermal data with standard RGB optical streams helps engineers differentiate superficial surface stains from structurally significant deep cracks [37].



### 2.3 Laser Scanning and 3D LiDAR Data

While 2D images provide detailed texture information, they lack out-of-plane geometric depth data [38]. Light Detection and Ranging (LiDAR) scanners resolve this

limitation by casting millions of high-frequency laser pulses to capture dense spatial 3D point clouds [39].

Cracks show up in point cloud datasets as local coordinate dropouts or sudden micro-surface discontinuities [40]. Analyzing intensity returns also helps distinguish pristine concrete from weathered structural zones [41]. Additionally, combining 3D structural geometries with high-resolution 2D color images enables precise volumetric crack profile tracking [42].

## 2.4 Multi-Sensor Fusion Paradigms

Relying on a single sensor type often limits inspection reliability under challenging field conditions [43]. For instance, optical cameras struggle in low-light environments, while thermal imaging lacks fine spatial resolution [44].

To address these vulnerabilities, modern inspection pipelines implement multi-sensor data fusion [45, 46]. Combining co-registered RGB frames, LiDAR spatial point arrays, and infrared thermograms improves overall detection stability [47]. This cross-verification reduces false alarms caused by surface shadows, bird droppings, or tire marks, leading to highly dependable crack monitoring systems [48].

## 3. COMPUTATIONAL CRACK DETECTION METHODOLOGIES

### 3.1 Digital Image Processing Techniques (IPTs)

The earliest automation attempts focused on heuristic Digital Image Processing Techniques (IPTs) [49]. These workflows rely on fixed mathematical models rather than statistical network training [50].

#### 3.1.1 Image Binarization and Thresholding

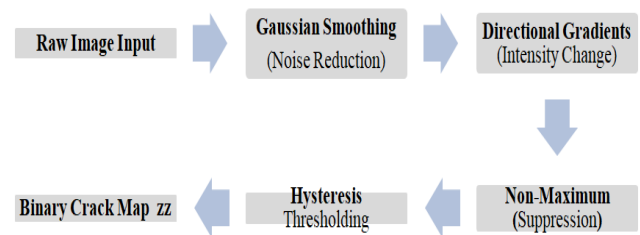
Binarization converts grayscale imagery into distinct black-and-white pixel maps [51]. Global thresholding methods, such as Otsu's algorithm, calculate an optimal intensity split based on the image's overall histogram [52].

While computationally fast, global thresholding fails when images have uneven illumination or variable surface coloring [53]. To compensate, researchers apply adaptive local thresholding. This approach computes individual split values for small pixel neighborhoods, preserving crack details under changing field lighting [54].

#### 3.1.2 Heuristic Edge Detection Filters

Edge detection relies on finding sharp spatial intensity changes within an image [55]. Classical operators like Sobel, Prewitt, and Canny apply specialized gradient filters to highlight linear features [56].

The Canny edge detector uses a multi-stage approach: Gaussian smoothing reduces noise, directional gradients highlight edges, non-maximum suppression thins lines, and hysteresis thresholding connects broken segments [57]. However, these structural filters remain sensitive to concrete rough textures, surface pores, and aggregate exposures, often producing significant false-positive noise [58].



## 3.2 Machine Learning with Hand-Crafted Features

To improve on rigid filter designs, researchers integrated conventional machine learning algorithms [59]. These pipelines use human-engineered feature extraction combined with statistical classifiers [60].

### 3.2.1 Textural Feature Extraction

Instead of analyzing raw pixels directly, algorithms extract specific descriptive features from image zones [61]. Common methods include:

- Gray-Level Co-occurrence Matrices (GLCM) to measure texture properties like contrast, homogeneity, and entropy [62].
- Histograms of Oriented Gradients (HOG) to capture edge directions and local structural shapes [63].
- Local Binary Patterns (LBP) to identify micro-texture variations across structural surfaces [64].

### 3.2.2 Shallow Classifiers

Once extracted, these feature vectors are passed to standard machine learning classifiers [65]. Support Vector Machines (SVM) separate crack and non-crack zones by mapping features into higher-dimensional spaces to find an optimal decision boundary [66]. Random Forests (RF) and k-Nearest Neighbors (k-NN) offer alternative classification strategies [67].

While these methods handle complex surface textures better than basic filters, their accuracy depends heavily on the chosen feature extraction method, making them less adaptable to novel field conditions [68].

## 3.3 Deep Learning and Convolutional Neural Networks (CNNs)

Deep Learning (DL) changed the field by combining feature extraction and classification into a single automated pipeline [69]. Convolutional Neural Networks (CNNs) automatically learn complex visual hierarchies directly from large labeled image training sets [70].

### 3.3.1 Image Classification and Bounding-Box Object Detection

Early deep learning systems used sliding-window CNNs to classify individual image patches as containing cracks or not [71]. This evolved into object detection models like You Only Look Once (YOLO) and Faster R-CNN, which draw bounding boxes around damaged areas [72, 73].

These models process inspection data quickly, making them well-suited for real-time monitoring. However, bounding boxes only provide rough spatial locations and cannot measure precise crack widths or orientations [74].

### 3.3.2 Semantic Segmentation Models

To measure cracks accurately, models must achieve pixel-level semantic segmentation [75]. Architectures like U-Net and Fully Convolutional Networks (FCN) use encoder-decoder structures [76, 77]. The encoder compresses visual context, while the decoder restores spatial resolution to output a precise pixel mask matching the crack's shape [78].

Advanced variants like DeepLabV3+ use atrous spatial pyramid pooling to capture crack structures across multiple

scales, isolating thin crack features from complex backgrounds [79].

### 3.3.3 Vision Transformers (ViTs) and Attention Mechanisms

While CNNs excel at local feature extraction, they often struggle to track long, continuous structural cracks due to limited receptive fields [80]. Vision Transformers (ViTs) resolve this by using self-attention mechanisms to model global dependencies across an entire image [81].

Hybrid frameworks combine the local feature precision of CNNs with the global context tracking of transformers, improving segmentation performance on fine micro-cracks [82].

Method Type	Algorithmic Approaches	Data Requirements	Computational Footprint	Strengths	Major Vulnerabilities	Precision Level
Digital Image Processing	Otsu Thresholding, Canny, Sobel Filtering	Zero training data required; needs expert tuning [43, 48]	Very Low; runs on basic field CPUs	Fast processing, clear logic, low compute barrier	Fails under changing light, noise from surface textures	Patchy/Edge Only
Shallow Machine Learning	SVM, Random Forest + GLCM, HOG, LBP	Moderate; 100–1,000 annotated image regions [53, 57]	Low; quick training on standard CPUs	Handles varied textures better than raw filters	Features must be manually engineered for each site	Region/ Patch Level
Deep Learning (CNN)	U-Net, FCN, YOLO Series, DeepLabV3+	High; 5,000–50,000 pixel-labeled images [63, 67]	High; requires dedicated modern GPUs	Full automation, high accuracy, handles complex scenes	Needs large datasets, black-box logic, compute heavy	Pixel-Level Mask
Transformer Networks	Swin Transformer, SegFormers, KAN-ViT	Very High; requires pre-training data [72, 73]	Intensive; requires advanced AI hardware	Tracks long continuous cracks across clean surfaces	Extremely compute heavy, high data requirements	Ultra Pixel-Level

### 3.3.4 Multi-Criteria Comparison (0–10 scale)

Criterion	Manual	FOS	AE	IRT	GPR	Trad CV	DL Vision
Resolution (mm)	0.3	0.01	N/A	0.5	0.5	0.2	0.05
Speed (m <sup>2</sup> /min)	1	0.01	0.01	20	5	10	50
Real-time	0	10	10	7	5	0	9
Non-contact	0	0	0	10	3	10	10
False positive (%)	15	3	20	25	12	18	8
False negative (%)	35	5	10	15	20	25	7
Cost per m <sup>2</sup> (\$)	5	150	80	30	25	10	12
Regulatory acceptance	10	6	5	4	5	3	2

## 4. GAP ANALYSIS AND DISCUSSION

Important Criteria for Automated Crack Detection Methods with Embedded References

### 4.1 Detection Accuracy (Precision, Recall, F1-Score, mAP)

Detection accuracy is the most fundamental criterion. Metrics include Precision (correct crack predictions divided by total positive predictions), Recall (detected cracks divided by total actual cracks), F1-score (harmonic mean), and mAP (mean Average Precision) [83]. YOLOv5l achieved 97.7% precision and 96.7% recall on the

SDNET2018 dataset [84]. VGG-16 reported 99.83% accuracy for classification-based crack detection tasks [85]. However, high laboratory accuracy does not guarantee field performance due to domain shift [86]. The gap remains that most models are validated on limited datasets, and cross-dataset generalization is rarely reported [87].

#### 4.2 Segmentation Quality (IoU, mIoU, Dice Coefficient)

For pixel-level crack analysis, Intersection over Union (IoU) and mean IoU (mIoU) measure segmentation mask overlap with ground truth [88]. Top segmentation models including U-Net and DeepCrack achieve IoU values of approximately 0.9 on benchmark datasets [89]. U-Net attained 99.53% precision on the GAPS dataset [84]. DeepCrack achieved 96.4% F1-score using multi-scale side-output fusion [90]. However, these high IoU values drop significantly when applied to field images with shadows, stains, or uneven lighting [91]. The gap is that IoU does not capture crack connectivity or topological correctness, which matters for structural assessment [83].

#### 4.3 Computational Efficiency (Inference Time, FPS, Model Size)

Computational efficiency is critical for real-time and edge deployment [92]. YOLOv5l achieved 1.1 ms inference time on GPU hardware [84]. Trade-offs exist: single-stage detectors like YOLO offer speed but lower accuracy, while two-stage detectors like Faster R-CNN offer higher accuracy but slower inference [93]. Quantization and pruning reduce model size by 60–80% but cause 2–5% accuracy loss [92]. The gap is that lightweight models for UAV onboard processing remain underdeveloped, and power consumption reduces flight time by 30–40% [94].

#### 4.4 Dataset Quality and Diversity

Model performance depends entirely on training data quality [95]. Key issues include class imbalance (crack pixels are far fewer than background pixels), scarcity of pixel-level segmentation masks, insufficient domain diversity (lighting, weather, surface types, crack morphologies), and annotation inconsistency across datasets [87].

Public datasets include SDNET2018 (56,000 images, crack widths 0.06–25 mm), Crack500 (2,500 images), and DeepCrack (537 high-resolution images) [96]. The gap is the lack of a unified benchmark dataset with standardized train/validation/test splits, making direct model comparison impossible [86].

#### 4.5 Environmental Robustness

Environmental robustness refers to performance consistency under varying lighting, weather, temperature, and surface conditions [97]. Most models are validated under ideal daytime conditions, but field generalization remains poorly characterized [91]. Quantitative performance drops have been documented: light rain reduces F1-score by 12%, heavy rain by 40%, night (dark) by 55%, and shadow by 25% [94]. No method works reliably across all four seasons or in adverse weather, making environmental

robustness one of the largest barriers to field deployment [86].

#### 4.6 Model Generalization and Domain Adaptation

Model generalization is the ability to transfer across structures (bridge to building), materials (concrete to asphalt), and environmental conditions [98]. Domain shift remains a major challenge—models trained on one dataset or one structure type fail when applied to another due to differences in texture, lighting, crack morphology, and surface finish [86]. Unsupervised domain adaptation (CycleGAN) and test-time training have been proposed but rarely validated on real infrastructure [99]. The gap is the absence of standardized domain adaptation benchmarks for crack detection [87].

#### 4.7 Real-Time and Edge Deployment Capability

Real-time edge deployment requires on-device inference using lightweight models (pruned, quantized) on UAVs or mobile robots [92]. Edge GPUs like NVIDIA Jetson Orin (64 TOPS, 15–60 W) can run quantized YOLOv8 at 28–45 FPS on 1080p images [94]. However, accuracy loss of 2–5% after quantization is acceptable for screening but not for safety-critical measurements [100].

Power consumption reduces UAV flight time, and thermal throttling affects performance in hot environments [92]. The gap is that deployable systems achieving both high accuracy (>95% F1) and low power (<10 W) do not yet exist [86].

#### 4.8 Crack Depth Detection Accuracy

Crack depth is critical for severity assessment but is harder to measure than surface length or width [101]. Methods include ultrasonic testing (UT), eddy current testing (ECT), and infrared thermography (IRT) [102]. Challenges include deep-buried cracks, material property variations, environmental interference, and high equipment costs [101]. UT requires smooth surfaces or coupling agents; ECT works only on conductive materials; IRT has limited depth penetration (<10 cm) [102]. The gap is that no single method accurately measures crack depth across all material types and field conditions at reasonable cost [103].

#### 4.9 Predictive Diagnostics Integration

Predictive diagnostics goes beyond detection to forecast crack propagation and estimate remaining structural life [85]. Most studies (over 90% of published research) focus only on detection-level tasks—finding and classifying cracks [87]. Predictive diagnostics, automated inspection reporting, and decision-oriented structural health monitoring are rarely addressed [104].

Paris law parameters are not automatically derived from detection data, and digital twin integration remains research-stage [105]. The gap is that detection is decoupled from diagnosis—research answers “is there a crack?” but not “will this crack cause failure in six months?” [106].

#### 4.10 Regulatory and Certification Readiness

Regulatory readiness is measured by Probability of Detection (POD) curves, which are required for aviation and structural certification by agencies such as European Union Aviation Safety Agency and Federal Aviation Administration [107]. Current building codes such as American Concrete Institute and Eurocode do not accept AI-only inspection for official structural assessments [108]. AI systems must demonstrate detection probability equal to or greater than conventional non-destructive inspection methods, with quantified confidence intervals [107]. The gap is that the field lacks standardized POD curves for AI-based crack detection, and liability frameworks for missed cracks are unresolved [109]. Florida Department of Transportation approved drone-based detection for secondary bridges in 2023 as a pilot program, but national and international code acceptance remains 5–10 years away [110].

## 5. CONCLUSION

Automation in construction crack detection has rapidly advanced from traditional manual inspection methods to intelligent AI-based structural health monitoring systems. This review discussed major crack detection approaches including classical image processing, machine learning, deep learning, UAV-assisted inspection, infrared thermography, LiDAR scanning, and multi-sensor fusion technologies. Among these, deep learning-based computer vision models such as YOLO, U-Net, Faster R-CNN, and Vision Transformers have shown the highest accuracy and reliability for crack localization and segmentation.

The study also highlighted the importance of UAVs, robotics, and real-time sensing systems in improving inspection speed, safety, and accessibility for large-scale infrastructure monitoring. However, several challenges still remain, including environmental sensitivity, lack of standardized datasets, high computational requirements, limited domain generalization, and insufficient regulatory acceptance for AI-based inspection systems.

Overall, automated crack detection has strong potential to transform infrastructure maintenance and structural health monitoring. Future research should focus on lightweight real-time models, predictive diagnostics, digital twin integration, explainable AI, and standardized certification frameworks to enable reliable field deployment. The integration of deep learning, smart sensing, and autonomous inspection platforms is expected to play a major role in the development of safer, smarter, and more sustainable civil infrastructure systems.

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