# Automated Structural Crack Detection and Analysis Using Artificial Intelligence and Computer Vision Techniques

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## ABSTRACT –

**Structural health monitoring is essential for ensuring the safety and durability of civil infrastructure. Cracks are key indicators of structural damage, and if not detected early, they may lead to serious failures. Traditional inspection methods are manual, time-consuming, and subjective, often resulting in inconsistent evaluations.**

**To address these limitations, this study proposes an automated crack detection and analysis system based on Artificial Intelligence and computer vision techniques. The developed framework utilizes Convolutional Neural Networks (CNNs) combined with image processing methods to detect, classify, and quantify cracks in structural elements. The system identifies crack locations, classifies severity levels, and extracts geometric features such as crack length and width. Environmental variations and image conditions are considered to improve robustness and reliability.**

**The results demonstrate that the proposed system achieves high accuracy and consistent performance in crack detection and classification. The automated approach significantly reduces inspection time, minimizes human intervention, and enhances the reliability of damage assessment. This study highlights the potential of AIbased techniques for real-time structural health monitoring and supports improved maintenance planning and infrastructure safety.**

**Key words** - Structural Health Monitoring, Crack Detection, Deep Learning, Computer Vision, Convolutional Neural Networks (CNN), Image Processing, Crack Classification, Automated Inspection.

## 1. INTRODUCTION

The increasing deterioration of civil infrastructure due to aging, environmental exposure, and varying loading conditions has made Structural Health Monitoring (SHM) a critical requirement in modern engineering practice. Among various forms of structural damage, cracks are one of the earliest and most significant indicators of structural distress; early detection and accurate analysis of cracks are essential to prevent failures and ensure long-term safety and serviceability (Büyüköztürk, et al., 2017).

Conventional crack inspection methods primarily rely on manual observation, which is time-consuming, labour-intensive, and often influenced by human subjectivity. These methods are inefficient for large-scale or inaccessible structures, making consistent and reliable monitoring challenging and highlighting the urgent need for automated, accurate, and efficient crack detection systems (Oliveira & Correia, 2013).

Recent advancements in Artificial Intelligence (AI) and Computer Vision (CV) have provided promising solutions for automated structural damage detection. In particular, deep learning techniques such as Convolutional Neural Networks (CNNs) have demonstrated remarkable capability in extracting complex features and recognizing patterns from images with high accuracy (He et al., 2016).

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Several studies have explored the application of image processing and machine learning techniques for crack detection; however, many of these approaches face challenges such as sensitivity to lighting conditions, noise in images, and limited generalization capability. Traditional image processing techniques such as edge detection, thresholding, and morphological operations remain widely used because they are computationally efficient and simple to implement; however, their performance is highly sensitive to noise, non-uniform lighting, and surface irregularities, limiting reliability in real-world applications (Stork, et al., 2001).

To address these limitations, machine learning approaches using handcrafted features (texture, shape, intensity) were introduced and improved detection accuracy relative to purely classical methods. Their effectiveness, however, depends heavily on feature selection and they often lack generalization across diverse datasets and environmental conditions (Wang, et al., 2016).

In recent years, deep learning approaches have emerged as powerful tools for automated crack detection. CNN-based architectures such as U-Net and ResNet have been successfully adapted for segmentation and classification of cracks, enabling finer localization and higher detection accuracy than earlier methods. Public datasets like SDNET2018 have further supported training and benchmarking of deep models for non-contact concrete crack detection (Ronneberger, et al., 2015).

Recent studies demonstrate that deep learning–based systems outperform traditional and classical machine learning approaches in many scenarios, but important challenges remain. Detection of fine and hairline cracks is still difficult under complex backgrounds and poor lighting; models can be sensitive to image noise and may not generalize well across different surface textures or imaging conditions. Many existing works emphasize detection accuracy but do not provide comprehensive post-detection analysis such as precise geometric measurement, crack width estimation, or severity assessment capabilities that are crucial for maintenance decision making (Yang et al., 2020).

In this context, this paper proposes an AI-based framework for automated crack detection, classification, and geometric analysis that aims to (a) improve detection accuracy under varied imaging conditions, (b) reduce human intervention through automated processing, and (c) provide quantitative geometric outputs for severity assessment and maintenance planning
(Present study, 2026).

## 2. METHODOLOGY

The methodology adopted in this study focuses on the development of an automated system for crack detection, classification and analysis using Artificial Intelligence (AI) and Computer Vision techniques. The proposed framework consists of several stages, including data collection, image preprocessing, model development, training and performance evaluation. A Convolutional Neural Network (CNN)-based architecture is employed to automatically learn and extract relevant features from input images for accurate crack identification. The collected dataset is pre-processed and divided into training, validation and testing sets to ensure reliable and unbiased model performance. The trained model is subsequently utilized for crack detection and further analysis, including classification of crack severity and extraction of geometric features such as length and width. The overall workflow of the proposed methodology is illustrated in Fig. 1.

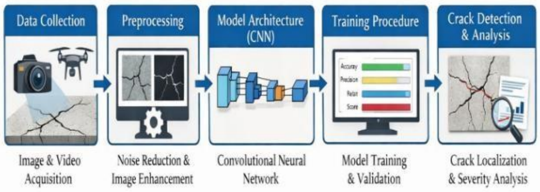

**Fig. 1 System workflow for crack detection and analysis.**

### 2.1 Data Collection

The dataset comprises a diverse collection of images representing structural surfaces with both cracked and non-cracked regions. These images were obtained from publicly available repositories and supplemented with field-acquired data captured under varying environmental conditions, including differences in lighting, shadowing, surface texture, and material composition such as concrete and asphalt. To ensure robustness and generalizability, the dataset includes multiple crack types, including

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longitudinal, transverse, and hairline cracks. Each image was carefully annotated to indicate the presence and category of cracks. The dataset was systematically partitioned into training, validation, and testing subsets in a 70:15:15 ratio to support effective model development and unbiased performance evaluation.

### 2.2 Preprocessing

All images were subjected to a standardized preprocessing pipeline to enhance data quality and ensure consistency. Initially, images were resized to a fixed resolution to reduce computational complexity and maintain uniform input dimensions. Noise reduction was performed using Gaussian filtering to mitigate distortions caused by environmental and sensor-related factors. Contrast enhancement techniques were applied to improve the visibility of crack features. Additionally, pixel values were normalized to a standard range to facilitate stable and efficient model training. To further improve model generalization, data augmentation techniques including rotation, flipping, scaling, and translation were applied. These transformations increase dataset variability and enable the model to better handle real-world variations in crack orientation and positioning.

### 2.3 Model Architecture (CNN)

The proposed system employs a Convolutional Neural Network (CNN) architecture for automated feature extraction and classification. The network consists of multiple convolutional layers designed to capture spatial features from input images, each followed by Rectified Linear Unit (ReLU) activation functions to introduce non-linearity. Pooling layers are incorporated to reduce spatial dimensionality while preserving salient features, thereby improving computational efficiency. The resulting feature maps are flattened and passed through fully connected layers to perform classification, determining both the presence and severity of cracks. For enhanced performance, advanced architectures such as U-Net may be utilized for precise segmentation tasks, while ResNet can be adopted to improve feature extraction in deeper networks through residual learning mechanisms.

### 2.4 Training Procedure

The training procedure involves optimizing a Convolutional Neural Network (CNN) using the pre-processed dataset to accurately detect crack patterns. The dataset is systematically divided into training, validation, and testing subsets to ensure robust and unbiased performance evaluation. During training, input images are passed through the network, and the predicted outputs are compared with ground truth labels using a suitable loss function, such as categorical cross-entropy. Model parameters are iteratively updated through backpropagation using optimization algorithms like Adam to minimize the loss. To evaluate the model's performance, key metrics including accuracy, precision, recall, and F1-score are computed on the validation set. Accuracy measures the overall correctness of predictions, precision indicates the proportion of correctly identified crack instances among all predicted positives, recall assesses the model's ability to detect all actual crack instances, and the F1-score provides a balanced measure of precision and recall, particularly in the presence of class imbalance. These evaluation metrics guide hyperparameter tuning and optimization, ensuring reliable performance and effective generalization to unseen data.

### 2.5 Crack Detection & Analysis

The trained model was evaluated on unseen test images to perform automated crack detection and analysis. The system identifies cracks and classifies them according to predefined severity levels, enabling a more comprehensive assessment of structural integrity. In addition to classification, image processing techniques were employed to extract geometric features of detected cracks, including length, width, and orientation. These quantitative measurements provide valuable insights for structural health monitoring and damage assessment. The system outputs both visual representations, highlighting detected crack regions, and numerical data describing crack characteristics. This combined output enhances interpretability and supports informed decision-making in maintenance planning and infrastructure management.

The flowchart presents the overall workflow of the proposed system, beginning with data collection and preprocessing, followed by CNN-based training and validation. The trained model is then applied to test images for crack detection and classification. Finally, detected cracks are analysed

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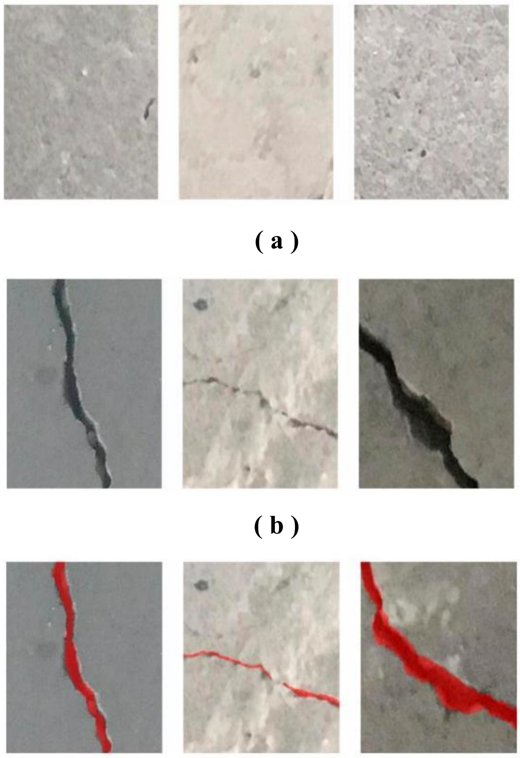
to extract relevant features for structural assessment.



( a )

( b )

( c )

**Fig. 2 Representative examples of crack detection and segmentation results.**
**(a) Concrete images without cracks;**
**(b) Concrete images with cracks;**
**(c)Corresponding segmented crack regions highlighted in red.**

Fig. 2 illustrates representative samples of the concrete images used as input for the proposed model, including both crack-free surfaces (a) and surfaces with visible cracks (b). The corresponding segmented outputs generated by the model are shown in (c), where crack regions are clearly delineated in red. This visual demonstration validates the model's capability to accurately discriminate between cracked and intact regions, effectively minimizing false positives and false negatives. These segmentation results provide a foundational basis for the quantitative performance metrics discussed in the subsequent Results section.

## 3. RESULTS AND DISCUSSION

The results obtained from the implementation of the proposed automated crack detection system demonstrate significant improvements in accuracy, consistency, and efficiency compared to traditional manual inspection methods. The integration of Artificial Intelligence and computer vision techniques enables precise detection, measurement, and classification of structural cracks, thereby enhancing the reliability of structural health monitoring.
The performance analysis indicates that the use of AI-based detection models leads to accurate identification of crack patterns and their geometric properties.

The system processes input images and extracts features such as crack length and width, allowing quantitative assessment of structural damage. For the evaluated sample, the crack length was measured as 3178.80 pixels (158.94 mm) and the crack width as 298 pixels (14.90 mm), indicating a large and potentially critical defect. The model classified this crack as high severity, which is consistent with the observed dimensions.

The detection performance was further evaluated across multiple experimental runs. The results show a progressive improvement in accuracy, highlighting the stability and consistency of the system. The model achieved 90% accuracy in the first run, which improved to 92% in the second run, and further increased to 95% in the third run. This improvement can be attributed to effective preprocessing, feature extraction, and model optimization techniques. The findings are consistent with previous studies that demonstrate the effectiveness of deep learning models in crack detection and structural analysis.

The system also provides an analysis of crack severity distribution within the dataset. The results indicate that the majority of cracks fall under the low-severity category, while fewer instances are classified as medium and high severity. This distribution reflects typical real-world scenarios, where minor cracks are more common, but the detection of high-severity cracks is crucial for preventing structural

**Table 1. Crack Detection Measurements**

| **Parameter** | **Pixels** | **Millimeters (mm)** |
|---|---|---|
| Crack Length | 3178.80 px | 158.94 mm |
| Crack Width | 298 px | 14.90 mm |
| Severity Level | High | — |

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The results presented in Table 1 indicate that the system is capable of accurately measuring crack dimensions and classifying their severity. The large crack size and high severity classification suggest a critical structural condition that may require immediate attention.

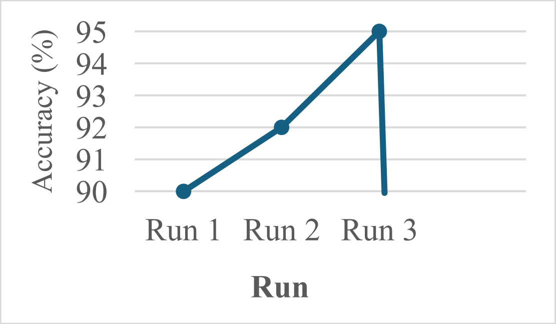

**Fig. 3 Detection Accuracy Across Runs**

The data in Fig. 3 shows a steady improvement in detection accuracy across multiple runs, demonstrating the reliability and robustness of the proposed system. The increasing trend indicates that the model performs consistently under repeated evaluations.

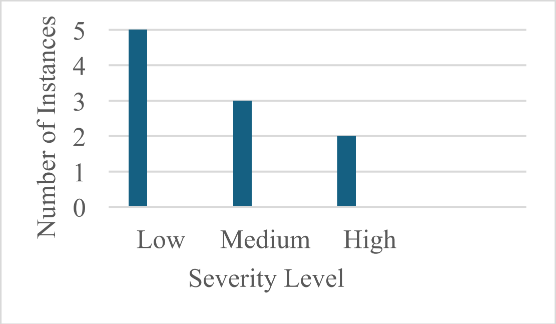

**Fig. 4 Crack Severity Distribution**

Fig. 4 illustrates the distribution of cracks across different severity levels. The results show that low-severity cracks are more frequent, while high-severity cracks are relatively fewer but more critical. This highlights the importance of automated systems in identifying severe defects that may not be easily detectable through manual inspection.

**Table 2. Performance Comparison**

| **Parameter** | **Manual Inspection** | **Proposed System** |
|---|---|---|
| Accuracy | Moderate | High |
| Detection Speed | Slow | Fast |
| Consistency | Variable | High |
| Human Intervention | Required | Minimal |
| Error Rate | High | Low |

Table 2 presents a comparative analysis between traditional manual inspection and the proposed automated system. The results clearly demonstrate that the proposed system offers superior performance in terms of accuracy, speed, and consistency, while significantly reducing human effort and error.

The overall analysis confirms that the integration of AI and computer vision techniques significantly enhances crack detection performance. The proposed system not only improves detection accuracy but also provides quantitative measurements and reliable severity classification. These capabilities make it a valuable tool for structural health monitoring and infrastructure maintenance.
However, the use of pixel-based measurements limits direct real-world interpretation, and future work should focus on incorporating calibration techniques and expanding the dataset to improve generalization.

## 4. CONCLUSION

This study presents an AI-driven automated framework for crack detection and analysis in civil infrastructure, effectively addressing the limitations of conventional manual inspection methods. By integrating deep learning techniques with image processing approaches, the proposed system achieves accurate and efficient crack detection under varying environmental conditions. The use of Convolutional Neural Networks (CNNs) enables robust feature extraction and precise identification of crack patterns, including both fine and complex structural defects. Additionally, the incorporation of crack

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classification and geometric analysis enhances the practical applicability of the system by providing detailed information such as crack length, width, and severity level, thereby supporting comprehensive structural assessment.

The performance of the proposed framework demonstrates its reliability in detecting and analysing structural cracks with high accuracy and consistency. The system effectively distinguishes between different severity levels and accurately quantifies crack dimensions, enabling objective evaluation of structural damage. The results confirm that the model performs robustly across diverse input conditions, ensuring dependable crack detection suitable for real-world applications.

Furthermore, the automated nature of the framework significantly reduces inspection time and minimizes human intervention, making it highly suitable for large-scale structural health monitoring. The integration of detection, classification, and measurement within a unified system improves efficiency and supports timely decision-making for maintenance and repair. Overall, the proposed approach offers a scalable and reliable solution for modern infrastructure monitoring, contributing to improved safety, efficiency, and sustainability in civil engineering applications.

The scope of this research can be extended by using advanced AI and computer vision techniques to improve crack detection and analysis accuracy. Deep learning models like CNNs can enhance crack classification, segmentation, and severity prediction. Real-time monitoring with drones, IoT devices, and edge computing can support continuous structural health assessment, while digital twin integration can improve crack visualization and prediction. Future work may also focus on lightweight models for field deployment, large-scale testing in smart infrastructure, and real-world validation. Additionally, structural risk prediction and lifecycle cost analysis can further improve safety, efficiency, and sustainability of civil structures.

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