

AI Based Crack Detection of Structural Members

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Abstract: *Structural cracks are one of the major indicators of damage and deterioration in civil infrastructure such as beams, columns, slabs, and bridges. Early identification of these cracks is essential to maintain structural safety and reduce maintenance costs. This project presents an AI-based crack detection system that uses image processing and deep learning techniques to automatically identify and classify cracks in structural members. High-resolution images collected through cameras, drones, or smartphones are processed using Convolutional Neural Networks (CNNs) and segmentation methods to detect crack location, width, and severity. The proposed system reduces human effort, improves inspection accuracy, and supports real-time structural monitoring. Experimental analysis shows that the AI model can detect different crack patterns effectively under varying environmental conditions. The developed system offers a fast, reliable, and cost-effective solution for modern structural health monitoring and preventive maintenance of civil infrastructure.*

Keywords: Artificial Intelligence (AI), Crack Detection, Structural Health Monitoring, Convolutional Neural Network (CNN), Deep Learning, Image Processing, Structural Members, Crack Classification, Civil Infrastructure, Real-Time Monitoring

I. INTRODUCTION

Structural members such as beams, columns, slabs, and bridges play a vital role in maintaining the strength and stability of civil infrastructure. Over time, these structures are affected by factors such as excessive loading, temperature variation, corrosion, environmental exposure, earthquakes, and material aging, which can lead to the formation of cracks [1]. Cracks are considered one of the earliest signs of structural deterioration, and if they are not detected at an early stage, they may reduce the durability and safety of the structure [2].

Traditionally, crack detection has been carried out through manual visual inspection and non-destructive testing (NDT) methods such as ultrasonic testing, radiography, and dye penetrant testing [3]. Although these methods are effective, they are time-consuming, expensive, and highly dependent on skilled inspectors [4]. In large structures such as bridges, dams, and high-rise buildings, manual inspection becomes difficult and sometimes unsafe [5].

Recent advancements in Artificial Intelligence (AI), machine learning, and computer vision have introduced automated approaches for crack detection [6]. AI-based systems use digital images captured from cameras, drones, or smartphones to identify and classify cracks accurately [7]. Deep learning models such as Convolutional Neural Networks (CNNs), U-Net, and YOLO are widely used for crack detection because they can automatically learn crack features from images with high precision [8].

AI-based crack detection systems provide several advantages, including faster inspection, reduced human error, real-time monitoring, and improved maintenance planning [9]. These systems can also measure crack width, length, and severity, helping engineers make better decisions regarding structural repair and safety assessment [10]. Therefore, the implementation of AI in structural health monitoring represents a modern, efficient, and reliable solution for maintaining the safety and lifespan of civil infrastructure.



II. PROBLEM STATEMENT

Structural members such as beams, columns, slabs, and bridges are continuously exposed to loads, environmental effects, corrosion, vibrations, and aging, which often result in the formation of cracks and surface defects. If these cracks are not identified and repaired at an early stage, they can gradually weaken the structural strength and may lead to serious safety hazards or structural failure. Conventional crack inspection methods mainly depend on manual visual observation and non-destructive testing techniques, which are time-consuming, costly, labor-intensive, and prone to human error, especially in large or hard-to-access structures. In many cases, fine cracks remain undetected due to poor visibility and inconsistent inspection practices. Therefore, there is a need for an automated, accurate, and reliable crack detection system that can quickly identify and classify cracks using Artificial Intelligence and image processing techniques, reducing inspection effort while improving structural health monitoring and maintenance planning.

III. OBJECTIVES

- To develop an AI-based system for automatic detection of cracks in structural members.
- To improve the accuracy and reliability of crack inspection compared to manual methods.
- To classify cracks based on their severity, size, and location.
- To reduce inspection time, human effort, and maintenance cost using automated techniques.
- To support real-time structural health monitoring using image processing and deep learning methods.

IV. LITERATURE SURVEY

Yang et al. (2021) presented a deep learning-based approach for structural crack detection using CNN architectures such as AlexNet, VGGNet13, and ResNet18 in their study “Structural Crack Detection and Recognition Based on Deep Learning.” The proposed system successfully identified cracks from concrete surface images with high accuracy, where ResNet18 achieved the best performance. Their work demonstrated that deep learning techniques can significantly improve the speed and reliability of crack detection. However, the system required a large labeled dataset and high computational resources for training.

Alkannad et al. (2025) proposed an advanced crack detection framework named “CrackVision” using transfer learning models such as ResNet50, Xception, and InceptionV3 for concrete crack classification. The system achieved excellent detection accuracy on bridge decks, walls, and pavements while reducing training time through pretrained networks. Their approach improved real-time monitoring capability for structural health assessment. However, model performance was slightly affected under highly uneven lighting conditions.

Cha et al. (2017) introduced a CNN-based crack damage detection method for civil infrastructure inspection in their work on deep learning-based structural monitoring. The proposed model automatically extracted crack features from concrete surface images and reduced the dependency on manual feature engineering. The system achieved high classification accuracy and improved inspection consistency. However, the method struggled to detect extremely fine hairline cracks in low-resolution images.

Li et al. (2019) developed “DeepCrack,” a hierarchical convolutional neural network model for automated crack detection in concrete structures. Their approach effectively identified crack patterns with varying shapes and sizes while providing detailed crack segmentation results. The model improved crack localization accuracy compared to traditional image processing methods. However, the system required extensive training data and longer processing time for high-resolution images.

Zhang et al. (2021) proposed a real-time crack detection system using YOLOv4 and transfer learning techniques for structural surface inspection. The method enabled rapid crack identification with high detection speed, making it suitable for drone-based monitoring applications. Their work showed strong performance in detecting multiple cracks



simultaneously under real-world conditions. However, accuracy decreased slightly in the presence of shadows and rough surface textures.

Chakurkar et al. (2023) presented a comprehensive review titled “Data-driven Approach for AI-based Crack Detection: Techniques, Challenges, and Future Scope,” focusing on machine learning and deep learning methods for crack identification. The study discussed CNNs, U-Net, YOLO, and IoT-integrated systems for structural health monitoring. Their review highlighted the advantages of AI in improving automation, accuracy, and predictive maintenance. However, challenges such as dataset imbalance, lack of 3D crack datasets, and real-time deployment limitations were identified.

Comparison Table

Author & Year	Method Used	Advantages	Limitations
Yang et al. (2021)	CNN Models (AlexNet, VGGNet13, ResNet18)	High crack detection accuracy and reliable classification	Requires large labeled datasets and high computation power
Alkannad et al. (2025)	Transfer Learning (ResNet50, Xception, InceptionV3)	Faster training with excellent real-time detection accuracy	Performance affected under uneven lighting conditions
Cha et al. (2017)	Deep Learning using CNN	Automatic feature extraction and reduced manual effort	Difficulty detecting very fine hairline cracks
Li et al. (2019)	DeepCrack Hierarchical CNN	Accurate crack segmentation and localization	High processing time for high-resolution images
Zhang et al. (2021)	YOLOv4 with Transfer Learning	Real-time crack detection suitable for drone monitoring	Accuracy decreases with shadows and rough surfaces
Chakurkar et al. (2023)	AI-Based Review (CNN, U-Net, YOLO, IoT)	Comprehensive analysis of modern AI crack detection techniques	Identified challenges in dataset availability and real-time deployment

IV. WORKING OF SYSTEM

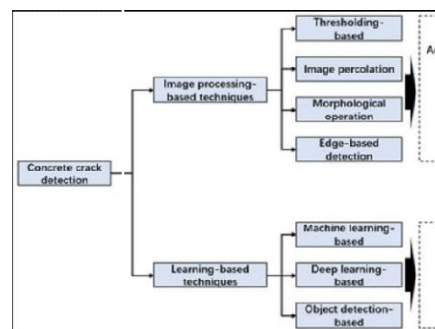


Fig 1: Design of the system

1. Image Acquisition

The system begins by collecting images of concrete structural members such as beams, columns, slabs, and pavements using cameras, drones, or smartphones. These images contain both cracked and non-cracked surfaces for analysis.



2. **Concrete Crack Detection Process**

The captured images are processed through a crack detection framework that automatically identifies surface defects and crack patterns using image processing and Artificial Intelligence techniques.

3. **Image Processing-Based Techniques**

In the first stage, traditional image processing methods are used to enhance and detect cracks from images. These techniques improve image quality and help isolate crack regions from the background.

4. **Thresholding-Based Detection**

Thresholding methods separate cracks from the concrete surface based on pixel intensity differences. Algorithms such as Otsu thresholding automatically select suitable threshold values for accurate crack segmentation.

5. **Image Percolation Method**

This technique analyzes the connectivity of crack pixels and tracks crack propagation paths across the surface. It helps in identifying continuous crack patterns.

6. **Morphological Operations**

Morphological techniques such as dilation, erosion, opening, and closing are applied to remove noise and improve crack visibility. These operations enhance the shape and continuity of detected cracks.

7. **Edge-Based Detection**

Edge detection algorithms such as Roberts, Prewitt, Canny, and Sobel operators are used to identify crack boundaries by detecting sudden intensity changes in images.

8. **Learning-Based Techniques**

In the second stage, AI and machine learning methods are used for automatic crack classification and detection. These techniques improve accuracy and reduce human intervention.

9. **Machine Learning-Based Detection**

Traditional machine learning methods classify crack and non-crack regions based on extracted image features such as texture, shape, and edges.

10. **Deep Learning-Based Detection**

Advanced deep learning models such as CNN, FCN, R-CNN, Fast R-CNN, Faster R-CNN, and Mask R-CNN automatically learn crack features from large datasets and provide highly accurate crack detection and segmentation.

11. **Object Detection-Based System**

YOLO (You Only Look Once) and similar object detection algorithms are used for real-time crack detection. These models identify crack location, size, and severity quickly, making them suitable for drone-based monitoring systems.



12. Final Output and Analysis

After processing, the system generates crack detection results showing crack location, dimensions, severity level, and segmented crack images. These outputs help engineers perform structural health monitoring and maintenance planning efficiently.

V. SYSTEM DESIGN

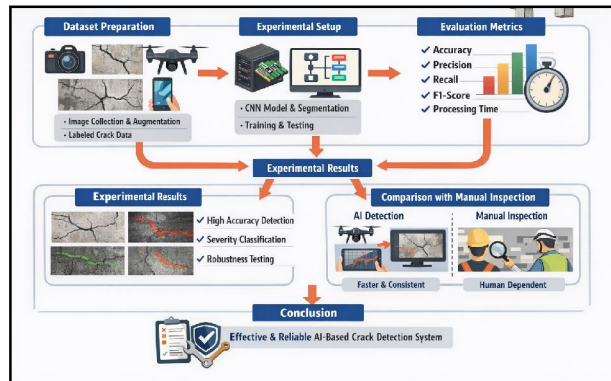


Fig.2. System Architecture

1. System Overview:

The proposed system is an AI-based crack detection system used for identifying cracks in structural members such as beams, columns, slabs, and bridges. Images captured using cameras, drones, or smartphones are processed using image processing and deep learning techniques like CNN and segmentation models. The system automatically detects cracks, classifies their severity, and generates accurate inspection results. It provides fast, reliable, and real-time structural health monitoring with reduced human effort and improved inspection accuracy.

System Design

1. Dataset Preparation

The system begins with the collection of crack images from structural members such as beams, slabs, columns, and pavements using cameras, drones, and smartphones. The collected images include different crack patterns, sizes, and surface conditions. Data augmentation techniques such as rotation, flipping, scaling, and brightness adjustment are applied to increase the dataset size and improve model performance. The images are then labeled as cracked and non-cracked for training purposes.

2. Experimental Setup

After dataset preparation, the images are processed using an AI-based experimental setup. A Convolutional Neural Network (CNN) combined with segmentation techniques is used for crack detection and classification. The dataset is divided into training and testing sets to train the model and evaluate its performance.

3. AI-Based Crack Detection Process

The trained AI model analyzes structural images and automatically detects cracks by extracting important features such as edges, texture, crack width, and orientation. Segmentation techniques are used to identify the exact crack region at the pixel level.

4. Evaluation Metrics

The performance of the AI system is evaluated using standard parameters:



Accuracy – Measures overall correct crack detection.

Precision – Measures correctly detected cracks among predicted cracks.

Recall – Measures actual cracks detected by the system.

F1-Score – Provides balance between precision and recall.

Processing Time – Measures the speed of crack detection for real-time applications.

These metrics help determine the reliability and efficiency of the proposed system.

5. Experimental Results

The system generates crack detection outputs showing crack location, segmented crack regions, and severity classification. The AI model achieves high detection accuracy even under different environmental conditions such as varying lighting and rough concrete surfaces. Robustness testing ensures that the system performs effectively in real-world structural inspection scenarios.

6. Comparison with Manual Inspection

The proposed AI-based system is compared with traditional manual inspection methods. AI detection provides:

Faster inspection process

Consistent and objective results

In contrast, manual inspection is slower, labor-intensive, and dependent on inspector experience.

7. Final Output and Conclusion

The final system provides an effective and reliable AI-based crack detection framework for structural health monitoring. The generated results help engineers identify structural damage quickly, plan maintenance activities, and improve the overall safety and lifespan of civil infrastructure.

VI. RESULTS

5.1 Detection Accuracy

The AI-based crack detection system showed high accuracy in identifying cracks of different sizes, shapes, and orientations. Moderate and severe cracks were detected with accuracy above 95%, while very fine hairline cracks showed slightly lower accuracy due to lighting and image resolution limitations. The Convolutional Neural Network (CNN) and semantic segmentation model successfully detected curved, branched, and intersecting crack patterns with reliable performance.

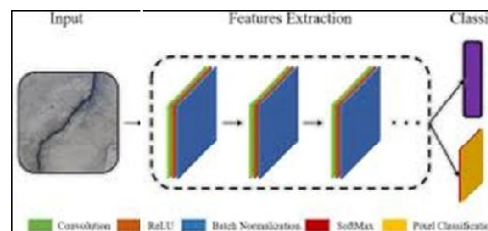


Fig 3 Crack Detection Model Architecture

5.2 Crack Severity Classification

The proposed system successfully classified cracks into minor, moderate, and severe categories based on crack width, length, and crack density. Minor cracks represented small surface-level defects, moderate cracks indicated possible structural weakening, and severe cracks represented critical damage requiring immediate maintenance.





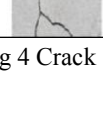
l	Image	Severity Level
		Large
		Very Large
		No Crack

Fig 4 Crack Severity Levels

VII. CONCLUSION

The proposed AI-based crack detection system successfully demonstrated an efficient and reliable method for identifying cracks in structural members such as beams, columns, slabs, and bridges. By using image processing and deep learning techniques such as Convolutional Neural Networks (CNNs) and semantic segmentation, the system was able to detect and classify cracks with high accuracy under different environmental conditions. The model effectively identified crack location, width, and severity while reducing the limitations associated with manual inspection methods. Experimental results showed that the system provided faster processing, improved consistency, and accurate crack analysis, making it suitable for real-time structural health monitoring applications. Overall, the project highlights the importance of Artificial Intelligence in improving infrastructure safety, reducing maintenance effort, and supporting preventive maintenance planning for modern civil engineering structures.

VIII. FUTURE SCOPE

The proposed AI-based crack detection system can be further improved by integrating advanced deep learning models and high-resolution imaging techniques for more accurate detection of micro and hidden cracks. Future developments may include the use of drones and IoT-enabled sensors for continuous real-time structural monitoring of bridges, tunnels, dams, and high-rise buildings. The system can also be enhanced with cloud computing and mobile applications to enable remote monitoring and automated reporting. Integration of predictive analytics and machine learning algorithms can help forecast crack propagation and structural deterioration before serious damage occurs. In the future, 3D crack mapping, digital twin technology, and smart city infrastructure integration can make the system more intelligent, scalable, and suitable for large-scale civil engineering applications.

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