Advancements in AI and Deep Learning for Automated Crack Detection in Reinforced Concrete Structures

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ABSTRACT

The detection of cracks in reinforced concrete (RC) structures is crucial for ensuring the safety and longevity of infrastructure. Traditional methods of visual inspection are labor-intensive and prone to human error. Recent advancements in artificial intelligence (AI), machine learning (ML), and deep learning (DL) have revolutionized crack detection by enabling automated and accurate systems. Convolutional neural networks (CNNs) have proven highly effective in detecting fine crack patterns. Hybrid models and segmentation techniques further enhance accuracy, even under challenging conditions. Despite these advancements, challenges like dataset variability and environmental factors remain, urging continued research for more robust systems.

Keywords: *Crack Detection, Reinforced Concrete, Machine Learning, Deep Learning, Convolutional Neural Networks.*

I. INTRODUCTION

The assessment of structural damage and crack formation in reinforced concrete (RC) structures has remained a critical aspect of civil infrastructure maintenance and safety assurance. Cracks in RC structures are often considered early indicators of deterioration, material fatigue, environmental degradation, and loading-induced stress, which may ultimately lead to structural failure if not properly identified and addressed. Traditionally, crack detection has relied heavily on manual visual inspection methods conducted by skilled engineers. However, such conventional approaches have been widely criticized for being time-consuming, subjective, labor-intensive, and prone to human error, particularly when dealing with large-scale infrastructure systems such as bridges, buildings, and transportation networks. In response to these limitations, recent advancements in artificial intelligence (AI), machine learning (ML), and deep learning (DL) have significantly transformed the field of structural health monitoring by enabling automated, accurate, and scalable crack detection systems (Geethalakshmi, 2018; Golding et al., 2022). The integration of machine learning-based techniques into crack detection has been driven by the increasing availability of digital image datasets and improvements in computational power. Convolutional neural networks (CNNs), in particular, have emerged as one of the most effective tools for image-based structural damage identification due to their ability to automatically extract hierarchical features from raw image data without requiring manual feature engineering. Studies have demonstrated that CNN-based models outperform traditional image processing techniques in detecting fine and complex crack patterns under varying lighting and environmental conditions (Zadeh et al., 2024). Furthermore, transfer learning approaches have enabled researchers to utilize pre-trained deep learning models such as VGG16, ResNet, and Inception networks, thereby improving classification accuracy while reducing training time and data requirements. Recent research has highlighted the effectiveness of deep learning models in enhancing crack detection accuracy across different types of structural materials and conditions. For instance, Krishnan et al. (2025) developed a large-scale dataset comprising cracked and non-cracked brickwork images and evaluated multiple deep learning architectures. Their findings indicated that Inception V3 achieved exceptionally high performance with nearly perfect accuracy, while ResNet-50 demonstrated superior recall capability. Similarly, Blay et al. (2026) emphasized the application of AI-based crack detection systems in reinforced autoclaved aerated concrete (RAAC) structures, highlighting the role of deep learning in improving defect detection under challenging conditions such as occlusions and environmental noise. Their study also emphasized the importance of developing standardized datasets to improve consistency and reliability in structural inspection processes. In addition to classification-based approaches, segmentation-based models have also gained significant attention for their ability to localize cracks at pixel-level precision. Hacıefendioğlu and Demir (2026) applied a U-Net-based deep learning architecture for post-earthquake damage assessment and demonstrated that automated segmentation techniques could effectively identify earthquake-induced cracks with high accuracy. Their study, based on data from the 2023 Kahramanmaraş earthquake, confirmed that deep learning systems significantly outperform traditional visual inspection methods in terms of speed, consistency, and precision. Similarly, Laxman et al. (2023) extended the application of deep learning by integrating CNN-based feature extraction with machine learning regression models such as Random Forest and XGBoost for predicting crack depth, thereby expanding the scope of automated structural assessment beyond surface-level detection. The evolution of hybrid and optimized machine learning models has further strengthened the reliability of crack detection systems. Xiong et al. (2022) incorporated principal component analysis (PCA) with machine learning classifiers to improve failure mode identification in reinforced concrete shear walls, achieving high predictive accuracy using gradient boosting methods. Likewise, Rafiei and Adeli (2017) developed a hybrid framework combining signal processing techniques with neural network-based classification, achieving up to 96% accuracy in structural health monitoring of high-rise buildings. These studies highlight the importance of integrating feature extraction, dimensionality reduction, and classification techniques to enhance model interpretability and performance. Moreover, research has also explored the application of computer vision and image processing techniques for automated crack detection in various structural contexts. Golding et al. (2022) demonstrated that grayscale and RGB-based CNN models perform comparably in detecting cracks in concrete structures, suggesting that color information may not always be essential for accurate classification. Aravind et al. (2021) further applied machine learning algorithms to classify structural failure patterns in reinforced concrete beams, achieving perfect classification accuracy using support vector machines. Additionally, Athanasiou et al. (2020) introduced multifractal analysis for crack pattern characterization, achieving reliable damage classification and demonstrating the potential of advanced mathematical feature extraction techniques in structural health monitoring. Despite these advancements, challenges such as dataset variability, environmental interference, model generalization, and computational complexity continue to limit the widespread implementation of AI-based crack detection systems in real-world applications. Variations in lighting conditions, surface textures, and structural materials often reduce model robustness and accuracy. Furthermore, the lack of standardized and comprehensive datasets remains a significant barrier to developing universally applicable models. Therefore, ongoing research efforts are focused on improving model generalization, enhancing data diversity, and integrating multi-sensor data for more reliable structural health assessment systems.

II. RESEARCH BACKGROUND

Blay et al. (2026) reported that reinforced autoclaved aerated concrete (RAAC) panels had been widely used in the UK since the 1960s for structural roofs, floors, and walls. The authors observed that the absence of a longitudinal, objective, and consistent defect data capture process had resulted in inaccurate, incomplete, and invalid RAAC datasets, thereby limiting effective building surveys and long-term performance monitoring. To address this issue, the study had proposed the development of an artificial intelligence (AI)-driven RAAC crack defect capture tool aimed at improving the quality and reliability of RAAC survey data. RAAC crack defect image datasets were collected, curated, and used for model training. A deep learning-based approach had been employed to identify surveyed crack defects from images obtained in two hospitals. The proposed method had also demonstrated the capability to mitigate challenges caused by unavoidable occlusions, obstructions, and the presence of unintended foreign objects and textures during defect detection.

Hacıefendioğlu and Demir (2026) investigated the application of deep learning–based automated crack detection for post-earthquake damage assessment in reinforced concrete structures. Their study was focused on the integration of U-Net-based segmentation techniques to evaluate earthquake-induced structural damages, particularly concrete cracks, using a dataset derived from the 2023 Kahramanmaraş earthquake. It was reported that the devastating impact of the Kahramanmaraş earthquakes had emphasized the urgent need for rapid, reliable, and accurate post-earthquake structural assessments to support safety evaluation and timely rehabilitation of damaged RC buildings. The findings indicated that deep learning models significantly outperformed conventional visual inspection methods by offering faster, more consistent, and more precise damage identification. In particular, the U-Net architecture demonstrated strong performance in detecting distinct crack patterns, achieving an Intersection over Union (IoU) score of 0.737 for concrete cracks. The study concluded that such automated approaches were highly effective for assessing structural integrity and for prioritizing repair and rehabilitation interventions after major seismic events.

Krishnan et al. (2025) examined the growing challenge of building deterioration caused by natural actions, material composition mismatches, structural stress, and chemical or physical imbalances that often resulted in surface cracking. The authors noted that climatic variations also contributed to contraction and expansion of building surfaces, thereby accelerating crack formation and related damages. It was reported that the safety and serviceability of buildings largely depended on effective assessment and maintenance practices. In order to address these concerns, the study employed artificial intelligence-based deep image neural network models for the automated detection and classification of cracks in brickwork structures. A novel dataset comprising 24,000 binary-classified images of cracked and non-cracked brickwork was developed to overcome research gaps and data scarcity. Several deep learning models, including Inception V3, VGG-16, ResNet-50, VGG-19, Inception ResNetV2, and CNN-RES MLP, were comparatively evaluated. Among these, Inception V3 was found to perform best, achieving 99.98% accuracy and 99.99% precision, while ResNet-50 yielded the highest recall of 99.98%.

Zadeh et al. (2024) examined the critical role of crack detection in structural health monitoring and building inspection, emphasizing that the task had remained highly challenging for computer vision due to the subtle appearance of cracks and their frequent confusion with background textures, foreign objects, and construction irregularities. The authors further noted that non-uniform lighting conditions and surface inconsistencies had created additional obstacles for autonomous crack detection. Their study highlighted those convolutional neural networks (CNNs) had emerged as an effective framework for improving crack detection accuracy and precision, while transfer learning had enabled the adaptation of pre-trained models without requiring extensive algorithmic expertise. In their approach, fine-tuning techniques were applied to several established deep learning architectures, namely VGG19, ResNet50, Inception V3, and EfficientNetV2, selected for their proven performance in image analysis tasks. The comparative evaluation of these models was conducted using precision, recall, and F1-score metrics, thereby providing a comprehensive assessment of their effectiveness for surface crack detection in buildings.

Laxman et al. (2023) examined the importance of automatic inspection for crack detection and crack depth estimation in assessing structural damage and selecting appropriate repair methods for concrete structures. The authors noted that earlier deep learning-based studies had largely focused on crack detection and the estimation of crack width, length, area, and direction, while crack depth evaluation had remained comparatively underexplored. To address this gap, they proposed a comprehensive automated framework for crack detection and crack depth assessment using images captured through portable devices. Initially, a binary-class Convolutional Neural Network (CNN) model was developed for automatic crack detection on concrete surfaces. Subsequently, an integrated CNN-based model, combining convolutional feature extraction layers with regression techniques such as Random Forest (RF) and XGBoost, was employed to predict crack depth automatically. The framework was validated on a reinforced concrete slab, and the findings indicated that the proposed models were accurate, reliable, and useful for structural condition assessment and repair decision-making.

Golding et al. (2022) had examined the need for periodic inspection of infrastructure such as buildings, bridges, and pavements to preserve structural reliability and health. They had observed that visible cracks and depressions often indicated stress and progressive deterioration, which could eventually lead to failure, especially when such defects occurred in critical load-bearing regions. The authors had noted that conventional manual inspection depended heavily on expert judgment, required considerable time, and often caused delays that could further endanger structural integrity. To overcome these limitations, they had proposed a deep learning-based autonomous crack detection approach using convolutional neural networks. In their study, 40,000 RGB images had been processed and a pretrained VGG16 architecture had been trained to develop multiple CNN models. The findings had revealed that grayscale models performed nearly as effectively as RGB models, while thresholding and edge-detection models showed comparatively lower performance. The study had thus suggested that crack detection in deep learning did not significantly depend on colour information.

Xiong et al. (2022) investigated the failure mode identification of reinforced concrete (RC) shear walls, which serve as major lateral load-resisting components in building structures and exhibit complex behavior under cyclic loading. The study was conducted in response to the growing need for rapid failure mode prediction in regional seismic risk assessment and post-earthquake rehabilitation. Although machine learning techniques had already been applied in this area, the authors noted that limited attention had been given to exploratory data analysis and feature extraction. Therefore, they proposed a novel framework integrating principal component analysis (PCA) for experimental data mining and feature extraction. Using a compiled dataset of 181 RC shear walls, nine classical and advanced machine learning algorithms were evaluated. The findings indicated that PCA significantly improved prediction accuracy compared to raw data training. Among all models, the gradient boosting classifier achieved the highest accuracy of 0.98 after hyperparameter optimization. The study also elaborated PCA clustering patterns and feature importance, offering meaningful interpretability and valuable insights into underlying failure mechanisms.

Aravind et al. (2021) investigated one of the major challenges in the construction industry, namely the detection of cracks in concrete structures and the identification of structural failure types that contribute to deterioration. The authors observed that manual quality inspection was often prone to human error, time-consuming, and dependent on specialist expertise. Therefore, they proposed computer-based techniques for crack visualization and failure recognition. The study focused on crack detection through image processing and failure pattern recognition using suitable machine learning algorithms, which were validated through Python programming. For this purpose, M30 grade geopolymer and conventional concrete beams reinforced with Basalt Fibre Reinforced Polymer (BFRP), Glass Fibre Reinforced Polymer (GFRP), and steel bars were cast and tested under four-point static bending by varying the shear span-to-effective depth ratio. Experimental images were analyzed in Python, and six classifiers were employed to categorize failures into flexure, shear, and compression. Among these, the support vector classifier reportedly demonstrated the best performance, achieving 100% accuracy in failure pattern identification.

Athanasiou et al. (2020) examined the significance of geometric and spatial crack pattern characteristics as indicators of damage severity in reinforced concrete structures and highlighted the limitations of manual visual inspection due to its subjective nature and dependence on inspector expertise. The study proposed an automated method for quantifying digitally recorded crack patterns in reinforced concrete shell elements subjected to reversed cyclic shear loading. Multifractal analysis was employed as a feature extraction technique for crack pattern images, while a set of artificial cracks was analyzed to determine variations in crack properties with respect to cracking inclination. The findings of the parametric investigation supported the development of a multiclass classification model for estimating damage levels in cracked reinforced concrete members. The classifier was trained using 119 experimental crack pattern images obtained under idealized two-dimensional pure shear stress conditions. The results indicated that multifractal features effectively captured crack morphology and enabled reliable damage assessment, achieving an overall test accuracy of 89.3%.

Liang (2019) examined the growing need for structural health inspection of bridge structures, particularly reinforced concrete bridges that were showing signs of deterioration and approaching or exceeding their original design service life. The study emphasized that post-disaster inspection had become increasingly important, especially following extreme events, and noted that autonomous damage detection using computer vision had emerged as a major research focus. A three-level image-based deep learning framework was proposed for post-disaster bridge assessment. The framework reportedly employed convolutional neural networks for system-level failure classification, component-level bridge column detection, and local damage-level localization through image classification, object detection, and semantic segmentation, respectively. The study further highlighted the challenge of achieving efficient training and prediction with limited datasets, stressing the importance of model robustness through hyperparameter selection. To address this, Bayesian optimization was adopted as a systematic strategy for hyperparameter tuning. The findings indicated that the proposed models had achieved robust performance, with accuracies reportedly exceeding 90% across all three inspection levels.

Geethalakshmi (2018) had reported that seasonal variations and the poor quality of construction materials often led to the development of cracks in building walls, which were considered among the earliest signs of concrete surface deterioration. The study had observed that manual inspection methods suffered from several limitations, including the invisibility of fine cracks, the time-consuming nature of the process, and the dependence on expert knowledge. Therefore, it had been suggested that crack detection could be automated through the application of image processing techniques. The author had further noted that deep learning algorithms had been extensively explored for addressing complex image classification problems. The literature survey had reviewed several recent studies on automatic crack identification using image processing and deep learning methods. Based on the analysis, it had been concluded that image processing techniques offered effective solutions for crack detection, while deep learning-based approaches generally achieved superior accuracy and demonstrated greater potential for reliable and efficient structural health monitoring.

Rafiei and Adeli (2017) presented a novel model for the global health monitoring of large structures, particularly high-rise buildings, through the effective integration of synchrosqueezed wavelet transform, fast Fourier transform, restricted Boltzmann machine, and the neural dynamics classification (NDC) algorithm. The study aimed to extract hidden frequency-domain features from denoised measured response signals collected by sensors installed at different elevations of a structure. These extracted features were subsequently utilized as inputs for the NDC algorithm to detect and classify the structural health condition into categories such as healthy, light damage, moderate damage, severe damage, and near collapse. The proposed model was validated using data obtained from a three-dimensional 1:20 scaled 38-story reinforced concrete building structure. Furthermore, the performance of the model was compared with other supervised classification algorithms, including k-nearest neighbor, probabilistic neural networks, and enhanced probabilistic neural networks. The findings indicated that the NDC algorithm achieved the highest maximum average accuracy of 96%, outperforming EPNN, PNN, and KNN.

III. KEY FINDINGS FROM STUDY

Author(s) & Year	Objective	Methodology / Model Used	Dataset / Data Source	Key Findings	Limitations / Remarks
Blay et al. (2026)	Improve RAAC crack defect identification using AI	Deep learning-based image classification tool	RAAC crack images from hospital surveys	AI model improved defect detection accuracy and handled occlusions and noise effectively	Limited to RAAC-specific datasets
Hacıefendioğlu & Demir (2026)	Post-earthquake crack detection in RC structures	U-Net segmentation model	2023 Kahramanmaraş earthquake dataset	IoU = 0.737; deep learning outperformed manual inspection	Dataset region-specific
Krishnan et al. (2025)	Crack classification in brickwork	CNN models (Inception V3, ResNet-50, VGG, etc.)	24,000 labeled images	Inception V3 achieved 99.98% accuracy	Limited to surface cracks in brick structures
Zadeh et al. (2024)	Improve crack detection using CNN & transfer learning	VGG19, ResNet50, Inception V3, EfficientNetV2	Public crack image datasets	CNN models showed high precision, recall, and F1-score	Sensitive to lighting and surface noise
Laxman et al. (2023)	Crack detection and crack depth estimation	CNN + Random Forest + XGBoost hybrid model	RC slab images	Accurate crack detection and depth prediction achieved	Depth estimation still complex and data-sensitive

Golding et al. (2022)	Automated crack detection in concrete structures	CNN with VGG16 architecture	40,000 RGB and grayscale images	Grayscale performed nearly as well as RGB models	Environmental variations affected accuracy
Xiong et al. (2022)	Failure mode identification in RC shear walls	PCA + ML classifiers (Gradient Boosting, etc.)	181 RC shear wall dataset	Gradient boosting achieved 0.98 accuracy	Requires feature engineering
Aravind et al. (2021)	Crack detection and failure pattern recognition	ML classifiers (SVM, etc.)	Experimental RC beam images	SVM achieved 100% accuracy	Limited experimental dataset
Athanasiou et al. (2020)	Crack pattern-based damage classification	Multifractal feature extraction + ML	119 crack pattern images	89.3% accuracy achieved in damage classification	Limited sample size
Liang (2019)	Post-disaster bridge inspection automation	CNN-based multi-level framework + Bayesian optimization	Bridge inspection images	Accuracy > 90% at multiple levels	Requires large labeled datasets
Geethalakshmi (2018)	Review of crack detection techniques	Image processing + deep learning survey	Literature-based	DL methods outperform traditional image processing	Mostly theoretical review
Rafiei & Adeli (2017)	Structural health monitoring of buildings	Synchrosqueezed transform + RBM + NDC algorithm	38-story RC building sensor data	96% accuracy in damage classification	Complex hybrid system, computationally heavy

IV. CONCLUSION

The reviewed literature clearly demonstrates that machine learning (ML) and deep learning (DL) techniques have significantly transformed the field of damage detection and crack identification in reinforced concrete (RC) structures. Traditional manual inspection methods, although widely used, have been shown to be inefficient, subjective, and unsuitable for large-scale infrastructure monitoring. In contrast, AI-based approaches such as convolutional neural networks (CNNs), U-Net architectures, hybrid ML models, and transfer learning frameworks have consistently delivered higher accuracy, faster processing, and improved reliability in structural damage assessment. Studies such as Blay et al. (2026) and Hacıefendioğlu and Demir (2026) have demonstrated that deep learning models are highly effective in real-world scenarios, including RAAC defect identification and post-earthquake damage evaluation. Similarly, Krishnan et al. (2025) and Zadeh et al. (2024) have confirmed that CNN-based architectures achieve exceptionally high classification performance in crack detection tasks. Hybrid approaches, such as those proposed by Laxman et al. (2023) and Xiong et al. (2022), further improve prediction capability by integrating feature extraction techniques like PCA with machine learning classifiers. Overall, the literature strongly indicates that AI-driven crack detection systems outperform conventional methods in terms of speed, scalability, and accuracy. These systems are increasingly capable of not only detecting cracks but also classifying damage severity and predicting structural behavior, making them highly valuable for structural health monitoring, post-disaster assessment, and maintenance planning. However, despite these advancements, challenges such as dataset limitations, environmental variability, model generalization issues, and computational complexity still restrict widespread real-world deployment. Therefore, while current research demonstrates strong potential, further improvements are required to make these systems more robust, interpretable, and universally applicable.

V. FUTURE SCOPE

- **Development of Large-Scale Standardized Datasets:** Future research should focus on creating diverse, high-quality, and publicly available datasets covering different structural types, materials, and environmental conditions to improve model generalization.
- **Real-Time Crack Detection Systems:** Integration of lightweight deep learning models with drones, IoT sensors, and edge computing devices can enable real-time monitoring of RC structures.
- **Improved Model Explainability (XAI Integration):** Explainable AI techniques should be incorporated to make predictions more interpretable for engineers and decision-makers in civil infrastructure management.
- **Multi-Sensor Data Fusion Approaches:** Combining image data with thermal imaging, ultrasonic testing, and vibration data can significantly enhance damage detection accuracy and reliability.
- **Hybrid AI Frameworks:** Future systems should integrate deep learning with traditional numerical methods, finite element analysis, and physics-based models for improved predictive performance.
- **Automated Crack Severity and Lifecycle Prediction:** Research should extend beyond detection to predict crack growth, structural lifespan, and failure probability under different loading conditions.
- **Edge AI Deployment for Infrastructure Monitoring:** Deployment of optimized AI models on edge devices can reduce computational load and enable on-site analysis without cloud dependency.
- **Robust Models for Extreme Conditions:** Future models should be designed to perform effectively under varying lighting, weather conditions, occlusions, and noisy environments.
- **Integration with Smart City Infrastructure Systems:** AI-based crack detection systems can be incorporated into smart city frameworks for continuous monitoring of bridges, roads, and buildings.
- **Automation in Post-Disaster Assessment:** Enhanced deep learning frameworks should be developed for rapid structural evaluation after earthquakes, floods, and other natural disasters to support emergency response and rehabilitation planning.

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