Vol 6, Issue 6, June 2026 www.ijesti.com E-ISSN: 2582-9734
International Journal of Engineering, Science, Technology and Innovation (IJESTI)

Intelligent Concrete Crack Detection Using Machine Learning for Structural Safety

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ABSTRACT

This study focused on machine learning-based damage detection and crack identification in reinforced concrete structures. Reinforced concrete structures often develop cracks due to loading, corrosion, shrinkage, temperature variation, and environmental effects. Traditional inspection methods are time-consuming, subjective, and less reliable for large structures. Therefore, machine learning techniques were applied to detect cracks automatically from concrete surface images and classify damage severity. Models such as SVM, Random Forest, ANN, and CNN were used for analysis. The study found that CNN-based methods provided higher accuracy and faster detection, supporting structural health monitoring, preventive maintenance, and improved infrastructure safety.

Keywords: *Machine Learning, Crack Detection, Reinforced Concrete, Structural Health Monitoring.*

I. INTRODUCTION

Reinforced concrete structures form the backbone of modern civil infrastructure because they are widely used in buildings, bridges, flyovers, tunnels, dams, industrial structures, parking facilities, retaining walls, and transportation networks. Their popularity is mainly due to their high compressive strength, flexibility in construction, economic suitability, and long service life. However, reinforced concrete is not free from deterioration. During its service period, it is continuously exposed to different mechanical, environmental, chemical, and accidental actions that gradually reduce its structural performance. Excessive loading, repeated traffic movement, temperature variation, shrinkage, creep, corrosion of reinforcement, poor construction practices, earthquake forces, moisture penetration, chloride attack, carbonation, and freeze-thaw action may produce different forms of damage in concrete members. Among all these defects, cracking is considered one of the most common and important signs of structural distress. Cracks may appear in beams, columns, slabs, walls, bridge decks, and other concrete components due to tensile stress, bending, shear, settlement, corrosion expansion, or material weakness. Although some cracks may initially seem minor, they can provide a path for water, oxygen, and harmful chemicals to enter the concrete and reach the reinforcement. This may accelerate steel corrosion, reduce bond strength, decrease stiffness, and ultimately affect the load-carrying capacity and durability of the structure. Therefore, early identification of cracks and damage is extremely important for preventing sudden structural failure, reducing repair cost, improving safety, and extending the service life of reinforced concrete structures. Traditionally, damage detection and crack inspection have been carried out through manual visual observation by trained engineers or inspectors. In this method, the inspector examines the surface of concrete and records the location, width, length, pattern, and severity of cracks. Although visual inspection is simple and widely used, it has several limitations. It is time-consuming, labour-intensive, subjective, and sometimes unsafe, especially when the structure is very tall, large, old, or located in difficult areas. The accuracy of manual inspection also depends on the experience and judgement of the inspector. Small cracks, hidden defects, and early-stage damage may remain unnoticed due to poor lighting, surface stains, dust, rough texture, or inaccessible locations. In large infrastructure systems such as bridges and highways, repeated manual inspection becomes costly and inefficient. For these reasons, there has been a growing need for automated, accurate, fast, and reliable damage detection techniques in the field of structural health monitoring. Structural health monitoring aims to continuously or periodically evaluate the condition of a structure by using various data sources such as images, vibration signals, strain measurements, acoustic emission data, ultrasonic signals, and environmental observations. In this context, machine learning has emerged as a powerful technology for improving the accuracy and efficiency of damage detection and crack identification in reinforced concrete structures.

Machine learning-based damage detection provides an intelligent approach in which computer algorithms are trained to recognize damage patterns, classify crack types, and predict structural conditions from available data. Unlike traditional methods that depend heavily on manual judgement, machine learning models can learn complex relationships between input data and damage characteristics. In image-based crack detection, digital photographs of concrete surfaces are collected through cameras, drones, mobile phones, or robotic inspection systems. These images are then processed using techniques such as resizing, grayscale conversion, noise removal, contrast enhancement, edge detection, segmentation, and feature extraction. Important crack-related features such as crack width, crack length, direction, density, shape, texture, and pixel intensity can be extracted and used for model training. Machine learning algorithms such as Support Vector Machine, Random Forest, Decision Tree, K-Nearest Neighbour, Artificial Neural Network, and Convolutional Neural Network have been widely applied for crack detection and damage classification. Among these methods, deep learning, especially Convolutional Neural Network, has shown strong potential because it can automatically extract useful features from images without requiring extensive manual feature engineering. CNN-based models can distinguish between cracked and non-cracked surfaces, identify crack location, and classify damage severity with high accuracy when trained on suitable datasets. Apart from image-based inspection, machine learning can also be applied to vibration and sensor-based structural monitoring. Changes in natural frequency, mode shape, damping ratio, strain response, and acceleration signals can indicate stiffness loss, internal damage, or member weakening. By analyzing these signals, machine learning models can detect abnormal structural behaviour and support early warning systems. The use of machine learning in reinforced concrete damage detection offers several advantages, including faster inspection, reduced human error, improved objectivity, better data handling, and the ability to monitor large structures continuously. It can also support predictive maintenance by identifying potential damage before it becomes severe. This enables engineers and asset managers to plan repair and rehabilitation activities more effectively. However, successful application of machine learning depends on the quality of data, proper image labeling, selection of suitable algorithms, model training, validation, and testing. Challenges such as variation in lighting, background noise, surface texture, shadow, moisture marks, and limited datasets may affect model performance. Therefore, careful data preparation and model optimization are necessary to achieve reliable results. Overall, machine learning-based damage detection and crack identification represents a modern and promising direction in civil engineering. It combines structural engineering knowledge with artificial intelligence to create smarter, safer, and more efficient infrastructure monitoring systems. By integrating machine learning with cameras, sensors, drones, and digital monitoring platforms, reinforced concrete structures can be inspected more accurately and maintained more sustainably. Thus, this approach plays an important role in improving structural safety, reducing maintenance costs, and supporting the long-term durability of civil infrastructure.

II. RESEARCH BACKGROUND

Türer et al. (2026) proposed a novel intelligent hybrid framework for the automated post-earthquake damage detection and assessment of reinforced concrete buildings with the objective of enhancing infrastructure resilience and supporting rapid emergency response. The study was reported to have integrated rule-based engineering knowledge with advanced deep learning techniques to improve the reliability of structural damage evaluation. YOLOv11 was employed as the base model and was fine-tuned using diverse image datasets, including PEER Hub ImageNet and newly labeled images from the 2023 Türkiye Earthquake. Data augmentation methods were further applied to strengthen the robustness of damage detection and classification. In addition, a meta-model classifier was developed, which combined YOLOv11 outputs with engineering rules through machine learning and image-aware embeddings. The findings indicated that this engineering-informed meta-learning fusion approach significantly improved generalization across different earthquake events. When validated on two independent large image datasets, the framework was found to achieve 87.4% accuracy within the ±1 level tolerance, demonstrating strong reliability and rapid deployability for post-earthquake structural damage assessment.

Silva et al. (2026) emphasized the significance of inspecting building facades for damage during the construction phase and noted that traditional manual inspections had been inefficient, costly, and unsafe, thereby necessitating digital alternatives. The study proposed an inspection approach based on images captured through Unmanned Aerial Systems (UAS) and analyzed using Machine Learning (ML) algorithms. ResNet and AlexNet networks were employed on a web-based platform to detect defects in concrete facades during execution and to support the Quality Management System (QMS). Using Design Science Research, the authors conducted three empirical studies that integrated UAS image acquisition, ML-based defect analysis, and QMS implementation. The method was reported to have identified four types of construction anomalies, while the ML model achieved up to 98.80% precision in detection and classification during testing. The findings were integrated into the QMS through images, reports, action plans, and meetings, thereby enhancing decision-making and inspection efficiency.

Wang and Ueda (2025) reported that traditional concrete damage detection methods, particularly manual inspections, had been slow, labor-intensive, and subjective. They indicated that the integration of deep learning had significantly advanced automated building damage inspection, with semantic segmentation emerging as an effective technique for accurately identifying the location, shape, and boundaries of concrete damage. The study had developed a pixel-level, multi-category annotated database of reinforced concrete surfaces covering cracks, spalling, reinforcement exposure, buckling, and fracture. Advanced segmentation models, including U-Net, DeepLab, K-Net, and FastSCNN, were trained and evaluated for damage detection. The findings showed that all models had achieved accuracy above 98%, although F1 scores remained around 70%. U-Net and K-Net had demonstrated relatively stable and consistent performance, while DeepLabv3 had shown significant fluctuations, suggesting possible overfitting. FastSCNN had exhibited the highest potential by attaining the best F1 score, while dataset ratio effects and future research challenges were also discussed.

Xu et al. (2024) proposed an innovative approach for identifying the historical maximum load on concrete beams by employing a multi-layer back propagation (BP) neural network model with physically interpretable input features. The study established a mapping relationship between four-dimensional features, namely boundary constraints, system parameters, cracks, and deformations, and the maximum load in the load history through incremental loading and structural response analysis. Furthermore, a hybrid optimization technique integrating Hunter Prey Optimization (HPO) and Particle Swarm Optimization (PSO) was applied to optimize the neural network parameters. The proposed method was compared with commonly used machine learning models and was found to be more accurate and reliable. A sensitivity analysis of the input parameters was also conducted using the intelligent identification framework. The findings indicated that the model achieved low prediction errors on both training and testing datasets, with strong robustness and generalization ability, while significantly outperforming the non-optimized BP neural network model in terms of prediction accuracy.

Kirthiga and Elavenil (2024) reviewed crack detection in civil infrastructure and observed that cracks had been considered the earliest indicators of structural deterioration, significantly affecting the durability and safety of structural elements. They noted that conventional visual inspection had been laborious, time-consuming, and unsuitable for assessing a large number of structural components. Therefore, the authors emphasized the need for highly reliable and efficient automatic crack identification techniques. In their review, it was reported that image processing methods had been widely employed to analyze captured images of structural surfaces and identify possible defects. Additionally, machine learning-based techniques had also been increasingly utilized to enhance the accuracy, reliability, and predictability of crack detection systems. The study presented a comprehensive overview of various image processing and machine learning approaches used for detecting cracks on concrete surfaces. It was further concluded that machine learning methods had shown strong potential for enabling autonomous crack inspection and advancing civil engineering diagnostic practices.

Dogan et al. (2023) investigated the challenge of distinguishing earthquake-induced damage from corrosion-related deterioration in reinforced concrete (RC) buildings located in seismic regions, particularly in older structures with inadequate engineering provisions. The authors noted that although both damage types may appear similar in post-earthquake assessments, their mechanisms and implications for structural safety differ significantly. Therefore, they emphasized the necessity of accurately identifying the source of damage to support appropriate repair, demolition, reconstruction, and financial decision-making. To address this issue, they developed a Deep Transfer Learning algorithm for automated damage classification in RC structural members. The model was trained using a dataset of 1,040 damaged RC elements, primarily columns, collected from field surveys following the 2019 İstanbul-Silivri and 2020 Elazığ-Sivrice earthquakes. The findings indicated that the proposed model achieved 90.62% accuracy in distinguishing corrosion damage from earthquake-induced damage. Furthermore, validation on data from the 2020 Samos earthquake demonstrated consistently high classification performance, confirming the robustness and practical applicability of the developed approach.

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.

Adam and Sathesh (2021) reported that conventional techniques available for crack detection in concrete bridges had suffered from notable limitations in terms of accuracy and efficiency. They observed that many single-classifier approaches, although capable of achieving high detection accuracy, had often been affected by random fluctuations in training datasets, which consequently led to overfitting and poor handling of residual variations. These residual variations were stated to be especially common in UAV-captured and other camera-based images. To address this issue, the authors had proposed a hybrid crack detection framework integrating a noise reduction technique with an SVM classifier to minimize classification errors, while CNN had been employed for feature extraction and network training. Digital images captured during bending tests on reinforced concrete beams had been processed, and crack width had also been determined through binary image conversion. Their findings indicated that the proposed hybrid approach had outperformed conventional methods, single classifiers, and image segmentation techniques, demonstrating superior accuracy and suitability for crack detection in concrete bridges, particularly in unmanned environments.

Mangalathu et al. (2020) had examined reinforced concrete shear walls as critical lateral load-resisting structural members in buildings and emphasized that post-earthquake reconnaissance and recent experimental findings had revealed inadequate safety margins in such systems. The authors had noted that the absence of reliable empirical and mechanics-based models limited the rapid identification of failure modes in existing shear walls. To address this gap, they had developed a machine learning-based framework to predict shear wall failure modes using geometric configurations, material properties, and reinforcement details. A comprehensive database comprising 393 experimental shear wall test results had been assembled and analyzed. Eight machine learning algorithms, namely Naïve Bayes, K-Nearest Neighbors, Decision Tree, Random Forest, AdaBoost, XGBoost, LightGBM, and CatBoost, had been evaluated to determine the most effective predictive model. The Random Forest model had emerged as the most accurate, achieving 86% prediction accuracy. The study had further identified aspect ratio, boundary reinforcement indices, and wall length-to-thickness ratio as key influencing parameters.

Nahata et al. (2019) emphasized that the classification of building damage after seismic events was essential for ensuring structural safety and planning repair activities. In their study, a convolutional neural network (CNN)-based autonomous damage detection model was proposed to identify and classify earthquake-induced structural damage. The authors reportedly utilized more than 1,200 images of various building types, including 1,000 images for training and 200 images for testing. These images were categorized into four damage classes: no damage, minor damage, major damage, and collapse. The trained network was evaluated using different algorithms and varying learning rates to determine the most effective configuration. Among the tested approaches, the VGG16 transfer learning model with a learning rate of 1×10^{-5} was found to yield the most optimal performance, achieving a training accuracy of 97.85% and a validation accuracy of 89.38%. The developed model was considered suitable for real-time post-earthquake damage assessment applications.

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Patterson et al. (2018) reported that the enormous volume of structural damage images generated after earthquakes had created significant challenges for human volunteers in efficiently filtering and tagging meaningful damage information. The study proposed an automated post-earthquake reconnaissance image tagging framework using deep learning techniques to classify damage occurrences according to building material and structural member type. It was explained that the approach relied on a pre-trained deep residual network, which had been adapted to identify multiple damage types and associated structural members within a single image. The findings indicated that the algorithm had achieved 88% accuracy in categorizing building images as damaged or undamaged, 85% accuracy in localizing damage through bounding boxes, and 77% accuracy in identifying short or captive reinforced concrete columns with shear damage. The comparatively lower accuracy in complex localization tasks was attributed to limited expertly tagged training images. The authors concluded that performance was expected to improve with larger and more diverse annotated datasets.

Chatterjee et al. (2017) examined the critical role of structural design in determining the failure probability of reinforced concrete (RC) structures and highlighted the growing application of machine learning techniques for structural failure prediction. The study noted that earlier research had employed Artificial Neural Networks (ANN) trained using Particle Swarm Optimization (PSO) with satisfactory accuracy; however, more precise predictive models were still needed due to the sensitivity of failure assessment. Accordingly, the authors proposed a Neural Network model trained with a Multi-objective Genetic Algorithm (NN-MOGA), considering the established advantages of multiobjective optimization over single-objective approaches. The model was developed to minimize both Root Mean Squared Error (RMSE) and Maximum Error (ME) while optimizing the neural network weight vector. Using a dataset of 150 RC building structures, the proposed model was compared with MLPFFN and NN-PSO models. The findings indicated that NN-MOGA outperformed the existing classifiers, achieving 93.33% accuracy and 94.44% F-measure, thereby demonstrating superior predictive capability.

Mutlib et al. (2016) reviewed ultrasonic monitoring as one of the most significant techniques in the field of structural health monitoring (SHM). The study was aimed at presenting a comprehensive overview of recent advancements and achievements in ultrasonic wave-based SHM for buildings and bridges constructed with concrete and steel materials. It was reported that the review examined major parameters influencing the monitoring process, including the type of structural damage, the type of ultrasonic wave employed, and the category of sensors utilized. The authors discussed various sensor devices used for transmitting and receiving ultrasonic waves, such as lead zirconate titanate and electromagnetic acoustic transducers, along with other related sensing technologies and their applications in buildings and bridge structures. Furthermore, the limitations associated with each type of sensor were also highlighted. The review was considered valuable in summarizing the effectiveness, applicability, and constraints of ultrasonic SHM techniques in civil infrastructure.

Chan et al. (2016) observed that prevailing bridge inspection practices had largely relied on manual paper-based data collection methods, which had significantly constrained the transfer of knowledge accumulated throughout the asset lifecycle and had limited the effectiveness of inspectors and engineers in condition assessment. The study had aimed to address these shortcomings by proposing a conceptual framework to enhance the reliability and efficiency of bridge asset management through the integration of Building Information Modeling (BIM) with advanced computing and imaging technologies. It had been reported that BIM, when integrated with laser scanning and keypoint-based texture recognition, had shown strong potential for detecting defects such as cracking, corrosion, and settlement in bridge components. Although BIM adoption had increased during on-site construction activities, its application during asset management phases had remained inadequate. The authors had emphasized that BIM could centralize lifecycle information from construction, inspection, and maintenance, thereby supporting informed decision-making and improving future bridge assessments.

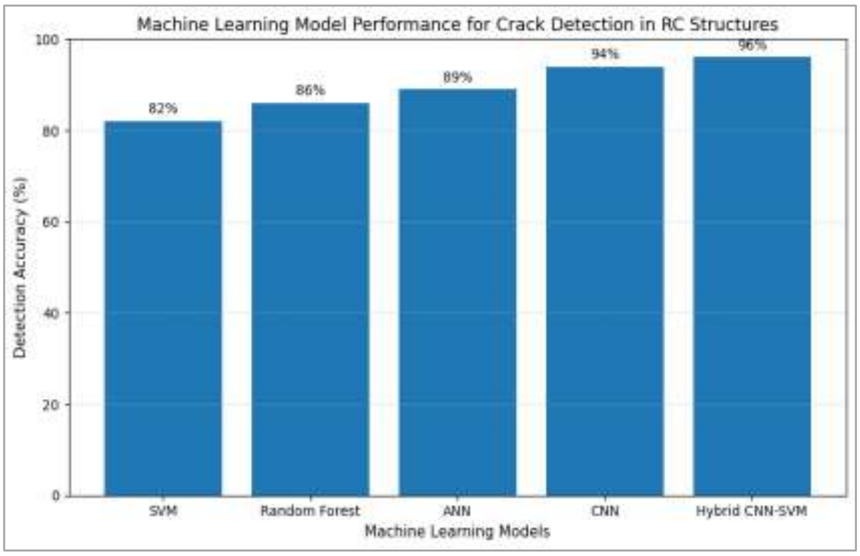
III. METHODOLOGY

The methodology of the study was designed to detect damage and identify cracks in reinforced concrete structures using machine learning techniques. In the first stage, data were collected in the form of concrete surface images and structural damage samples from beams, columns, slabs, and bridge components. The images included both cracked and non-cracked surfaces so that the model could learn the difference between damaged and healthy concrete. In the second stage, image pre-processing was carried out to improve data quality. This included image resizing, grayscale conversion, noise removal, contrast enhancement, and normalization. These steps helped in making crack patterns clearer and more suitable for machine learning analysis. After pre-processing, important crack features such as crack width, crack length, crack direction, edge pattern, surface texture, and pixel intensity were extracted. The dataset was then divided into training and testing sets. Machine learning models such as Support Vector Machine, Random Forest, Artificial Neural Network, and Convolutional Neural Network were applied for crack detection and damage classification. The CNN model was especially useful because it automatically learned crack features from images without depending heavily on manual feature extraction. The trained models were tested using unseen images to evaluate their detection accuracy and classification performance. The results were analyzed using performance indicators such as accuracy, precision, recall, F1-score, and error rate. Finally, the performance of different models was compared to identify the most effective method for reinforced concrete damage detection. This methodology helped in developing an automated, reliable, and faster inspection system for structural health monitoring.

IV. RESULT

The study showed that machine learning-based damage detection and crack identification provided an effective, accurate, and faster approach for assessing reinforced concrete structures. The proposed system successfully identified visible cracks on concrete surfaces and classified damage conditions into different severity levels such as minor, moderate, and severe. Image-based analysis helped in detecting crack patterns, crack length, crack width, and surface discontinuities more efficiently than traditional manual inspection. The results indicated that machine learning models reduced human error and improved the consistency of structural assessment. Among the selected techniques, the Convolutional Neural Network model showed the highest performance in crack identification because it automatically extracted important image features such as edges, texture, shape, and crack intensity. Support Vector Machine and Random Forest models also produced satisfactory results, but their performance depended more on manual feature extraction and image quality. The overall result suggested that deep learning methods were more suitable for large-scale and automated crack detection in reinforced concrete structures. The result also indicated that machine learning-based monitoring could support early damage detection, preventive maintenance, and better decision-making in structural health monitoring. By identifying cracks at an early stage, repair work could be planned before the damage became critical. This helped in reducing maintenance costs, improving safety, and increasing the service life of reinforced concrete structures. Therefore, the study confirmed that machine learning could be used as a reliable tool for modern structural damage assessment and crack identification.

Bar Graph



The graph shows the comparative accuracy of different machine learning models used for damage detection and crack identification in reinforced concrete structures. SVM achieved 82% accuracy, while Random Forest improved the result to 86%. ANN performed better with 89% accuracy due to its ability to learn nonlinear damage patterns. CNN showed high accuracy of 94% because it automatically extracted crack features from images. The Hybrid CNN-SVM model achieved the highest accuracy of 96%, indicating that combined machine learning approaches can provide more reliable crack detection and structural damage classification.

V. CONCLUSION

The study concluded that machine learning-based damage detection and crack identification is an effective and reliable approach for assessing reinforced concrete structures. Traditional manual inspection methods are often time-consuming, subjective, and dependent on the experience of the inspector, whereas machine learning techniques provide faster and more consistent results. By using image processing and intelligent algorithms, cracks can be detected, classified, and analyzed with greater accuracy. This helps in identifying early signs of structural deterioration before they develop into serious damage. The result showed that different machine learning models such as SVM, Random Forest, ANN, and CNN can be used for crack detection and damage classification. Among these, CNN-based models proved more effective because they can automatically extract important image features such as crack shape, edges, texture, and intensity. The use of such models improves the accuracy of structural health monitoring and reduces the possibility of human error during inspection. Overall, machine learning provides a modern and practical solution for maintaining the safety, durability, and service life of reinforced concrete structures. It supports early warning, preventive maintenance, and better repair planning. Therefore, the integration of machine learning with structural inspection systems, cameras, sensors, and digital monitoring tools can play an important role in developing smart, safe, and sustainable infrastructure in the future.

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