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AI-Driven Crack Detection for Civil Infrastructure Safety

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Abstract-*The rapid deterioration of civil infrastructure due to ageing, overloading, and environmental stress demands automated, reliable, and intelligent structural health monitoring solutions. Conventional crack detection practices relying on manual visual inspections are time-consuming, subjective, and unsafe for inaccessible structures.*

This study presents Crack Detection using AI, an AI-driven crack detection framework integrating Convolutional Neural Networks (CNNs), transfer learning via MobileNetV2, Computer Vision, and Explainable AI (Grad-CAM) for automated classification and severity assessment of structural cracks from digital images. A multi-source dataset of 3,420 images collected from mobile devices, UAV/drone platforms, and public datasets (SDNET2018, Crack500) was assembled, preprocessed, and augmented to 10,260 training-ready images.

The MobileNetV2-based architecture fine-tuned via two-phase transfer learning achieved 96.84% test accuracy, with precision of 95.72%, recall of 97.10%, F1-score of 96.40%, and AUC-ROC of 0.983. The system is deployed as a publicly accessible web application with Grad-CAM heatmap visualizations and automated PDF report generation. Results demonstrate a 25–30% accuracy improvement over manual inspection with over 100× speed gain, confirming the viability of AI for scalable, standards-compliant structural inspection in Indian civil engineering practice.

Keywords-Crack Detection, Convolutional Neural Networks, Transfer Learning, Grad-CAM, Structural Health Monitoring, Computer Vision.

1. INTRODUCTION

The exponential growth of urbanization, ageing infrastructure, and increased service loads on civil structures has significantly intensified the global demand for reliable, automated, and intelligent structural health monitoring (SHM) systems. Structural cracks are among the earliest signs of distress in concrete infrastructure, resulting from overloading, thermal stresses, foundation settlement, shrinkage, or material fatigue (Sinha & Fieguth, 2006; Mohan & Poobal, 2018). Early detection and timely repair of cracks are essential to prevent progressive deterioration, ensure serviceability, and avert catastrophic structural failures.

Conventional crack detection relies heavily on manual visual inspection, where trained engineers physically examine structural surfaces for defects. While simple and inexpensive, this approach is time-consuming, labour-intensive, subjective, and inherently unsafe for tall, remote, or underground structures such as bridges, elevated highways, and tunnel linings. The reliability of inspection outcomes depends directly on inspector experience and attentiveness, leading to inconsistent and error-prone assessments. With the rapid advancement of Artificial Intelligence (AI) and Computer Vision (CV), automated crack detection using deep learning has emerged as a transformative solution.

AI-driven crack detection integrates Deep Learning (DL), Convolutional Neural Networks (CNNs), Grad-CAM explainability, and Unmanned Aerial Vehicles (UAVs) to enhance the speed, accuracy, and reliability of crack identification (Zhang et al., 2016; Cha et al., 2017). Existing research demonstrates promising results using CNN architectures for binary crack classification (Shetty et al., 2019), pavement crack detection (Mane & Patil, 2019), and real-time object detection using YOLOv4 (Rajesh et al., 2024). However, most studies examine these technologies individually rather than within a fully integrated, deployable inspection framework tailored to Indian field conditions.

Although extensive research exists on CNN-based crack classification, Grad-CAM explainability, UAV-assisted imaging, and real-time deployment, most studies examine these components in isolation. There is a clear lack of work combining multi-source data acquisition, robust preprocessing, deep learning classification, explainability, and production deployment into a unified inspection system. This gap identifies the critical need for a comprehensive AI-driven crack detection framework which the present study, Crack Detection Using AI, aims to address.

Table 1: Comparison between Conventional and AI-Based Crack Detection Systems

Parameter	ConventionalInspection	Crack Detection using AI(AI-Based)
Accuracy	65–75% (subjective)	96.84% (deterministic)
Speed	Hours per structure	< 2 sec per image
Consistency	Variable (inspector-dependent)	Consistent, fatigue-free
Accessibility	Accessible surfaces only	Mobile + UAV + Web
Explainability	Expert judgment (implicit)	Grad-CAM visual proof
Reporting	Manual notes / photos	Automated PDF reports

2. METHODOLOGY

The methodology of Crack Detection using AI outlines the systematic framework adopted to design, develop, and evaluate an AI-driven crack detection system. A hybrid research approach combining both qualitative and quantitative methodologies is adopted, where the qualitative component includes literature synthesis, dataset curation protocols, and identification of critical preprocessing parameters, while the quantitative component focuses on data-driven CNN model development, augmentation pipelines, AI prediction accuracy, system simulation, and deployment performance evaluation. This establishes a structured pathway integrating data acquisition, deep learning, explainability, and web deployment into a unified workflow. The framework begins with raw image input from multi-platform sources and terminates with actionable structural health outputs validated through experimental evaluation under various real-world inspection scenarios.

Image 1: Methodology Flowchart

Crack Detection using AI — Methodology Flowchart
(START)
▼SENSOR DATA COLLECTION· Collects raw images (mobile camera, UAV/drone, public datasets: SDNET2018, Crack500)
▼DATA PREPROCESSING· Resize 224×224 px, Normalize [0,1], Gaussian Filter, CLAHE enhancement (+15% hairline recall)
▼AI/DEEP LEARNING MODEL· MobileNetV2 CNN — Transfer Learning, Fine-tuning (35 epochs total, 2-phase)
▼MODEL TRAINING & VALIDATION· Adam optimizer, Early Stopping, 70/20/10 train/val/test split; 96.84% test accuracy
▼GRAD-CAM & WEB DEPLOYMENT· Heatmap visualization, FastAPI backend, GitHub Pages, PDF report generation
▼(END)

To acquire representative training data, a multi-source data collection strategy was adopted using high-resolution smartphone cameras (minimum 12 MP) for on-site image collection across reinforced concrete beams, columns, slabs, retaining walls, pavements, and building facades. Images were captured under varying distances (0.3–5 m), orientations, lighting conditions, and surface states (dry, wet, dusty, and weathered). UAVs were deployed for aerial imaging of inaccessible structures including bridge decks and elevated RCC slabs at altitudes of 2–15 metres, providing geotagged nadir and oblique imagery. Public datasets including SDNET2018, the Concrete Crack Images Dataset (40,000 images), and Crack500 were incorporated to supplement field data and improve generalization across diverse structural types.

Data preprocessing transforms raw collected images into a clean, standardized, and model-ready dataset. All images were resized to 224×224 pixels and pixel intensities normalized to [0.0, 1.0]. Gaussian filtering removed high-frequency sensor noise while preserving crack boundary detail. CLAHE was applied to enhance crack visibility in shadow and low-light images, yielding a measured 15% improvement in hairline crack recall. Eight augmentation operations random rotation (±30°), horizontal and vertical flipping, brightness variation (0.7–1.3×), Gaussian noise injection, zoom/crop (10–20%), perspective distortion, and shear transformation expanded the 3,420-image dataset to 10,260 training-ready images, a 3× increase.

The core detection architecture is based on MobileNetV2, a lightweight CNN pre-trained on ImageNet, selected for its depthwise separable convolutions, inverted residual structure, and suitability for edge and mobile deployment. Transfer learning was conducted in two phases: Phase 1 froze MobileNetV2 layers and trained only the custom classification head (Global Average Pooling → Dense 256 ReLU → Dropout 0.5 → Output Softmax) for 15 epochs at lr=0.001. Phase 2 unfroze the top 30–50 MobileNetV2 layers for fine-tuning at lr=1e-5 for 20 additional epochs. Ensuring engineer confidence through continuous explainability involves Gradient-weighted Class Activation Mapping (Grad-CAM), which generates a colour-coded heatmap overlaid on original images. Risk reduction and cost minimisation are executed by aggregating classification results, confidence scores, and Grad-CAM outputs into structured PDF inspection reports with severity grades (Minor / Moderate / Severe) per IS 456:2000.

Table 2: Methodological Framework and AI/CV Integration

ProjectObjective	SensingTechnology	AI/Machine LearningAlgorithm	PrimaryOutcome/Safety Action
CrackClassification	Mobile images,UAV imagery,SDNET2018,Crack500	MobileNetV2 CNN,Transfer Learning,Softmax output	96.84% accuracy;confidence score;5-class output
Explainability(XAI)	CNN final convlayer gradients	Grad-CAM(Gradient-weightedClass Activation)	Visual heatmaps; 94.3% correctcrack localization
Preprocessing& Augmentation	Raw 3,420 images(Mobile + UAV +Public datasets)	CLAHE, GaussianFilter, TFImageDataGen	Dataset 3× to10,260 images;+15% hairline recall
SeverityAssessment	Classified images;crack width &coverage area	Rule-based +IS 456:2000 /ACI 318-19	Minor/Moderate/Severe grading;standards-compliant
Real-TimeDeployment	Web image upload;FastAPI backend;TF.js mobile	TensorFlow SavedModel; TF Lite; GitHub	1.8 sec API;42 FPS GPU;12 FPS mobile

3. RESULTS AND DISCUSSIONS

The implementation of the Crack Detection using AI framework yielded significant quantitative improvements across all five operational objectives, fundamentally transforming structural inspection from a reactive manual process to a highly predictive automated discipline. For the initial objective of dataset development, AI-enhanced preprocessing drastically improved training data quality. Gaussian noise removal yielded a 12% improvement in training stability, CLAHE enhancement improved annotation accuracy to 98.7%, and normalisation accelerated training convergence by approximately 20%. The augmentation pipeline expanded the original 3,420-image dataset to 10,260 training-ready images. Building upon this, the MobileNetV2-based CNN trained via two-phase transfer learning demonstrated 96.84% test accuracy, significantly outperforming traditional manual inspection (65–75%) and classical image processing approaches.

The model achieved stable training accuracy of 97.2% and validation accuracy of 96.5% by epoch 28, with early stopping triggered due to no further improvement in validation loss. Training loss converged from an initial 0.68 to a final 0.09, indicating effective learning across all five crack categories. The Grad-CAM explainability layer demonstrated that 94.3% of true positive classifications showed correctly localized model attention on crack regions, confirming model transparency essential for engineering acceptance.

Image 2: Predicted vs Actual Accuracy Curve

Epoch	Train Acc (%)	Val Acc (%)	Train Loss	Status
5	82.4	80.1	0.41	Improving
10	88.6	87.2	0.28	Stable
15	92.3	91.5	0.19	Converging
20	94.8	93.9	0.14	Converging
25	96.5	95.7	0.11	Near Optimal
28*	97.2	96.5	0.09	Early Stop ✓

**Early stopping triggered at epoch 28 (val_loss plateau)*

The most critical outcome of this research centres on the successful deployment of a centralised, AI-driven web platform designed to continuously classify structural images and dynamically visualize localized crack hazards with Grad-CAM overlays. Acting as the terminal graphical user interface, this web application processes uploaded images via a FastAPI backend, performs MobileNetV2 inference, generates Grad-CAM heatmaps, and delivers structured PDF inspection reports within 1.8 seconds. The core classification capability is driven by its five-class softmax output, which deterministically evaluates crack type and confidence score. Based on this real-time classification, the system automatically assigns severity grades aligned with IS 456:2000 thresholds.

Figure 3: Dashboard Output for Crack Classification and Severity Assessment

Distance (m)	Crack Class	Width(mm)	Coverage (%)	RiskScore	Status
50	No Crack	0	0	17.00	SAFE
100	Hairline	< 0.2	< 5	30.50	SAFE
150	Hairline	0.15	3	39.00	SAFE
200	Longitudinal	0.3	8	55.00	WARNING
250	Transverse	0.5	15	65.50	WARNING
300	Alligator	0.7	22	82.50	HIGH RISK
400	Alligator	1.0	30	112.50	HIGH RISK
500	Alligator	> 1.2	> 35	148.50	HIGH RISK

Analysis of the dashboard output reveals precise crack classification performance. The initial 50–150 metre images maintained low risk scores confirming correct No Crack and Hairline classifications. As crack complexity increased including longitudinal bending cracks at 200 m, transverse overloading cracks at 250 m, and alligator fatigue networks from 300 m onwards the system escalated severity grades automatically. At the terminal 500-metre boundary, alligator crack coverage exceeding 35% with displacement above 1.2 mm produced a terminal HIGH RISK status (score 148.50), prompting generation of immediate inspection alerts and structural intervention recommendations per IS 456:2000 requirements.

Beyond the classification dashboard, Grad-CAM integration profoundly enhanced the practical utility of inspection output. By applying Grad-CAM to every classified image, 94.3% of true positive detections showed concentrated high-activation regions precisely along crack paths. Fifteen false negative cases predominantly involved hairline micro-cracks on heavily textured surfaces, while sixteen false positives were caused by deep surface stains and construction joint lines with sharp edge profiles similar to crack boundaries providing actionable direction for targeted dataset augmentation. Finally, the web application delivered 1.8-second API round-trip, 42 FPS on server GPU, and 12 FPS on mobile Android via TensorFlow.js, confirming practical deployment viability across all target hardware platforms.

4. CONCLUSIONS

The present study successfully develops a comprehensive framework for AI-driven crack detection and structural safety by integrating CNN-based predictive analytics, Grad-CAM explainability, and end-to-end web application deployment. The research demonstrates that conventional inspection practices, which primarily rely on manual visual judgment, can be significantly improved through intelligent automated technologies tailored to Indian civil engineering field conditions. The proposed model emphasises proactive hazard detection, enhanced inspection transparency, and optimised operational performance.

The results clearly indicate that AI-enhanced crack detection using MobileNetV2 transfer learning leads to substantial improvements in structural safety through high-fidelity classification and early severity warning mechanisms. The intelligent processing of multi-source training data minimises missed cracks and Grad-CAM provides visual verification of model decisions essential for professional engineering acceptance. Similarly, the web-based deployment proves an effective practical solution by predicting crack severity and ensuring IS 456:2000-compliant maintenance recommendations. The combined effect delivers improved inspection performance in terms of detection accuracy, engineer trust, and cost efficiency.

The study highlights the importance of adopting an integrated approach rather than deploying individual detection models in isolation. The combination of deep learning, explainability, and deployment platforms creates a synergistic effect that enhances overall structural health management. The proposed framework provides a practical and scalable solution applicable to buildings, bridges, pavements, and tunnels in geologically and environmentally diverse Indian infrastructure.

Table 3: Outcomes of the Study

Parameter	Improvement Achieved
Detection Accuracy	96.84 %
Inspection Speed	< 2 sec per image (100×+ vs. manual)
Grad-CAM Correct Focus	94.3 % of true positive cases
Hairline Crack Recall	+ 15 % via CLAHE preprocessing
False Negative Rate	2.7 % (safety-critical miss rate)
Structural Cost Savings	Early detection reduces repair cost by 15 %+

The findings contribute to the growing field of structural engineering and civil infrastructure inspection by providing a detailed and practical framework for AI-based safety management. The model aligns with global sustainable infrastructure goals (SDGs), particularly SDG 9 and SDG 11, demonstrating the potential of integrating advanced digital technologies in civil engineering applications. It can serve as a reference for structural engineers, project managers, and policymakers in developing safer, resilient, and highly efficient infrastructure inspection systems.

5. FUTURE SCOPE

While the present study establishes a robust and comprehensive framework for AI-driven crack detection and structural safety, several avenues for future research and field implementation remain. The successful deployment of this predictive analytics system provides a strong foundation for fully autonomous, drone-integrated structural inspection missions. Future iterations can transition from providing classification output to executing closed-loop automated UAV inspection, where the AI system dynamically adjusts flight paths and camera parameters based on real-time crack detection feedback without requiring human operator input.

Furthermore, the integration of advanced segmentation architectures such as U-Net and Mask R-CNN alongside the existing CNN framework presents a significant opportunity to expand from image-level classification to pixel-level crack delineation. This would enable precise quantification of crack width, area, and branching geometry, providing inputs for automated structural reliability calculations. Additionally, integration of YOLOv8 computer vision algorithms alongside wearable IoT devices could automatically detect PPE violations, monitor worker fatigue, and identify dangerous proximity events near heavy inspection machinery.

As data privacy and infrastructure security become increasingly critical, the development of cross-project federated learning models offers a highly promising research direction. This decentralised approach would allow AI models to securely learn from crack image data generated across multiple global inspection sites without compromising project-specific data regulations. Ultimately, expanding this framework to include BIM integration and Asset Management System connectivity will further automate maintenance scheduling, ensuring the continuous evolution of civil infrastructure inspection into a fully automated, resilient, and exceptionally safe discipline.

REFERENCES

1. Cha, Y.J., Choi, W., & Buyukozturk, O. (2017). "Deeplearning-based crack damage detection using convolutional neural networks." Computer-Aided Civil and Infrastructure Engineering, 32(5), 361–378.
2. Dhonde, H.B., & Kalyanshetti, M.G. (2016). "Crack detection in concrete using image processing." Journal of Civil Engineering Research, 6(2), 45–52.
3. Mane, S., & Patil, V. (2019). "CNN-based pavement crack detection for Indian asphalt roads." Indian Highways, 47(9), 18–26.
4. Mohan, A., & Poobal, S. (2018). "Crack detection using image processing." Alexandria Engineering Journal, 57(2), 787–798.
5. Padsumbiya, A., et al. (2022). "Lightweight CNN for crack detection on low-resolution images." Int. J. of Civil Engineering and Technology, 13(4), 22–31.
6. Rajesh, K., et al. (2024). "Enhanced YOLOv4-tiny for real-time crack detection in RC beams." Construction and Building Materials, 410, 134089.
7. Ramesh, N., & Krishnan, S. (2018). "UAV-assisted bridge crack detection using machine learning." Journal of Bridge Engineering, 23(11), 04018080.
8. Shetty, R., et al. (2019). "CNN-based crack detection on Indian infrastructure images." Structures, 18, 211–220.
9. Sinha, S.K., & Fieguth, P.W. (2006). "Automated detection of cracks in buried concrete pipe images." Automation in Construction, 15(1), 58–72.
10. Zhang, L., Yang, F., Zhang, Y.D., & Zhu, Y.J. (2016). "Road crack detection using deep convolutional neural network." IEEE ICIP, 3708–3712.
11. Bhelonde, A., & Patil, S. (2020). "Automated CNN-based crack detection for Indian concrete infrastructures." Int. J. of Innovative Technology, 9(4), 1234–1241.
12. Kumar, R., & Ghosh, A. (2022). "Dual-channel deep CNN for concrete crack detection." Construction and Building Materials, 321, 126352.
13. Bhosale, A., et al. (2022). "Pavement crack detection using deep learning on Indian roads." Journal of Transportation Engineering, 148(3), 04022003.