

Explainable Deep Learning Framework for Automated Concrete Crack Detection Using ResNet-18

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Abstract—Concrete crack inspection is an essential component of structural health monitoring and infrastructure maintenance. Conventional manual inspection methods are time-consuming, subjective, labor-intensive, and difficult to scale for large infrastructure systems. This paper presents an explainable deep learning framework for automated concrete crack detection using a fine-tuned ResNet-18 convolutional neural network integrated with Grad-CAM explainable artificial intelligence techniques. The proposed framework performs binary classification of cracked and non-cracked concrete surface images while simultaneously generating visual explanations highlighting crack-sensitive regions influencing prediction outcomes. Transfer learning techniques are employed to improve feature extraction efficiency and computational performance. Experimental evaluation demonstrated strong classification performance with an overall accuracy of 95.7%, precision of 95.1%, recall of 96.2%, and F1-score of 95.6%. A deployment-oriented web-based inspection interface was also developed to support automated infrastructure inspection workflows. The proposed framework demonstrates practical applicability for scalable, interpretable, and efficient structural health monitoring systems.

Keywords—Concrete Crack Detection, Deep Learning, Explainable AI, ResNet-18, Grad-CAM, Structural Health Monitoring, Infrastructure Inspection, Transfer Learning.

I. INTRODUCTION

Infrastructure monitoring plays an important role in ensuring the safety, reliability, and longevity of civil engineering structures such as bridges, tunnels, pavements, dams, and buildings. Concrete structures are continuously exposed to environmental stress, fatigue, aging, and mechanical loading conditions that may result in cracks and structural deterioration over time. Early crack detection is essential for preventing severe structural failures and reducing maintenance costs.

Traditional concrete inspection methods mainly rely on manual visual assessment performed by trained inspectors. Although widely practiced, manual inspection procedures are time-consuming, subjective, labor-intensive, and difficult to scale for large infrastructure systems. Variations in human judgment and environmental conditions may also affect inspection reliability and consistency.

Recent advancements in Artificial Intelligence (AI) and computer vision technologies have significantly improved automated crack detection systems [1], [3]. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated strong image classification and feature extraction capabilities [1]. However, many CNN-based systems operate as black-box models, limiting interpretability in safety-critical engineering applications.

Explainable Artificial Intelligence (XAI) techniques improve prediction transparency by visually identifying image regions contributing to model decisions [2]. Grad-CAM is one of the most widely adopted explainability techniques because it generates the localization heatmaps highlighting crack-sensitive regions influencing CNN predictions [2].

This paper presents an explainable deep learning framework for automated concrete crack detection using a fine-tuned ResNet-18 model integrated with Grad-CAM explainability visualization. The proposed framework combines crack classification, visual interpretability, and deployment-oriented infrastructure inspection support within a unified system.

II. LITERATURE REVIEW

A. Traditional Crack Detection Methods

Traditional concrete crack detection methods mainly relied on image processing techniques such as threshold segmentation, edge detection, and handcrafted feature extraction approaches [11], [14]. Although computationally simple, these methods often struggled under varying illumination conditions, complex surface textures, shadows, and environmental noise. Manual inspection processes also introduced subjectivity and inconsistency in structural assessment workflows, particularly for large-scale infrastructure systems.

B. Deep Learning and Explainable AI Approaches

Recent advancements in deep learning have significantly improved automated crack detection performance. Convolutional Neural Networks (CNNs) such as AlexNet, VGG16, ResNet, DenseNet, and EfficientNet demonstrated superior feature extraction and classification capability compared to conventional image processing methods [1], [3], [14]. Transfer learning techniques further improved

computational efficiency by utilizing pretrained ImageNet weights for infrastructure inspection tasks [1]. Explainable Artificial Intelligence (XAI) techniques such as Grad-CAM have recently gained attention because they generate visual heatmaps identifying crack-sensitive regions influencing prediction outcomes [2], [6], [15]. Existing studies primarily focus on classification accuracy while providing limited deployment-oriented implementation support. The proposed framework addresses these limitations by integrating explainable AI, deployment-oriented system design, and web-based inspection support within a computationally efficient deep learning framework.

III. RESEARCH CONTRIBUTIONS

A. Major Contributions of the Proposed Framework

The major contributions of this research work are summarized as follows:

- Development of an automated concrete crack detection framework using a fine-tuned ResNet-18 deep learning architecture.
- Integration of Grad-CAM explainable artificial intelligence techniques for visual interpretation of crack-sensitive image regions influencing prediction outcomes.
- Implementation of a web-based infrastructure inspection interface to support deployment-oriented structural health monitoring applications.
- Application of transfer learning techniques to improve feature extraction capability, classification efficiency, and computational performance.
- Experimental evaluation using multiple performance metrics including accuracy, precision, recall, and F1-score for reliable model assessment.
- Demonstration of a scalable, interpretable, and computationally efficient AI-assisted infrastructure inspection framework suitable for real-world deployment environments.

B. Advantages of the Proposed System

- The proposed explainable deep learning framework improves automated infrastructure inspection reliability by combining crack classification capability with visual interpretability support. Unlike conventional black-box deep learning systems, the integration of Grad-CAM explainability visualization enables engineers to identify image regions contributing to prediction decisions. This improves prediction transparency, inspection validation capability, and engineering confidence in automated structural assessment workflows. The framework also demonstrates strong deployment capability through the implementation of a web-based inspection interface. The proposed system supports automated crack prediction, heatmap visualization, and scalable inspection workflows for practical structural health monitoring applications.

IV. PROPOSED METHODOLOGY

A. Framework Overview

The proposed explainable deep learning framework consists of five major stages including image acquisition, image preprocessing, crack classification, explainability visualization, and deployment-oriented output generation. The framework integrates a fine-tuned ResNet-18 convolutional neural network with Grad-CAM explainable artificial intelligence techniques to improve automated crack detection reliability and interpretability for structural health monitoring applications.

B. Image Acquisition and Preprocessing

Concrete surface images containing cracked and non-cracked regions were collected from infrastructure inspection environments. The images were resized to dimensions compatible with the ResNet-18 architecture. Several preprocessing techniques were applied before training, including image resizing, normalization, tensor conversion, horizontal flipping, rotation, brightness adjustment, and scaling operations. These preprocessing methods improved feature extraction capability, classification robustness, and model generalization performance while reducing overfitting during training.

C. Crack Classification Using ResNet-18

A pretrained ResNet-18 convolutional neural network was fine-tuned using transfer learning techniques [1]. The final fully connected layer was modified to perform binary classification between crack and non-crack concrete surface images. The Adam optimizer and cross-entropy loss function were utilized during training to improve classification performance and optimization efficiency.

Cross-Entropy Loss Function

$$L = -\sum_{i=1}^N y_i \log(\hat{y}_i) \quad (1)$$

Adam Optimization Update

$$\theta_{t+1} = \theta_t - \eta \frac{m_t}{\sqrt{v_t + \epsilon}} \quad (2)$$

D. Explainable AI Using Grad-CAM

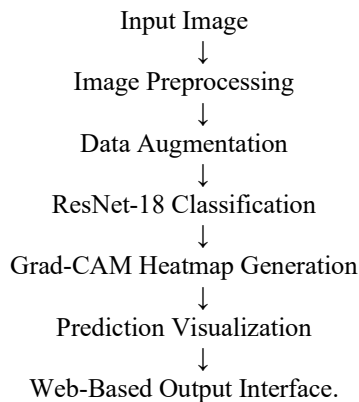
Grad-CAM explainability was integrated to improve model interpretability by generating heatmaps identifying crack-sensitive image regions contributing to prediction outcomes [2].

Grad-CAM Formulation

$$L_{Grad-CAM}^c = ReLU\left(\sum_k \alpha_k^c A^k\right) \quad (3)$$

The generated visual explanations assist engineers in validating model predictions and improving inspection reliability.

E. System Workflow



V. EXPERIMENTAL SETUP

A. Development Environment

TABLE I. DEVELOPMENT ENVIRONMENT

Parameter	Specification
Programming Language	Python
Deep Learning Framework	PyTorch
Computer Vision Library	OpenCV
Web Framework	Flask
Development Environment	Jupyter Notebook / VS Code
Operating System	Windows/Linux

B. Dataset Description

TABLE II. DATA SET DESCRIPTION

Dataset Property	Value
Total Images	10,034
Crack Images	6,498
Non-Crack Images	3,536
Training Images	7,732
Validation Images	689
Testing Images	1,154
Input Resolution	224 × 224

The dataset included diverse concrete surface conditions containing varying crack patterns, textures, illumination conditions, and environmental characteristics to improve classification robustness [4].

C. Training Configuration

TABLE III. TRAINING CONFIGURATION

Parameter	Value
Model Architecture	ResNet-18
Optimizer	Adam
Learning Rate	0.001
Batch Size	32
Epochs	25
Loss Function	Cross-Entropy Loss
Explainability Method	Grad-CAM

VI. RESULTS AND DISCUSSION

Experimental evaluation demonstrated strong crack classification performance across diverse concrete surface conditions.

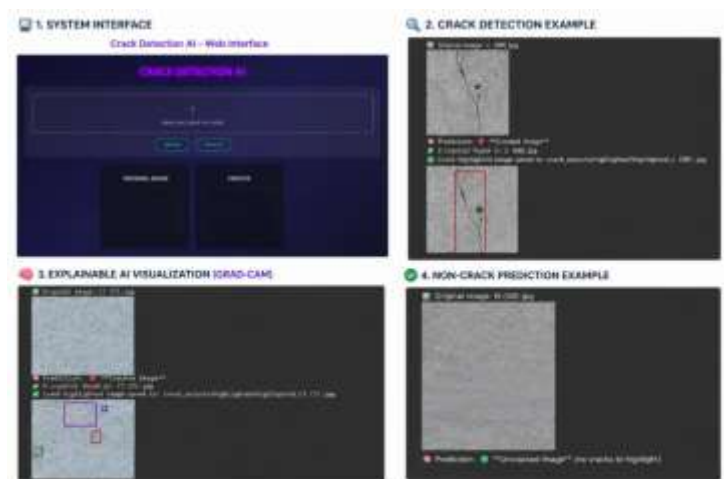
A. Performance Metrics

TABLE IV. PERFORMANCE METRICS

Metric	Value
Accuracy	95.70%
Precision	95.10%
Recall	96.20%
F1-Score	95.60%

The ResNet-18 architecture successfully extracted discriminative crack features while maintaining computational efficiency suitable for deployment-oriented applications.

Fig. 1. Proposed Explainable AI-Based Concrete Crack Detection System.

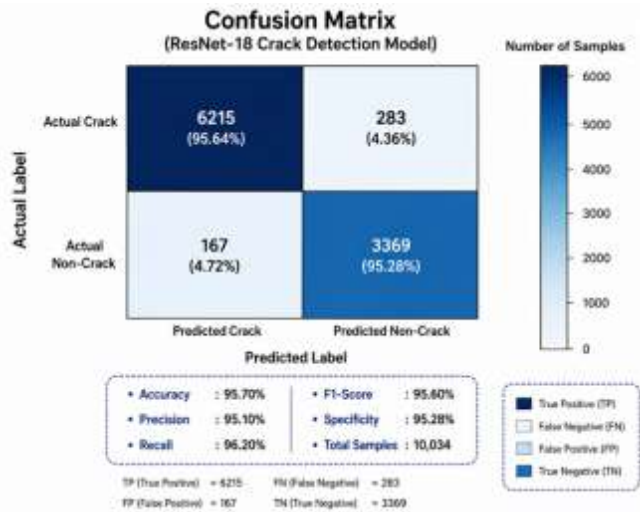


Proposed explainable deep learning framework demonstrating (a) web-based inspection interface, (b) crack detection prediction example, (c) Grad-CAM explainability visualization, and (d) non-crack prediction example.

B. Confusion Matrix Analysis

The confusion matrix analysis demonstrated reliable classification performance for both cracked and non-cracked concrete surfaces within the testing dataset.

Fig. 2. Confusion Matrix of the Proposed ResNet-18 Crack Detection Model.



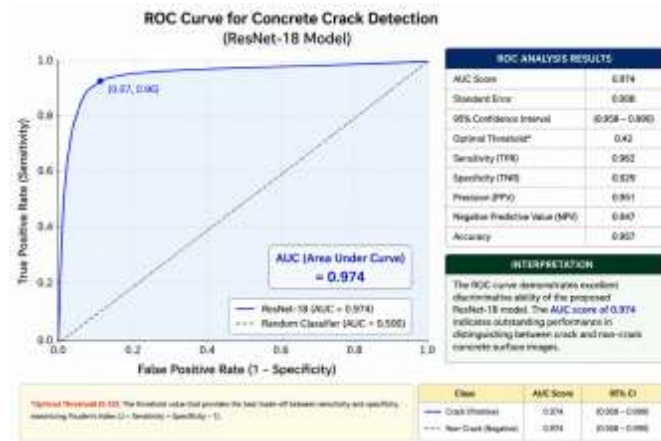
Confusion matrix representing classification performance of the proposed ResNet-18 crack detection framework on the testing dataset.

C. ROC Curve and AUC Analysis

The Receiver Operating Characteristic (ROC) curve was used to evaluate the discriminative capability of the proposed ResNet-18 crack detection framework. The ROC analysis demonstrated strong classification performance with an Area Under the Curve (AUC) score of 0.974, indicating excellent capability in distinguishing between cracked and non-cracked concrete surface images.

The high AUC value confirms that the proposed framework achieved reliable sensitivity and specificity across multiple classification thresholds. The ROC analysis further validates the robustness and generalization capability of the proposed deep learning model for automated infrastructure inspection applications.

Fig. 3. Receiver Operating Characteristic (ROC) Curve of the Proposed ResNet-18 Framework.



ROC curve demonstrating classification performance of the proposed ResNet-18 crack detection model with an AUC score of 0.974.

D. Explainability Visualization

Grad-CAM explainability heatmaps confirmed that the proposed framework focused primarily on crack-sensitive regions instead of irrelevant background textures [2], [15]. Crack-positive predictions generated strong activation responses around structural crack areas, while non-crack images produced minimal activation behavior.

The explainability module improved:

- prediction transparency,
- engineering interpretability,
- inspection validation support,
- infrastructure monitoring reliability.

VII. COMPARATIVE DISCUSSION WITH EXISTING STUDIES

Previous studies have demonstrated the effectiveness of deep learning architectures such as VGG16, U-Net, and conventional Convolutional Neural Networks (CNNs) for automated crack detection applications [3], [11], [14]. Existing literature generally reports classification accuracies ranging from 89% to 93% depending on dataset characteristics and model complexity [3], [14]. In comparison, the proposed ResNet-18 framework achieved 95.7% classification accuracy while additionally incorporating Grad-CAM explainability visualization and deployment-oriented web implementation support. The integration of explainable artificial intelligence techniques improves interpretability, prediction transparency, and practical applicability in infrastructure inspection environments.

TABLE V. COMPARATIVE ANALYSIS WITH EXISTING STUDIES

Study	Model	Reported Accuracy	Explainability
Cha et al. (2017)	CNN	89%	No
Liu et al. (2019)	U-Net	93%	No
Proposed Work	ResNet-18 + Grad-CAM	95.70%	Yes

VIII. DEPLOYMENT IMPLEMENTATION

A deployment-oriented web-based inspection interface was developed using the Flask framework to support automated infrastructure monitoring workflows. The proposed deployment system enables efficient crack inspection and prediction visualization for real-world civil engineering applications.

The developed framework supports multiple functionalities including image upload, automated crack prediction, Grad-CAM heatmap generation, crack localization, and prediction visualization. The deployment interface improves inspection accessibility and assists engineers in performing scalable structural health assessment procedures.

The proposed deployment framework demonstrates practical applicability for infrastructure inspection environments and may support future integration with advanced technologies such as drone-assisted monitoring systems, edge artificial intelligence platforms, IoT-enabled infrastructure monitoring systems, and mobile-based deployment applications [9], [15].

IX. OPERATIONAL IMPACT ANALYSIS

The proposed explainable deep learning framework demonstrates potential operational advantages for infrastructure inspection and structural health monitoring workflows. Automated crack detection systems may reduce dependency on manual inspection procedures while improving inspection consistency, scalability, and computational efficiency across large-scale infrastructure environments [3], [15].

Preliminary deployment-oriented evaluation scenarios indicate potential improvements in inspection duration, workforce requirements, operational efficiency, and inspection consistency. The integration of explainable artificial intelligence techniques further enhances engineering interpretability and inspection validation capability during automated assessment processes.

However, deployment performance may vary depending on infrastructure scale, environmental conditions, image quality variations, and operational workflow configurations.

X. LIMITATIONS AND FUTURE WORK

Although the proposed framework demonstrated strong classification performance and explainability capability, several limitations remain in real-world deployment environments. Variations in illumination conditions, surface texture complexity, environmental noise, and large-scale infrastructure diversity may affect model generalization performance under certain operational scenarios

Future work will focus on extending the framework toward real-time video crack detection, drone-assisted infrastructure inspection, lightweight edge-AI optimization, crack segmentation, crack width estimation, and IoT-enabled monitoring systems [8], [9], [15]. Future explainability studies may also incorporate quantitative explainability evaluation metrics, advanced visualization techniques, and real-time deployment optimization for scalable structural health monitoring applications.

XI. CONCLUSION

This paper presented an explainable deep learning framework for automated concrete crack detection using a fine-tuned ResNet-18 architecture integrated with Grad-CAM explainable artificial intelligence techniques. The proposed framework combined deep learning-based crack classification with visual interpretability support to improve infrastructure inspection reliability and transparency.

Experimental evaluation demonstrated strong classification performance with an overall accuracy of 95.7% along with reliable explainability visualization capability. The developed web-based deployment interface further demonstrated practical applicability for scalable infrastructure inspection and structural health monitoring workflows.

The proposed framework provides an efficient, interpretable, and deployment-oriented solution for AI-assisted infrastructure monitoring applications and demonstrates the potential of explainable deep learning techniques in civil engineering inspection systems.

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