ISSN 2277-2685
IJESR/April. 2026/ Vol-16/Issue-2s1/182-186
Mohd Maaz Taqi *et. al.*, / International Journal of Engineering & Science Research

Full Length Article

Crack Vision: Sophisticated Concrete Crack Identification Through Transfer Learning and Deep Learning

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Accepted 27-04-2026

Abstract:
Crack Vision is a deep learning-powered application designed to detect and classify cracks in concrete surfaces with exceptional accuracy. Unlike traditional manual inspection methods, which are time-consuming and prone to human error, Crack Vision leverages state-of-the-art convolutional neural networks and transfer learning techniques—enhanced with alternative architectures such as EfficientNetB3—to deliver reliable, real-time predictions. The system has been trained on the METU concrete crack dataset, containing balanced sets of cracked and non-cracked surface images, enabling robust binary classification. Integrated into a user-friendly Flask web interface, Crack Vision allows users to easily upload images, preview them, and instantly receive classification results along with confidence scores. Additional visualization tools, including accuracy/loss charts and confusion matrices, provide transparency into model performance. This scalable solution offers a practical tool for engineers, inspectors, and infrastructure maintenance teams, enabling faster, more consistent assessments and contributing to improved structural safety and long-term durability in civil engineering projects.

Keywords:
Deep learning, Concrete crack detection, Convolutional neural networks, Transfer learning, Binary classification, Flask web interface, Structural safety, Infrastructure maintenance

Introduction:

Concrete is one of the most widely used construction materials in the world, forming the backbone of modern infrastructure such as bridges, pavements, and buildings. However, over time, factors like environmental stress, load-bearing fatigue, and poor maintenance can lead to the formation of cracks, which significantly compromise the structural integrity and safety of these constructions. Traditional manual inspection methods for crack detection are often labor-intensive, time-consuming, and prone to human error, making them less reliable for large-scale applications. Recent advancements in Artificial Intelligence (AI) and Computer Vision have enabled automated systems to outperform conventional inspection techniques in terms of speed, accuracy, and scalability. Deep learning, particularly Convolutional Neural Networks (CNNs), has shown remarkable success in image classification tasks, including defect detection in construction materials. Transfer learning, which leverages pre-trained models such as Efficient Net, further enhances performance by reducing training time and improving generalization on diverse datasets. In this work, we present Crack Vision, an advanced deep learning-based framework for detecting cracks in concrete surfaces. The system is trained and fine-tuned using the METU concrete crack dataset, ensuring a balanced distribution of cracked and non-cracked samples. By integrating fine-tuned EfficientNetB3 architecture with robust preprocessing techniques, Crack Vision achieves high detection accuracy while maintaining computational efficiency. This makes it a practical and scalable solution for real-world structural health monitoring, enabling faster decision-making and proactive maintenance in civil engineering.

LITERATURE SURVEY:

1. Title: A Review on the Latest Advancements and Innovation Trends in Vibration-Based Structural Health Monitoring (SHM) Techniques for Improved Maintenance of Steel Slit Damper (SSD)
Year: 2024
Author: J. M. G. Payawal and D.-K. Kim
Description: This paper provides a comprehensive review of the most recent advancements in vibration-based SHM techniques, focusing on steel slit dampers used in structural safety. The study explores modern sensing technologies, data processing methods, and AI-driven diagnostic models, emphasizing their role in enhancing maintenance strategies. The review identifies research gaps and suggests future trends to improve SHM reliability and reduce maintenance costs.

2. Title: Using Deep Learning for Profitable Concrete Forecasting Methods

Year: 2024
Author: A. Al-Hinawi and R. Alelaimat
Description: This work proposes a deep learning-based approach to forecast concrete production and demand, optimizing profitability in the construction industry. By leveraging historical data and predictive modeling, the system improves operational planning and reduces waste. The authors highlight the role of AI in achieving cost efficiency and sustainable practices in concrete manufacturing.

3. Title: Deep Learning for Concrete Crack Detection and Measurement
Year: 2024
Author: M. A. Nyathi, J. Bai, and I. D. Wilson
Description: This paper presents a deep learning framework for detecting and quantifying cracks in concrete surfaces. The authors employ convolutional neural networks (CNNs) to automatically identify crack patterns from high-resolution images, achieving high accuracy in both detection and crack width measurement. The system aims to replace manual inspection methods with faster, more consistent automated solutions.

4. Title: Transfer Learning for Cross-Scene 3D Pavement Crack Detection Based on Enhanced Deep Edge Features
Year: 2023
Author: R. Gui, Q. Sun, W. Wu, D. Zhang, and Q. Li
Description: This research introduces a transfer learning-based method for detecting pavement cracks in diverse environmental conditions using 3D scene data. The enhanced deep edge feature extraction method improves crack visibility across various textures and lighting conditions, enabling robust detection in real-world road maintenance scenarios.

5. Title: Automatic Concrete Crack Identification Based on Lightweight Embedded U-Net
Year: 2024
Author: B. Li, H. Guo, Z. Wang, and F. Wang
Description: This paper develops a lightweight U-Net model optimized for embedded systems to perform real-time crack detection on concrete surfaces. The architecture reduces computational requirements while maintaining high accuracy, making it suitable for deployment on mobile devices and drones for on-site infrastructure inspection.

METHODOLOGIES

MODULES NAME:

- **User Authentication Module**
- **Image Upload & Preview Module**
- **Image Pre-processing Module**
- **Crack Detection Model Module**
- **Prediction & Confidence Display Module**
- **Charts & Performance Visualization Module**

MODULES EXPLANATION:

1. User Authentication Module
This module handles user registration, login, and logout using session management in Flask. Register Page: Allows users to create an account by entering their username, email, password, and confirm password. Login Page: Authenticates registered users before granting access to the upload and prediction features. Session Management: Ensures secure login persistence until the user logs out.

2. Image Upload & Preview Module
This module allows users to upload concrete surface images for crack detection. Supports JPEG, PNG, and other common image formats. Displays an instant preview of the selected image before prediction using JavaScript. Ensures the uploaded image is stored in a designated uploads directory for processing.

3. Image Pre-processing Module
This module prepares uploaded images for model prediction. Resizing all images to the model's input size (224×224 pixels).Normalizing pixel values between 0 and 1 for better model performance. Converts the image into a NumPy array and reshapes it for the model's expected input format.

4. Crack Detection Model Module
This module loads the fine-tuned EfficientNetB3 deep learning model trained on the METU concrete crack dataset. Uses transfer learning with pre-trained ImageNet weights. Performs binary classification: Cracked or Non-cracked. Achieves high accuracy (99.85%) with minimal false predictions.

5. Prediction & Confidence Display Module
This module displays the classification results and confidence score. Prediction Label: Shows "Cracked" or "Non-cracked."Confidence Score: Displays the model's certainty as a percentage. The uploaded image and results are shown together for clarity.

Implementation:
The implementation phase focuses on converting the designed system into a working application. In this project, the Crack Vision system is implemented using Python with deep learning frameworks and deployed through a web-based interface. The implementation integrates model training, image processing, prediction, and user interaction into a single system.

Algorithm used:

- **ResNet50**

ResNet50, or Residual Network with 50 layers, is a deep learning architecture designed to address the challenges of training very deep neural networks. It introduces residual connections, which allow the

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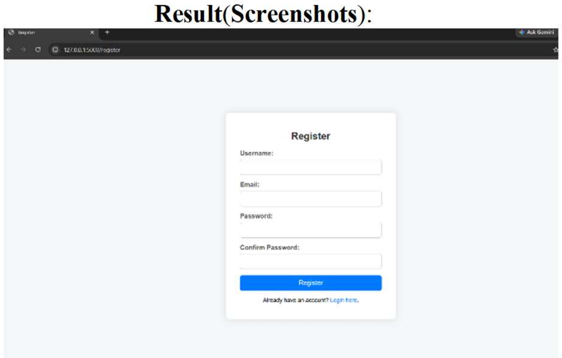
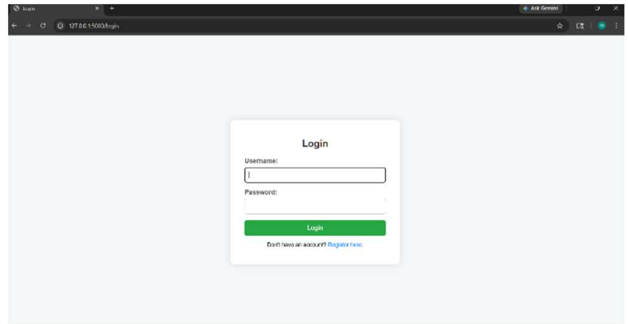
network to learn residual functions (differences between input and output) rather than learning the entire transformation directly. This is achieved by adding shortcut connections that bypass one or more layers, enabling the model to combine the input of a layer with its output. This approach mitigates the vanishing gradient problem, where deeper networks struggle to learn due to diminishing gradients during back propagation. ResNet50 consists of a series of convolutional layers, starting with a 7x7 convolutional layer with 64 filters, followed by max-pooling and multiple residual blocks with varying filter sizes (e.g., 64, 128, 256, 512, and 1024 filters). In the context of Crack Vision, ResNet50 is pre-trained on the ImageNet dataset to recognize general image features like edges and textures, then fine-tuned to detect crack-specific patterns in concrete images. This transfer learning approach reduces training time, enhances generalization, and makes the model highly effective for classifying concrete surfaces as cracked or non-cracked, even with imbalanced datasets.

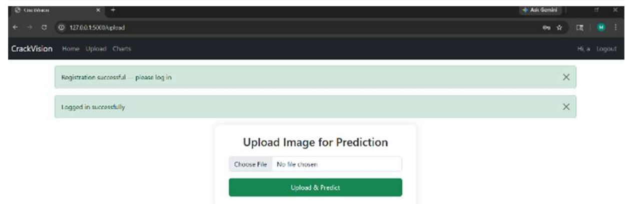
EfficientNetB3 (Fine-Tuned Transfer Learning)

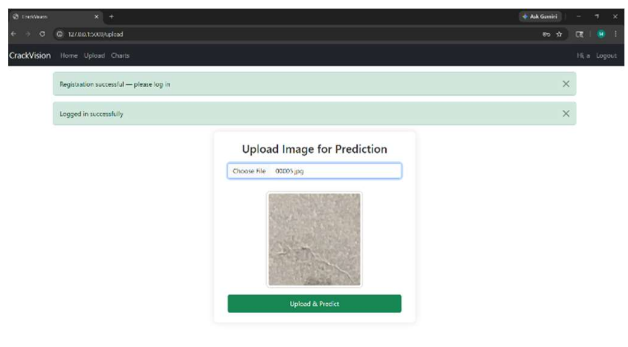
EfficientNetB3 is a convolutional neural network architecture that balances model depth, width, and resolution using a compound scaling method to achieve high accuracy with fewer parameters. Developed by Google AI, EfficientNet models are designed to maximize performance while maintaining computational efficiency. In this project, EfficientNetB3 is used as the backbone for feature extraction, with the final layers customized for binary classification (crack vs. no crack). The network is initially loaded with ImageNet weights and then fine-tuned on the target dataset, enabling it to capture domain-specific features while retaining the general visual understanding learned from large-scale data. This approach significantly boosts model performance and reduces training time compared to building a model from scratch.

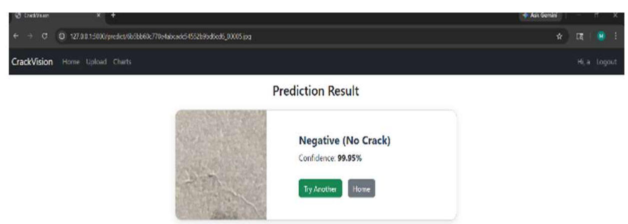
Result(Screenshots):











Conclusion:

The Crack Vision system demonstrates the potential of combining deep learning and transfer learning techniques to deliver highly accurate and efficient concrete crack detection. By leveraging the EfficientNetB3 architecture and fine-tuning with a balanced dataset, the model achieves superior performance compared to traditional inspection methods and the base paper results. This approach significantly reduces human error, inspection time, and operational costs while ensuring consistent and reliable predictions. The project's modular design allows easy integration into web-based applications, making it accessible to engineers, inspectors, and infrastructure managers for real-time structural health monitoring. With its scalability, adaptability to various structural environments, and potential for future enhancements such as multi-class defect detection and drone-based inspections, Crack Vision stands as a robust and practical solution for improving the safety, durability, and maintenance efficiency of critical infrastructure.

FUTURE ENHANCEMENTS:

The proposed Crack Vision system can be further enhanced by incorporating multi-class classification to detect and categorize different types of structural defects beyond simple crack/no-crack prediction, such as spalling, corrosion, and surface wear. Integration of 3D image analysis and thermal imaging could improve crack depth estimation and detection under challenging environmental conditions. Future work can also focus on developing an edge-computing-compatible lightweight model for real-time inspections using drones or mobile devices, enabling on-site detection without dependency on high-end computing resources. Additionally, expanding the dataset with images from diverse structural materials and geographical regions will improve model generalization. An interactive dashboard with real-time monitoring, defect severity grading, and maintenance scheduling suggestions could transform the system into a complete structural health monitoring solution. Cloud integration for collaborative inspections and AI-driven trend analysis will make Crack Vision scalable for large-scale infrastructure management projects.

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