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Automated Crack Detection in Roads and Buildings

1. Problem Statement

Road and building cracks are among the first indicators of structural damage that can result in severe issues if not identified early enough. On roads, cracks create openings that permit water to enter, damaging the pavement and causing potholes over time, threatening accidents for moving vehicles. In buildings, cracks lower the structural integrity, and this can result in safety risks and collapse in extreme scenarios. Historically, cracks have been inspected manually by walking on roads or scaling walls, which is time-consuming, expensive, and greatly reliant on the inspector's experience. Further, manual inspection cannot be performed on a regular basis or over extensive infrastructures. As such, the need for an automated method of detecting cracks speedily, reliably, and uniformly based on Digital Image Processing and Artificial Intelligence is dire.

2. Motivation

• Ensure **public safety** through early detection of cracks.

• Time, cost, and effort savings in manual inspection.

• Real-time monitoring of cracks in roads and buildings.

• Support **SDG 9 (Infrastructure)** and **SDG 11 (Sustainable Cities)**.

3. Objectives

a. Study automated crack detection using methods of Digital Image Processing and AI.

b. Analyze deep learning models (U-Net, YOLO, and R-FCN) for crack detection.

c. Compare traditional manual methods with AI-based modern approaches.

d. Expected benefits shown can include faster, more accurate, and less cost detection.

4. Introduction

Damage detection in general has always been an important part of infrastructure maintenance. Traditionally, image processing methods like edge detection, thresholding, morphological filters, and so forth were used to detect cracks in roads and buildings. These classical ways have their own simplicity but often fail in various scenarios, namely, poor lighting, shadow presence, or faintness of the cracks themselves. After the explosion of AI and Deep Learning techniques, modern crack detection systems were birthed. Encoder–Decoder models like U-Net can detect cracks at the pixel level even in low contrast images. Object detection methods like YOLO treat cracks as "objects" within the image to classify the type of cracks in real time, while image segmentation methods like R-FCN focus on cracks in buildings, walls, and bridges at very high accuracy. These modern techniques, hence, ensure faster detection of cracks and their precise location in catching important infrastructure network-maintaining operations, directly supporting the development of sustainable and safer cities.

5. Related Work

Sr. No	**Study Name**	**Authors**	**Features**	**Methodology**	**Research Gaps**
1	Crack Detection in Concrete using Microwave Imaging	E. A. Jiya, N. S. N. Anwar, M. Z. Abdullah View here	Detects cracks as small as 5 mm, high resolution	Delay-and-Sum Beamformer with Antennas and FDTD simulation	Only lab-tested, hard for real-world use
2	Road Crack Detection using Convolutional Neural Network	Sharmad Bhat, Saish Naik, Mandar Gaonkar View here	Detects road and longitudinal cracks using CNN, high accuracy	CNN architecture with convolutional layers, max-pooling, flatten and dense layers	Limited by dataset diversity, needs high-res images for better accuracy
3	Intelligent Detection of Building Cracks based on Deep Learning	Minjuan Zheng, Zhijun Lei, Kun Zhang View here	Detects and segments building cracks using FCN, R-CNN, and RFCN; Best results with RFCN	Deep learning models (FCN, R-CNN, RFCN) trained on building surface images; Feature extraction and semantic segmentation	Needs more diverse datasets; Computational cost; Only lab-tested models
4	Automated Road Crack Detection Using Deep	Vishal Mandal	Detects and classifies road cracks using YOLOv2,	YOLOv2 deep learning framework; Transfer learning from	Struggles with transverse cracks; Dataset imbalance

	Convolutional Neural Networks	View here	trained on large dataset	COCO dataset; CNN layers detect cracks and classify type in real time	affects accuracy; Needs more diverse images
5	Crack Detection in Buildings Using Convolutional Neural Network	Ankit Narendrakumar Soni View here	Detects cracks in building concrete structures; assesses crack thickness	FCN (Fully Convolutional Network) with VGG16 backbone; Semantic segmentation to classify every pixel as crack or non-crack	Difficulty in measuring crack size independently; small noisy features cause false positives; needs more robust thickness estimation

6. Methodology

The phases under the methodology for automated crack detection of roads and buildings consist of some major phases designed to capture, process, detect, and analyse cracks swiftly and precisely:

1. Image Acquisition :

- It is the first step of capturing excellent images of roads and buildings.
- For roads, he/she can either use a smartphone camera or any camera to be mounted on the vehicle while driving slowly along the road.
- Drones or manual cameras are used while capturing images of walls, bridges, and dams from various angles.
- Images are collected keeping constant lighting from the surroundings, under normal circumstances for better detection.

2. Pre-processing :

- The acquired images usually include noise, shadows, and changes in illumination, all of which cause confusion with the detection algorithms.
- The preprocessing improves the quality of the image by performing such operations as:
- Removal of shadows via top-hat filtering or homomorphic filtering.
- Contrast enhancement using Contrast Limited Adaptive Histogram Equalization (CLAHE).
- Noise reduction by using median or bilateral filter to smooth the image without eliminating important details such as edges of cracks.

3. Crack Detection :

- Detection is the core step where cracks are detected by either traditional image-processing techniques or advanced deep learning algorithms:

a. Classical Methods

- Edge Detection (e.g., Canny or Sobel filters): Identifies strong edges caused due to sharp changes in the pixel intensities and presumably represent cracks.
- Thresholding (Otsu's method or adaptive thresholding): Pixel intensities are converted into black and white trying to isolate cracks.
- Morphological Operations: Removes small artifacts and joins cracks segments through dilation or erosion.
- However, these methods may fail where cracks are thin, contrasted poorly, or under shadows.

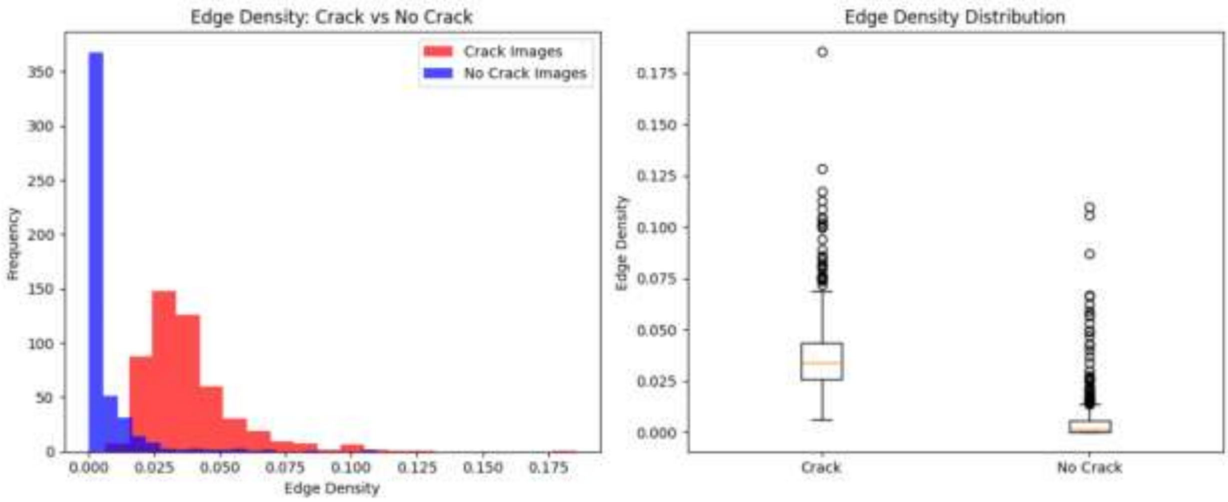
b. Deep Learning Methods

- U-Net / U-HDN (Encoder–Decoder Networks):
- The models process the images for segmentation by classifying pixels into crack or non-crack.
- Due to U-Net's architecture, the system can learn global and local features that are useful to detect cracks of various sizes and appearances.
- It works well when cracks are thin and blurred.
- YOLO (You Only Look Once):
- It treats cracks as objects inside an image.
- The model divides the image into grids and for each identified crack type (longitudinal, transverse, alligator, etc.) it forecasts bounding boxes and classes.

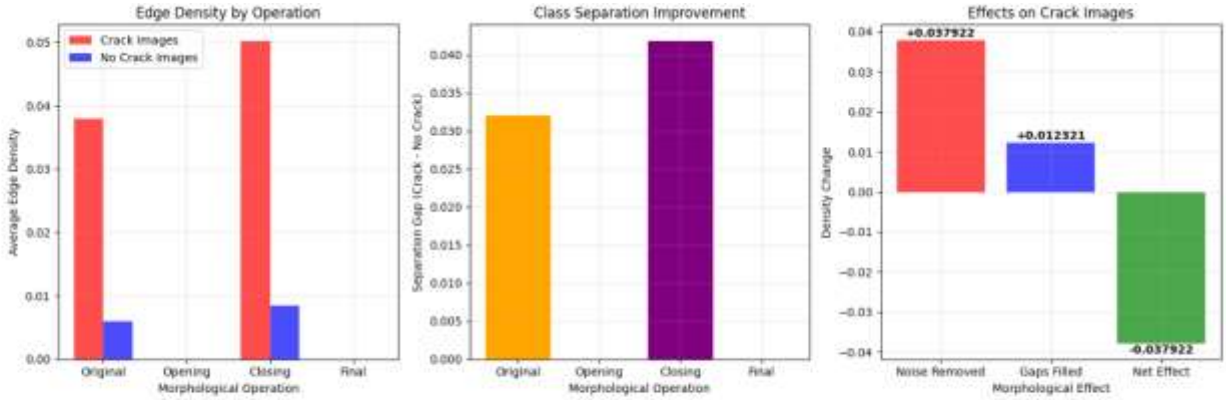
5. Measurement :

- Once cracks are detected and cleaned, their **geometry is measured**:
  - **Width (in mm)** and **length (in meters)** are computed using image calibration (known reference sizes).
  - The **density of cracks (total length per area)** is calculated to estimate severity.
  - Based on these measurements, cracks are classified by severity levels (minor, moderate, severe).

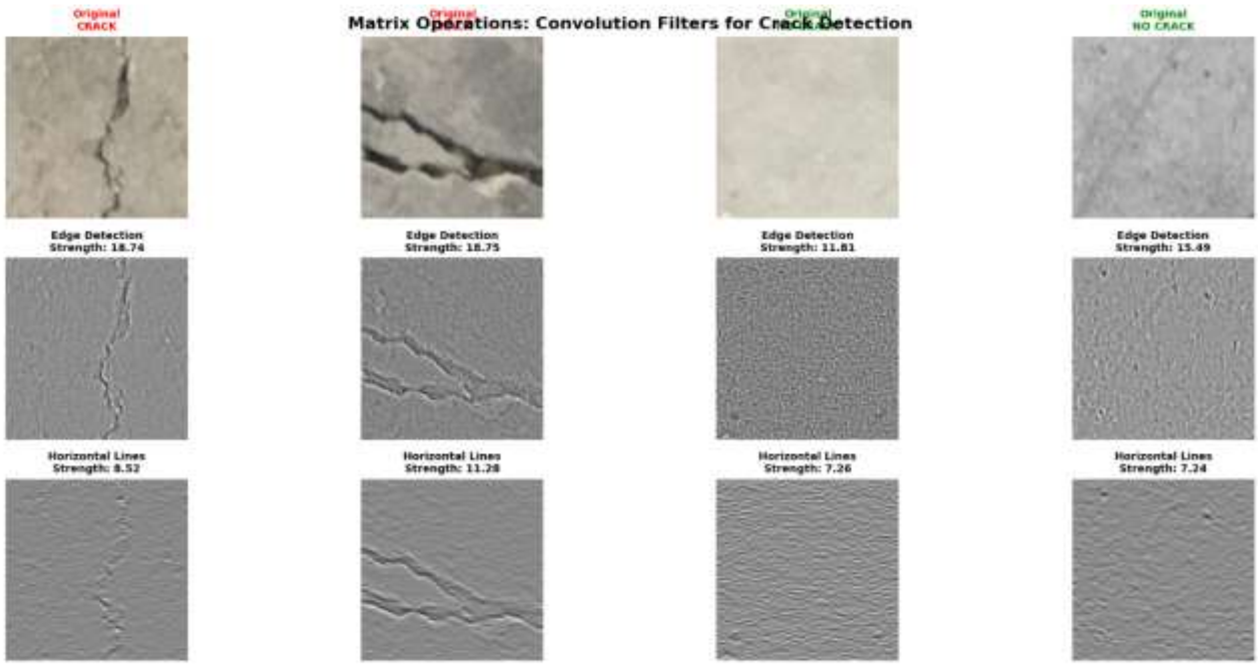
6. Results :



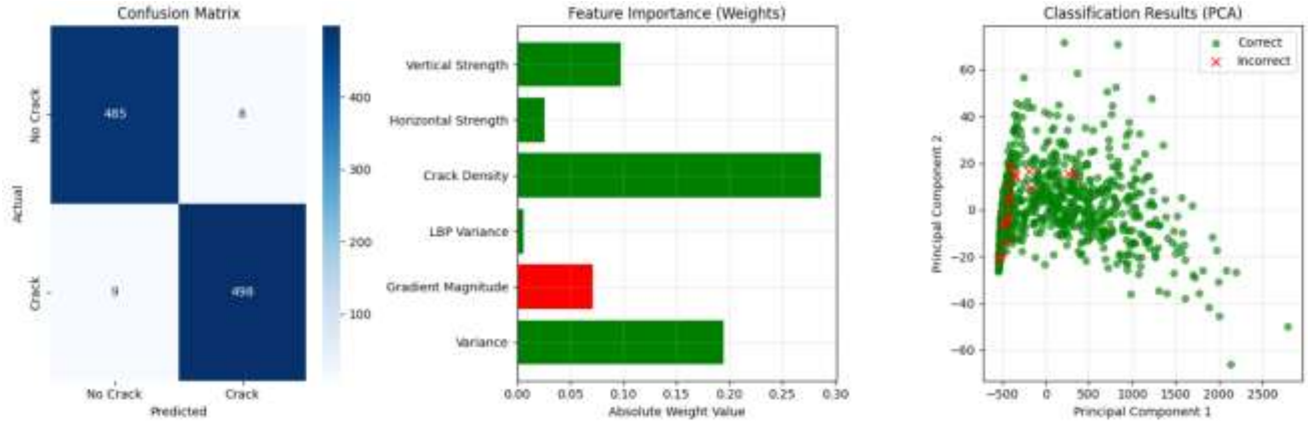
Edge Density: Crack vs No Crack
Crack Images
No Crack Images
Frequency
Edge Density
Edge Density Distribution
Edge Density
Crack
No Crack



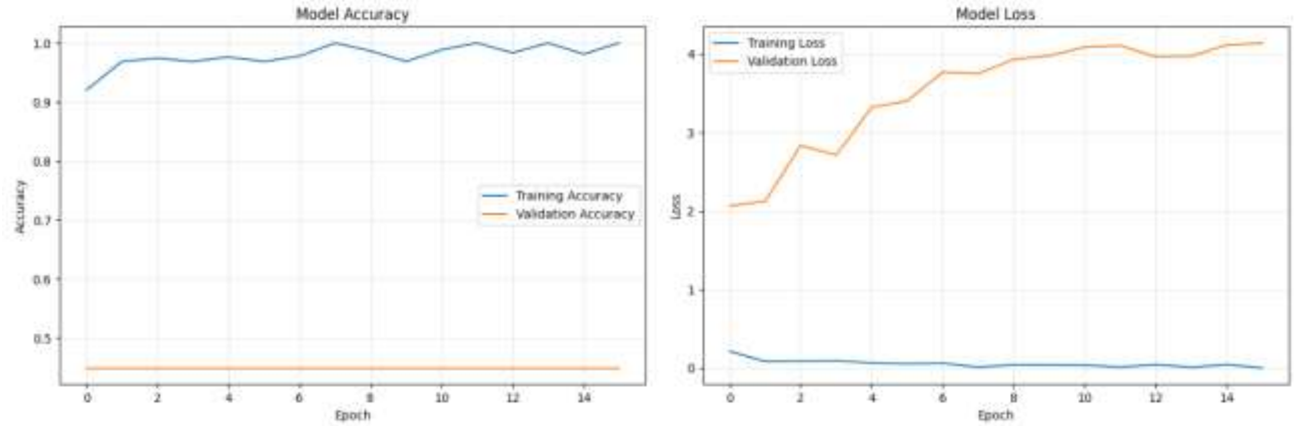
Edge Density by Operation
Crack Images
No Crack Images
Average Edge Density
Original
Opening
Closing
Final
Morphological Operation
Class Separation Improvement
Separation Gap (Crack - No Crack)
Original
Opening
Closing
Final
Morphological Operation
Effects on Crack Images
+0.037922
+0.012321
-0.037922
Density Change
Noise Removed
Gaps Filled
Net Effect
Morphological Effect

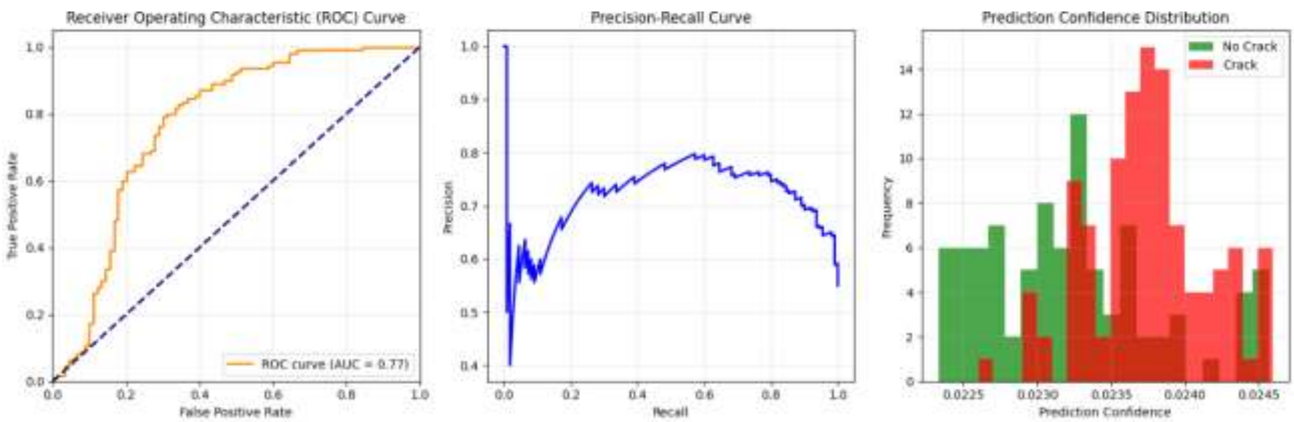


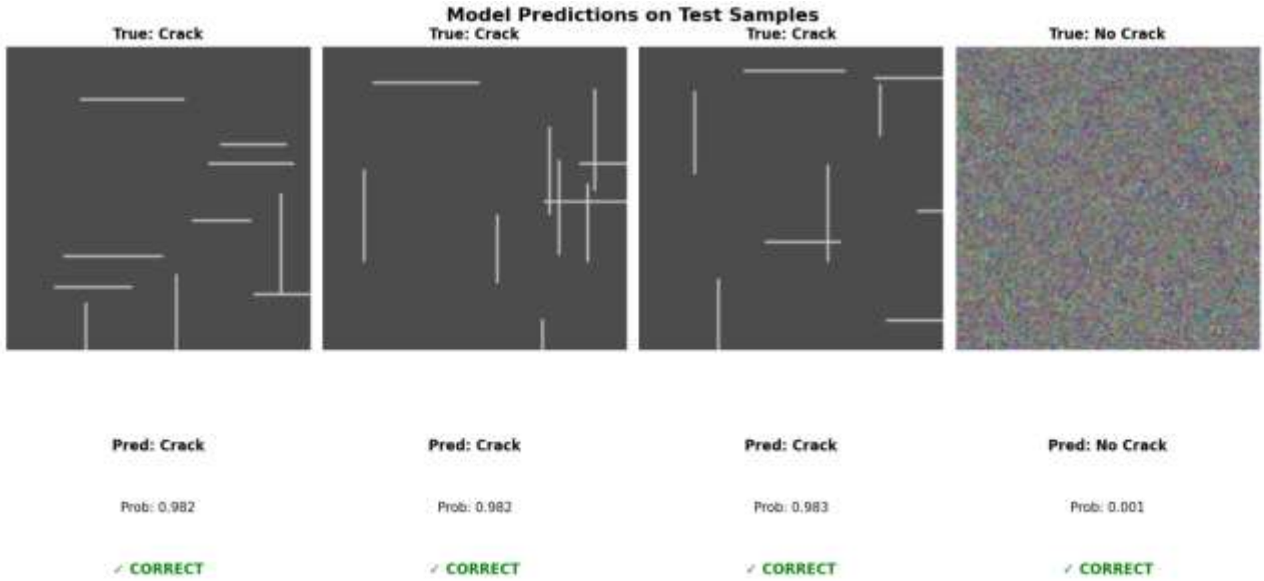
Matrix Operations: Convolution Filters for Crack Detection
Original
CRACK
Original
NO CRACK
Edge Detection
Strength: 18.74
Edge Detection
Strength: 18.75
Edge Detection
Strength: 11.81
Edge Detection
Strength: 15.49
Horizontal Lines
Strength: 8.52
Horizontal Lines
Strength: 11.28
Horizontal Lines
Strength: 7.26
Horizontal Lines
Strength: 7.24


Confusion Matrix
No Crack
Crack
Actual
485
8
9
498
400
300
200
100
No Crack
Crack
Predicted
Feature Importance (Weights)
Vertical Strength
Horizontal Strength
Crack Density
LBP Variance
Gradient Magnitude
Variance
0.00
0.05
0.10
0.15
0.20
0.25
0.30
Absolute Weight Value
Classification Results (PCA)
Correct
Incorrect
Principal Component 2
Principal Component 1


Density Distribution: Before vs After
Crack (Orig)
No Crack (Orig)
Crack (Final)
No Crack (Final)
Frequency
Edge Density
Class Separation Improvement
Crack Images
No Crack Images
Average Edge Density
Before
After
Morphological Processing
Morphological Operations Impact
+0.0047
-0.0255
-0.0302
Density Change
Separation Gap
Crack Enhancement
Noise Reduction
Improvement Type


Model Accuracy
Training Accuracy
Validation Accuracy
Accuracy
Epoch
Model Loss
Training Loss
Validation Loss
Loss
Epoch


Receiver Operating Characteristic (ROC) Curve
ROC curve (AUC = 0.77)
True Positive Rate
False Positive Rate
Precision-Recall Curve
Precision
Recall
Prediction Confidence Distribution
No Crack
Crack
Frequency
Prediction Confidence



7. Conclusion

Automated crack detection is revolutionizing the way we approach infrastructure maintenance by providing solutions that are not only faster and more accurate but also budget-friendly. Techniques like U-Net, YOLO, and R-FCN have shown great success in analyzing roads and buildings. Looking ahead, there are exciting improvements on the horizon:

- Enhanced detection of thin cracks.

- Quicker processing times for real-time applications.

- Access to larger datasets to boost training effectiveness. This technology aligns perfectly with Sustainable Development Goals 9 and 11, contributing to safer and more sustainable infrastructure.

8. References

[1] Jiya, E. A., Anwar, N. S. N., & Abdullah, M. Z. (2016). Detection of cracks in concrete structure using microwave imaging technique. *International Journal of Microwave Science and Technology*, *2016*(1), 3195716.Mandal et al., YOLOv2 for Road Crack Detection.

[2] Mohan A, Poobal S. Crack detection using image processing: A critical review and analysis. Alexandria Engineering Journal. 2018;57(2):787–798

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[4] Park, S. E., Eem, S. H., & Jeon, H. (2020). Concrete crack detection and quantification using deep learning and structured light. *Construction and Building Materials*.