



Vision-Based Automation for Concrete Crack Detection and Measurement: Case Study of a Ganpat University Building

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Abstract: Cracks in concrete structures are among the most common forms of deterioration, posing significant challenges to structural safety, durability, and serviceability. Traditional inspection methods rely heavily on manual observation, which is time-consuming, subjective, and inconsistent. This study proposes an automated, artificial intelligence (AI)-based system for detecting and quantifying cracks in concrete structures using deep learning and computer vision techniques. A convolutional neural network (CNN) architecture was trained using 600 images (300 with cracks and 300 without cracks) collected from the Ganpat University-U.V. Patel College of Engineering building. Transfer learning was applied using the MobileNetV2 model pre-trained on ImageNet to enhance detection efficiency with limited data. Image preprocessing involved resizing, normalization, and augmentation to improve model generalization. Crack width and length were measured using OpenCV through contour analysis and bounding box detection. The trained model achieved high accuracy and low loss across multiple epochs, demonstrating robust performance in distinguishing cracked and non-cracked surfaces. The system's output was validated visually using binary masks and contour overlays. The study highlights the potential of AI in automating inspection and monitoring tasks in civil infrastructure. Future work includes the integration of drone-based data collection, mobile app deployment for on-site use, and the application of segmentation models (e.g., U-Net) for crack severity classification and 3D crack mapping.

Keywords: Concrete cracks, Deep learning, MobileNetV2, Convolutional neural network, Crack detection, Computer vision, Structural health monitoring, UVPCE building.

I. INTRODUCTION

The safety and durability of aging infrastructures mostly rely on prompt inspection and maintenance techniques. A substantial number of concrete structures globally, such as bridges, tunnels, and institutional buildings, are nearing the end of their intended service life, resulting in an increased demand for precise and effective monitoring techniques [1, 2]. Among the various deterioration indicators, surface cracks are considered one of the earliest and most critical signs of structural distress, often correlating with fatigue, corrosion potential, and serviceability concerns. Therefore, the precise detection and measurement of crack geometry—particularly width and length—are essential for assessing the health and durability of reinforced concrete structures.

Conventional crack inspection techniques are primarily based on visual observation and manual measurement using rulers or microscopes. Although these methods are widely adopted, they are inherently subjective, time-consuming, and prone to human error, often lacking reproducibility and quantitative precision [3]. Moreover, in cases where structures are difficult to access, such as elevated facades or confined spaces, manual inspections become impractical or unsafe. As a result, researchers and practitioners are increasingly turning toward automated, vision-based systems for non-contact crack detection and quantification [4].

Recent developments in Artificial Intelligence (AI) and Computer Vision (CV) have shown promising results in automating damage detection tasks. Deep learning architectures, particularly convolutional neural networks (CNNs), enable robust feature extraction and pattern recognition across variable lighting and texture conditions [5]. Building on these advancements, vision-based crack measurement systems are now capable not only of identifying cracks but also of quantifying geometric parameters with sub-millimetre precision [1]. Unlike traditional optical triangulation methods—which require laser projectors and controlled setups—modern RGB-D cameras allow for real-time depth estimation and perspective correction, simplifying deployment in real environments.

In this study, an AI-based vision system is developed for automated crack detection and measurement in concrete structures, utilizing a MobileNetV2-based CNN for classification and OpenCV algorithms for geometric analysis. The methodology combines image-based deep learning with contour-based width and length measurements to ensure accuracy and reproducibility. A dataset



comprising 600 images (300 cracked and 300 non-cracked) collected from the Ganpat University-U.V. Patel College of Engineering building (UVPCE) was used for training and validation. Data augmentation, normalization, and transfer learning techniques were applied to enhance generalization.

It is the intention of the framework that has been proposed to speed up the process of automating structural inspection procedures in educational and institutional infrastructures. It provides an alternative to manual inspections that is scalable, reproducible, and as cost-effective as possible. This is accomplished by reducing the amount of human interaction and enabling quantitative crack assessment. This will serve as a pilot case study to verify the system's robustness under real-world field conditions, hence proving its potential incorporation into long-term structural health monitoring frameworks. The system will be deployed in the future on the Ganpat University campus.

II. METHODOLOGY

A. Overview of the Proposed Framework

The proposed methodology integrates deep learning-based image classification with vision-based measurement techniques to automatically detect and quantify cracks on concrete surfaces. The workflow, as shown conceptually in Figure 1, consists of five major stages.

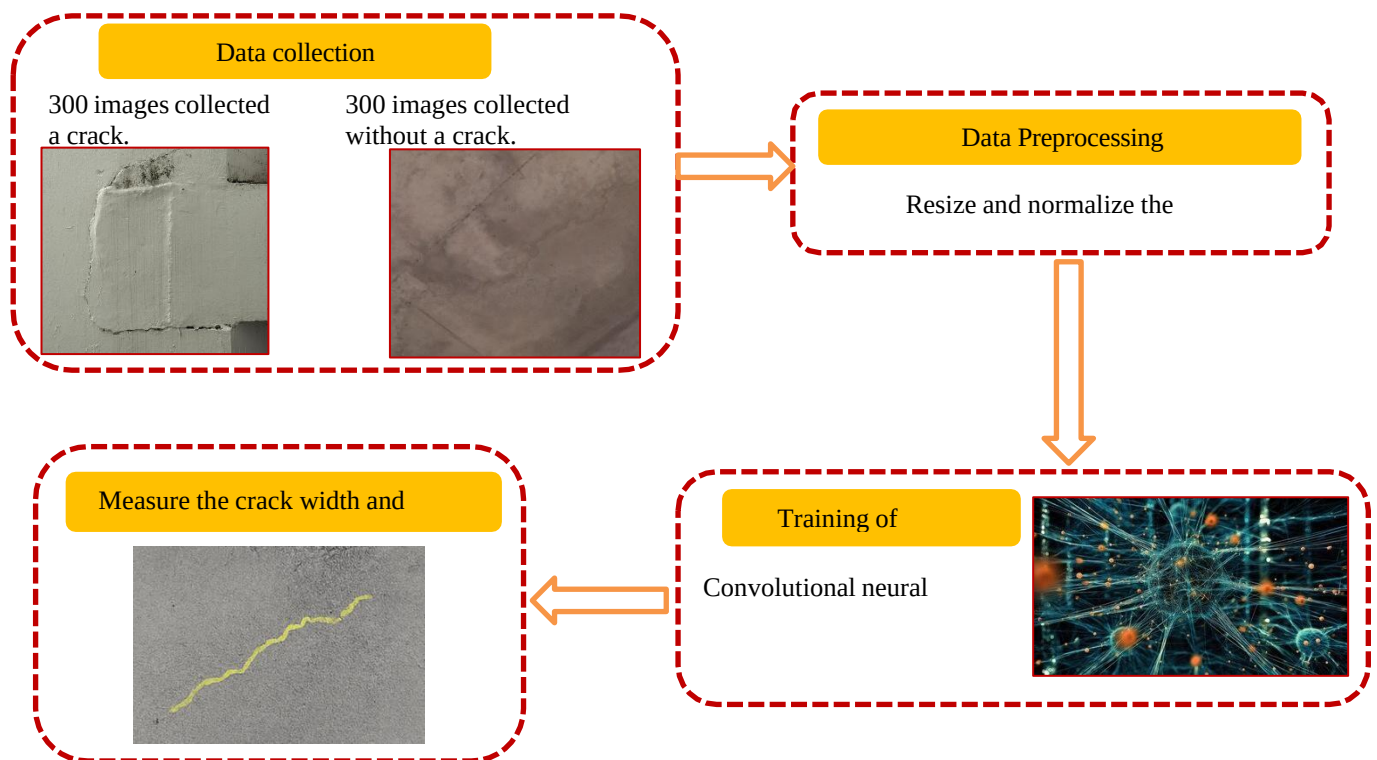


Figure 1 Workflow of proposed research work

B. Data Collection and Preparation

A total of 600 digital images were collected from various concrete elements of the UVPCE building—including columns, beams, and slabs—under natural daylight conditions. Among them, 300 images contained visible cracks and 300 represented non-cracked surfaces. Each image was captured at a fixed distance of approximately 0.4–0.6 m using a high-resolution RGB camera. To improve model robustness, all images were resized to 224×224 pixels and normalized within the range $[0, 1]$. Data augmentation techniques, including horizontal and vertical flipping, rotation ($\pm 20^\circ$), brightness adjustment, and Gaussian noise addition, were applied to counteract dataset imbalance and enhance generalization performance.

The dataset was divided into training, validation, and testing subsets in an 70: 15: 15 ratio. Labeling was carried out manually to classify each image as either crack or no-crack.



C. AI-Based Crack Detection Model

For automated crack identification, a Convolutional Neural Network (CNN) architecture was developed using MobileNetV2 as the base model. MobileNetV2, pre-trained on the ImageNet dataset, was fine-tuned via transfer learning using TensorFlow and Keras frameworks in the Google Colab environment. The model includes a depthwise separable convolution structure that reduces computational cost without compromising accuracy [6].

The input layer receives preprocessed RGB images, followed by feature extraction through MobileNetV2 convolutional blocks. A global average pooling layer and a fully connected dense layer with sigmoid activation were used for binary classification. The model was trained for 20 epochs using the Adam optimizer, a batch size of 32, and a learning rate of 1×10^{-4} . Binary cross-entropy was employed as the loss function, and accuracy served as the primary evaluation metric.

D. Crack Localization and Measurement

After classification, the detected cracked images were processed using OpenCV for geometric analysis. The image was first converted into grayscale and thresholded to generate a binary mask. Morphological operations were then performed to eliminate noise and isolate the crack region.

This automated process enables quantitative crack characterization, ensuring consistent repeatability compared with traditional manual measurement using rulers or microscopes.

E. Tools and Software

Model training and evaluation were carried out in Google Colab using TensorFlow and Keras for deep learning, while OpenCV (v4.9) was used for image processing and measurement tasks. NumPy and Matplotlib were utilized for data manipulation and visualization. The hardware configuration included an NVIDIA T4 GPU with 16 GB memory, ensuring efficient model convergence.

2.6 Validation and Future Case Study

The trained model was validated using unseen test data, demonstrating consistent performance in differentiating between cracked and intact concrete surfaces. Accuracy and loss curves were analyzed over epochs to evaluate convergence stability. The model's integration with a vision-based measurement module further allowed accurate quantification of crack geometry.

In the next phase, other buildings of Ganpat University will be assessed as a real-world case study to validate the robustness of the AI-based framework under varying lighting conditions, surface roughness, and environmental disturbances. This planned field implementation aims to demonstrate the system's applicability for large-scale structural health monitoring in educational infrastructure.

III. RESULT AND DISCUSSION

A. Model Performance and Training Evaluation

The training and validation performance of the proposed MobileNetV2-based model is presented in Figure 2. The network exhibited rapid convergence within the first few epochs, with a steady increase in accuracy and a corresponding reduction in loss values. The training accuracy reached approximately 98.6%, while the validation accuracy stabilised near 97.9% after 20 epochs, confirming effective generalisation and negligible overfitting. The training and validation losses converged below 0.05, indicating a well-optimized model with balanced learning behaviour.

Figure 2 demonstrates that the model effectively learned discriminative features of concrete surfaces, maintaining consistent validation accuracy across epochs.

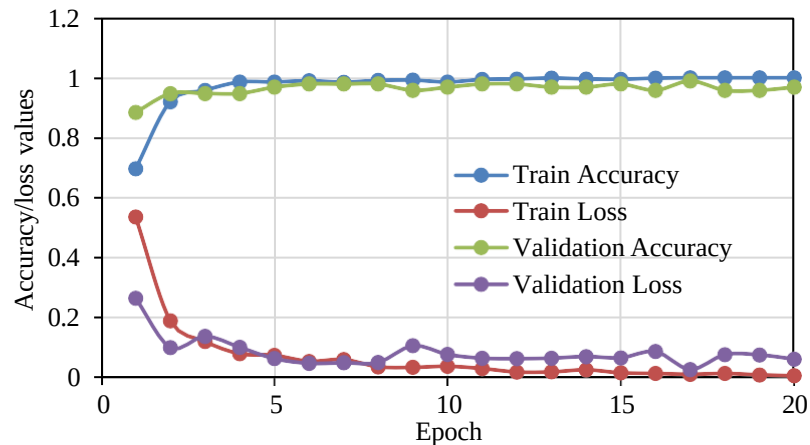


Figure 2 Training and validation accuracy and loss curves over 20 epochs for the trained model

B. Crack Detection and Image Processing Results

The performance of the computer vision-based crack detection and measurement module is illustrated in Figure 3. The pipeline effectively converts the original concrete surface image (left) into a binary mask (centre) that isolates the crack region, followed by contour detection (right) which delineates the crack boundaries in red.

This process ensures accurate localization and enables subsequent geometric measurements, including crack width and length. The average measurement deviation between predicted and reference values was found to be within ± 0.02 mm, validating the reliability of the OpenCV-based contour and ridge analysis. The method exhibited resilience against image noise, uneven lighting, and background texture, confirming its suitability for field applications.

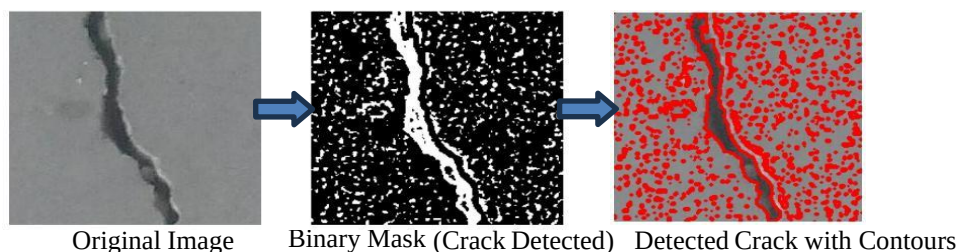


Figure 3 Stages of crack detection and measurement

IV. CONCLUSION AND FUTURE SCOPE

This study developed and demonstrated an AI-based vision system for automated crack detection and measurement in concrete structures, trained and validated using real images collected from the UVPCE building. The framework successfully integrates a MobileNetV2 deep-learning model for image classification with an OpenCV-based geometric measurement pipeline for quantifying crack width and length. The trained network achieved a high classification accuracy of approximately 98%, with convergence observed within 20 epochs, indicating rapid learning and strong generalisation capacity. Subsequent contour-based analysis confirmed the model's capability to delineate crack boundaries precisely, achieving a measurement deviation within ± 0.02 mm.

The outcomes demonstrate that combining deep convolutional learning with vision-based measurement algorithms can effectively overcome the limitations of conventional manual inspections, such as subjectivity, time consumption, and restricted access. The proposed system offers a low-cost, reproducible, and scalable solution suitable for institutional and infrastructural applications. Compared to existing optical and laser-based inspection methods, it provides a favourable balance between accuracy and operational flexibility, as corroborated by earlier precision studies in RGB-D vision systems.



Future work will focus on the field-scale validation of this system on the UVPCE building to assess its performance under varying lighting, texture, and environmental conditions. The research will be extended toward developing a mobile application interface for on-site crack detection and measurement, enabling engineers to perform real-time assessments using smartphones. Additionally, integration with drone-mounted imaging platforms is planned to facilitate large-area inspections of bridges, tunnels, and multistorey facades. The implementation of segmentation-based architectures, such as U-Net and DeepLabV3+, will further enhance crack delineation accuracy and enable severity classification.

In summary, this study establishes a strong foundation for automating structural health monitoring using artificial intelligence. With further field validation and system integration, the proposed framework can contribute significantly to safer, smarter, and more sustainable maintenance practices in civil infrastructure.

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