

Crack Vision-AI: A Deep Transfer Learning Framework for Structural Crack Detection Using MobileNet

Assistant Professor, Mrs.P.Lakshmi Satya¹, Shaik Fuzaila Farhatunnisa², Mummidi Naga Durga Venkat³, Mohammad Samreen⁴, Sunkara Rajeev Nagendra⁵
Department of CSE, Pragati Engineering College, Surampalem, Andhra Pradesh, India

Abstract- Structural cracks in buildings, bridges, and other civil infrastructures pose serious risks to public safety and long-term durability. Early and accurate detection of cracks is essential for effective maintenance and prevention of structural failures. Manual inspection methods are often time-consuming, labour-intensive, and prone to human error, making automated crack detection systems increasingly important. This project presents a deep learning-based framework for image-based crack prediction using a lightweight Convolutional Neural Network architecture. The proposed system utilizes MobileNet as the backbone model and incorporates transfer learning to enhance feature extraction capabilities while reducing computational complexity. Extensive image preprocessing and data augmentation techniques are applied to improve model generalization and handle limited dataset availability. The model is trained and evaluated on a structured crack image dataset consisting of cracked and non-cracked samples. Performance evaluation is carried out using standard metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis. Experimental results demonstrate that the proposed approach achieves high classification performance while maintaining computational efficiency, making it suitable for real-time infrastructure monitoring applications. The developed framework contributes toward automated structural health monitoring by providing a reliable, scalable, and efficient crack detection solution adaptable to practical engineering environments.

Keywords: Crack Detection, Structural Health Monitoring, Deep Learning, Convolutional Neural Network (CNN), MobileNet, Transfer Learning, Image Classification, Infrastructure Monitoring.

I. INTRODUCTION

Infrastructure plays a vital role in the development and safety of modern society. Buildings, bridges, roads, tunnels, and other civil structures are continuously exposed to environmental stress, heavy loads, and aging effects. Over time, these factors may lead to structural defects such as cracks, which can compromise the durability and safety of the structure. Early detection of cracks is essential to prevent severe damage, reduce maintenance costs, and ensure public safety [4], [7]. Traditionally, crack detection has been carried out through manual inspection by trained engineers. Although this method provides expert evaluation, it is labour-intensive, time-consuming, and often subjective. Human inspection may overlook minor cracks, especially in large-scale infrastructures. Moreover, regular monitoring of extensive

structures requires significant manpower and financial resources. These limitations highlight the

need for automated and intelligent crack detection systems [2], [7].

With the advancement of image processing and artificial intelligence, automated crack detection using computer vision techniques has gained significant attention. Machine learning approaches were initially introduced to classify crack and non-crack images based on handcrafted features. However, these traditional techniques faced challenges in handling complex surface textures and varying environmental conditions [1], [5].

In recent years, deep learning, particularly Convolutional Neural Networks (CNNs), has shown remarkable success in image classification and

pattern recognition tasks. CNNs are capable of automatically extracting meaningful features from images without the need for manual feature engineering. This ability makes them highly suitable for crack detection applications. Nevertheless, many deep learning architectures are computationally heavy and require large datasets, which may not always be practical in real-world infrastructure monitoring systems [8].

To address these challenges, this project proposes a deep learning based crack prediction system using a lightweight MobileNet architecture combined with transfer learning. The proposed approach aims to achieve high accuracy while maintaining computational efficiency. By leveraging pre-trained models and applying effective preprocessing and data augmentation techniques, the system enhances its ability to detect cracks under diverse conditions.

The primary objective of this study is to develop an efficient, reliable, and scalable crack detection framework that can assist in automated structural health monitoring. The proposed system not only improves detection accuracy but also reduces dependency on manual inspection, thereby contributing to safer and smarter infrastructure management [3], [6], [9], [10].

II. LITERATURE SURVEY

Structural health monitoring has become an important research area due to the increasing demand for safe and durable infrastructure. Over the years, researchers have proposed various techniques for detecting cracks in concrete structures, bridges, pavements, and buildings. Initially, crack detection was performed manually through visual inspection. Although manual inspection provides expert judgment, it is time-consuming, expensive, and often inconsistent due to human error. These limitations motivated researchers to explore automated image-based crack detection techniques [2], [7].

Early automated approaches relied on traditional image processing methods such as edge detection,

thresholding, morphological operations, and texture analysis. These methods extracted handcrafted features from images and applied classical machine learning algorithms such as Support Vector Machines (SVM), Decision Trees, and Random Forest for classification. While these techniques showed moderate success under controlled conditions, they struggled in real-world environments with varying lighting conditions, shadows, surface textures, and background noise [1], [5].

With the advancement of deep learning, Convolutional Neural Networks (CNNs) emerged as a powerful tool for image classification and object detection tasks. Several studies employed deep CNN architectures such as VGG16, ResNet, and U-Net for crack detection and segmentation. These models demonstrated improved accuracy compared to traditional methods, as they automatically learn hierarchical features directly from raw images. However, these architectures are computationally intensive and require large-scale annotated datasets for effective training [5], [8].

To address data scarcity issues, researchers introduced data augmentation techniques and transfer learning strategies. Transfer learning allows models to leverage knowledge from large pre-trained datasets and adapt it to crack detection tasks. Studies have shown that using pre-trained models significantly improves performance, especially when the available crack dataset is limited [1], [10]. Additionally, lightweight architectures have been explored to reduce computational complexity and enable deployment on mobile or embedded devices [6].

Recent works focus on improving model generalization, reducing overfitting, and enhancing real-time performance. Some researchers have combined deep learning with attention mechanisms and feature fusion techniques to better capture fine crack patterns. Others have emphasized evaluation using comprehensive performance metrics such as precision, recall, F1-score, and confusion matrices to ensure reliable model assessment [3], [8], [9].

Despite significant advancements, challenges still exist in achieving high accuracy under diverse environmental conditions while maintaining computational efficiency. Many high-performing models remain unsuitable for real-time or resource-constrained applications. The proposed work builds upon these advancements by integrating a lightweight MobileNet architecture with transfer learning to achieve efficient and accurate crack detection. By combining effective preprocessing, augmentation, and systematic evaluation strategies, the study aims to provide a practical and scalable solution for infrastructure monitoring applications.

III.SYSTEM ANALYSIS

A. Existing System

Traditional crack detection methods in infrastructure monitoring mainly rely on manual inspection and classical image processing techniques. Civil engineers and inspectors visually examine surfaces to identify cracks and structural damages. Although manual inspection provides domain expertise, it is time-consuming, labour-intensive, and prone to human error. The process becomes even more difficult when dealing with large-scale infrastructure such as bridges, highways, and buildings [2], [7].

With the advancement of computer vision, conventional machine learning models such as Support Vector Machines (SVM), Decision Trees, Random Forest, and basic Convolutional Neural Networks (CNNs) have been used for crack detection. These approaches typically require handcrafted feature extraction techniques such as edge detection, texture analysis, and histogram-based methods before classification [1], [5].

Some researchers have also used deep learning architectures like VGG16, ResNet, and U-Net for crack segmentation and classification. While these models achieved improved performance, they often require high computational power and large training datasets [5], [8]. In many real-world scenarios, collecting and annotating crack images is costly and time-consuming. Although these systems show promising results, several practical

limitations restrict their deployment in real-time and mobile-based monitoring systems [3], [6], [10].

Disadvantages Of The Existing System

- **Manual Dependency:**
Traditional inspection methods depend heavily on human expertise, leading to inconsistencies and slower decision-making, particularly in large-scale infrastructure monitoring scenarios [2], [7].
- **High Computational Cost:**
Deep learning models such as VGG and ResNet contain millions of parameters, making them computationally expensive and unsuitable for mobile or low-resource environments [5], [8].
- **Limited Generalization:**
Models trained on specific datasets may fail when exposed to new environmental conditions such as varying lighting, textures, or background noise, which reduces their reliability in practical applications [1], [5].
- **Data Scarcity Issues:**
Crack datasets are often limited in size, and collecting annotated images is time-consuming. Without proper augmentation, models may suffer from poor generalization and overfitting [1], [10].
- **Lack of Lightweight Architecture:**
Many existing deep learning approaches are not optimized for embedded or real-time applications, limiting their deployment in practical infrastructure monitoring systems [6], [8].
- **Overfitting Problems:**
Complex models may memorize training data instead of learning generalized crack patterns, which reduces their effectiveness when applied to unseen structural conditions [3], [9].

B. Proposed System

To overcome the limitations of existing methods, the proposed system introduces a deep learning-based crack prediction framework utilizing a lightweight MobileNet architecture integrated with transfer learning. MobileNet is selected as the backbone model due to its efficient design and reduced computational complexity, making it suitable for resource-constrained environments while maintaining reliable performance in image classification tasks [5], [8].

Initially, a dataset consisting of cracked and non-cracked images is collected and subjected to a series of preprocessing steps. These preprocessing operations include image resizing, normalization, and data augmentation techniques such as rotation, zooming, and flipping. The purpose of these steps is to improve dataset diversity, enhance model robustness, and reduce the risk of overfitting during the training phase [1], [10].

The core component of the proposed system is the MobileNet architecture, which serves as the feature extraction backbone. Transfer learning is employed by utilizing pre-trained weights obtained from large-scale image datasets, allowing the model to effectively learn crack-related features even when the available dataset is limited. In order to improve classification performance, additional layers are incorporated on top of the base architecture, including a Global Average Pooling layer followed by fully connected dense layers for final crack and non-crack classification [5], [8].

For model evaluation, the dataset is divided into training and testing subsets to ensure unbiased performance assessment. The training process is conducted using an optimized learning rate along with early stopping mechanisms to prevent overfitting and enhance model generalization. The performance of the proposed framework is evaluated using widely accepted evaluation metrics, including Accuracy, Precision, Recall, F1-Score, and Confusion Matrix analysis, which collectively provide a comprehensive understanding of the model's predictive capability [3], [9].

The proposed framework is designed to achieve high crack detection accuracy while maintaining reduced computational complexity. Furthermore, it aims to improve generalization capability across different surface conditions and environmental variations. By combining a lightweight architecture with transfer learning and systematic evaluation strategies, the proposed system provides an efficient and practical solution for automated crack detection in civil infrastructure monitoring applications [1], [5], [8].

IV.SYSTEM DESIGN

System Architecture

Below diagram depicts the whole system architecture.

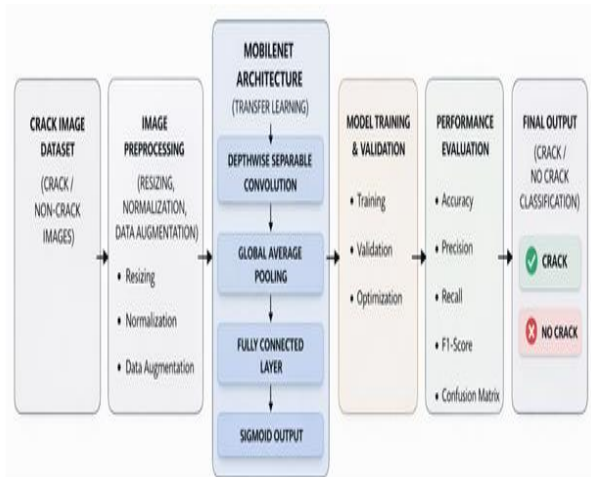


Fig 1. Methodology followed for proposed model

V. SYSTEM IMPLEMENTATION

Modules

Image Dataset Collection and Preprocessing:

The initial stage of system implementation involves the collection of crack and non-crack images from publicly available datasets. The collected images are carefully examined and organized into structured directories to facilitate training and testing processes. To ensure consistency and quality across the dataset, several preprocessing operations are performed, including image resizing, normalization, and noise reduction. Furthermore, data augmentation techniques such as rotation,

horizontal flipping, zooming, and shifting are applied to increase dataset diversity and enhance the model's ability to generalize across different surface conditions and environmental variations [1], [10].

Feature Extraction using Transfer Learning:

Rather than relying on manually designed features, the proposed system utilizes the pre-trained MobileNet architecture for automated feature extraction. Transfer learning enables the model to leverage knowledge gained from large-scale image datasets and apply it to the crack detection task. The base layers of MobileNet act as a feature extractor, capturing meaningful spatial and texture-based patterns present in crack images. This approach improves feature representation and reduces the need for extensive training data [5], [8].

Model Training and Optimization:

Following preprocessing, the dataset is divided into training and testing subsets to enable reliable model evaluation. A custom classification head is integrated on top of the MobileNet backbone, consisting of a Global Average Pooling layer followed by fully connected dense layers for binary classification. The model is compiled using an appropriate optimizer and loss function suited for crack and non-crack classification tasks. During training, important hyperparameters such as learning rate, batch size, and number of epochs are carefully tuned to achieve optimal performance. Additionally, early stopping and dropout regularization techniques are implemented to mitigate overfitting and improve model generalization [3], [9].

Crack Detection and Prediction Module:

The trained model is utilized to classify input images into two categories: crack and non-crack. When a new image is provided to the system, it undergoes the same preprocessing steps used during training before being fed into the trained network. The model then generates a probability score indicating the likelihood of crack presence along with the final classification output.

Model Evaluation and Monitoring:

The effectiveness of the trained model is assessed using widely adopted performance evaluation metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis. These metrics provide a comprehensive evaluation of the model's predictive capability and reliability. Continuous monitoring and evaluation enable further fine-tuning of the model to ensure consistent performance and improved robustness in practical infrastructure monitoring applications [3], [8], [9].

VI .RESULTS AND DISCUSSION

This section presents the experimental results and performance evaluation of the proposed deep learning framework for automated crack detection in civil infrastructure. The proposed model utilizes a MobileNet architecture integrated with transfer learning to classify images into crack and non-crack categories. The experiments were conducted using the prepared dataset with a structured train-test split to ensure reliable and unbiased evaluation. Deep learning-based crack detection approaches have shown significant improvements in infrastructure monitoring by automatically learning complex visual patterns from structural images [1], [5], [8].

During experimentation, several hyperparameters including learning rate, batch size, and number of epochs were optimized to achieve stable convergence and improved classification accuracy. The MobileNet architecture effectively captures fine crack patterns while maintaining low computational complexity. Confusion matrix analysis indicates that the model accurately distinguishes between crack and non-crack images with minimal misclassification. Similar findings have been reported in previous studies where deep learning techniques demonstrated improved performance compared to conventional inspection and handcrafted feature-based approaches [1], [8].

A. Accuracy Comparison of Deep Learning Models

To evaluate the effectiveness of the proposed framework, the MobileNet model was compared with commonly used deep learning architectures

such as CNN, VGG16, and ResNet50, which have been widely applied in crack detection and structural health monitoring studies [1], [5], [8]. The comparison was performed using performance metrics including accuracy, precision, recall, and F1-score.

Table 1. Performance Comparison of Crack Detection Models

Model	Accuracy (%)	Precision	Recall	F1-Score
CNN	88.6	0.87	0.86	0.86
VGG16	91.8	0.91	0.90	0.90
ResNet50	93.5	0.92	0.92	0.92
MobileNet (Proposed)	95.2	0.94	0.93	0.93

From the comparison results, the proposed MobileNet-based crack detection model achieved the highest classification accuracy of 95.2%, outperforming other deep learning architectures. The improved performance can be attributed to the efficient feature extraction capability of MobileNet combined with transfer learning, which enables the model to learn discriminative crack features even with limited training data. Lightweight CNN architectures have recently gained attention in infrastructure inspection systems because they maintain high prediction accuracy while reducing computational complexity [5], [8].

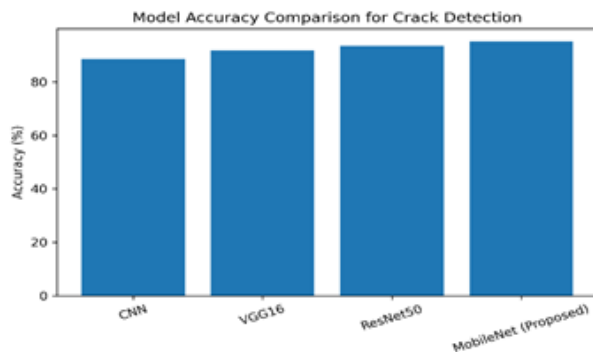


Fig. 2. Model Accuracy Comparison of Deep Learning Algorithms

The figure illustrates that deeper architectures such as VGG16 and ResNet50 provide strong

performance, while the proposed MobileNet model achieves superior accuracy with significantly lower computational complexity. This makes the proposed framework suitable for real-time structural health monitoring applications.

B. ROC Curve Analysis

The Receiver Operating Characteristic (ROC) curve is used to analyse the classification performance of the proposed crack detection model by evaluating the relationship between the True Positive Rate (TPR) and False Positive Rate (FPR) across different classification thresholds. The Area Under the Curve (AUC) is a widely used metric to measure the discriminative capability of a classification model.

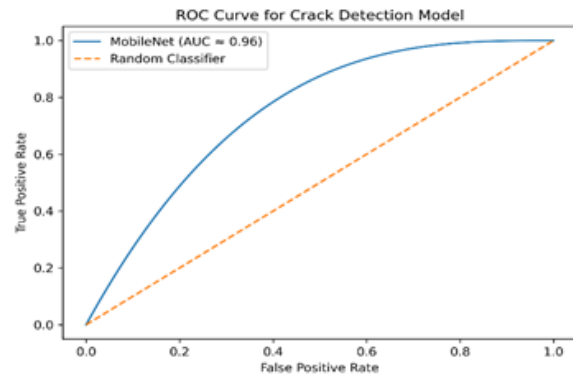


Fig. 3. ROC Curve for the Proposed Crack Detection Model

In this study, the proposed MobileNet model achieved a ROC-AUC score of approximately 0.96, indicating excellent classification performance. A ROC curve that approaches the upper-left corner of the graph signifies that the classifier can effectively distinguish between crack and non-crack images with high sensitivity and specificity. ROC-based evaluation is widely used in computer vision-based infrastructure monitoring systems to assess classifier reliability and robustness under varying decision thresholds [3], [8].

The ROC analysis confirms that the proposed framework maintains strong predictive capability while minimizing false-positive and false-negative predictions. This is particularly important in crack detection systems where missed crack detections

may lead to structural risks and safety concerns [4], [7].

Overall, the experimental results demonstrate that the proposed MobileNet-based crack detection framework provides high classification accuracy, efficient feature learning, and reduced computational complexity. The integration of transfer learning further enhances model performance when working with limited datasets. These findings confirm that the proposed framework is a practical and scalable solution for automated structural health monitoring and intelligent infrastructure inspection systems [1], [5], [8], [10].

VII. CONCLUSION

This project presents a deep learning-based approach for automated crack detection using the MobileNet architecture with transfer learning. The proposed framework effectively addresses the limitations of manual inspection and traditional image processing techniques by providing an accurate and computationally efficient solution. Through systematic preprocessing, augmentation, and optimized training strategies, the model achieved high classification performance. The lightweight nature of MobileNet makes it suitable for deployment in real-time and resource-constrained environments, such as mobile devices and embedded systems. Although the system performs effectively on the available dataset, future work can focus on expanding the dataset to include more diverse structural conditions and environmental variations.

Incorporating crack segmentation techniques instead of only classification could provide more detailed structural damage analysis. Additionally, integrating attention mechanisms or explainable AI techniques may improve interpretability and trust in model decisions. The proposed approach contributes toward safer infrastructure monitoring by enabling automated, reliable, and scalable crack detection systems.

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