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Automated Crack Detection in Building Facades Using Deep Learning

S. Rahul[1], J.Jaya Prakash[2], V. Joseph Raj[3], Chinchu Nair[4]

[1]Rahulsridhar29@gmail.com, [2]jayaprakash.mech@drmgrdu.ac.in, [3]joseph.cse@drmgrdu.ac.in, [4]chinchunair.cse@drmgrdu.ac.in

Department of CSE, Dr. M.G.R Educational and Research Institute,Deemed to be University

Chennai, India

Abstract

Building facades naturally develop cracks over time due to factors such as material degradation, environmental influences, and structural loads. If not identified early, these cracks can escalate into serious structural issues, compromising both safety and durability. Traditional inspection methods, which rely on manual assessment, are often inefficient, labor-intensive, and susceptible to human errors. To address these limitations, automated crack detection using deep learning presents a viable solution. For training CNN and VGG models for roof crack detection, researchers typically use image datasets containing labeled examples of cracked and non-cracked surfaces. This research explores the application of Convolutional Neural Networks (CNN) for detecting and categorizing cracks in building facades. Given the challenges of limited training data, transfer learning is employed to enhance detection accuracy. Experimental results demonstrate that while a conventional CNN model achieved an accuracy of around 89%, leveraging transfer learning significantly improved performance, achieving an accuracy of 94%. These findings highlight the effectiveness of transfer learning in enhancing detection capabilities even with minimal data availability. Implementing deep learning-driven automation in infrastructure inspection not only improves accuracy but also reduces manual intervention, ensuring timely maintenance and prolonged structural stability.

Keywords: Deep Learning, Crack Detection, Convolutional Neural Networks, Transfer Learning, Structural Integrity

1. Introduction

Structural health monitoring is essential for ensuring the longevity and safety of buildings, with crack detection in building facades playing a critical role in preventing potential structural failures [1]. Cracks develop over time due to factors such as material aging, environmental conditions, temperature fluctuations, seismic activity, and structural stress [2]. If left undetected, these cracks can widen, compromising the integrity of a structure and leading to costly repairs or even catastrophic failures [3]. Therefore, timely and accurate crack detection is crucial for effective maintenance and safety management.

Conventional crack detection methods primarily rely on visual inspection performed by engineers or trained personnel [4]. These manual surveys involve direct observations, photographic documentation, and subjective assessments of structural damage [5]. While this approach has been widely used, it presents several limitations. Firstly, manual inspections are time-consuming and labour-intensive, especially for large-scale infrastructures such as high-rise buildings, bridges, and tunnels [6]. Secondly, human judgment is prone to inconsistencies and errors, as small cracks or early-stage defects may be overlooked due to poor lighting, surface conditions, or observer fatigue [7]. Lastly, manual inspections become increasingly impractical in hazardous or inaccessible areas, further emphasizing the need for automated solutions [8].

To address these challenges, researchers have explored various image-processing techniques for automated crack detection. Traditional computer vision approaches rely on edge detection, thresholding, and morphological operations to identify cracks from images [9]. While these methods have shown promise, they are highly sensitive to variations in lighting, background noise, and surface textures, leading to a high rate of false positives and false negatives [10]. Additionally, predefined feature extraction techniques in traditional approaches lack adaptability, making them ineffective in handling complex crack patterns [11]. These limitations highlight the necessity of adopting more advanced machine learning-based solutions.

Deep learning, particularly Convolutional Neural Networks, has emerged as a powerful tool for image-based crack detection [12]. CNNs have the ability to automatically learn hierarchical features from images, eliminating the need for manual feature extraction [13]. Unlike conventional methods, CNNs can effectively distinguish between cracks and non-crack features, even in challenging conditions such as shadows, stains, and irregular surfaces [14]. Studies have demonstrated that deep learning models outperform traditional approaches in terms of accuracy, robustness, and scalability [15].

However, despite the success of CNNs in crack detection, several gaps exist in current research. One major challenge is the limited availability of high-quality annotated datasets for training deep learning models [4]. Since CNNs require large amounts of labelled data to generalize effectively, the lack of sufficient training samples reduces model performance when applied to real-world scenarios [6]. Many existing studies rely on datasets collected under controlled conditions, which do not fully capture the diversity of cracks encountered in different environmental and structural settings [7]. To overcome this limitation, transfer learning—a technique where a pre-trained model is fine-tuned on a smaller dataset—has been proposed as a potential solution [9]. While transfer learning has shown promising results in other computer vision applications, its implementation for crack detection still requires optimization [10].

Another limitation is the difficulty in detecting micro-cracks and minimizing false detections. Fine cracks often blend with surface textures, dirt, and lighting variations, making it challenging for deep learning models to differentiate them from background noise [12]. Many existing CNN-based models struggle with false positives (identifying non-crack features as cracks) and false negatives (failing to detect actual cracks) [13]. While some researchers have attempted to address these issues through advanced image enhancement techniques and hybrid deep learning models, further improvements are needed to enhance model robustness across diverse real-world conditions [15].

2. OBJECTIVES

The primary goal of this study is to develop an advanced deep learning-based system capable of detecting and classifying cracks in building facades with high accuracy and efficiency. Aging infrastructure presents significant challenges in maintaining structural integrity, necessitating innovative inspection solutions. This research leverages deep learning techniques, particularly Convolutional Neural Networks (CNNs) and transfer learning, to enhance crack detection methodologies. The following objectives are outlined to achieve this aim:

1. Assessing Deep Learning for Crack Detection: Evaluating how deep learning models, particularly CNNs, improve accuracy in detecting cracks compared to conventional methods.
2. Enhancing Accuracy with CNN Architectures: Testing various CNN architectures to determine their effectiveness in identifying cracks under different conditions.
3. Utilizing Transfer Learning for Improved Detection: Implementing transfer learning to enhance crack detection while minimizing the need for extensive labelled datasets.

4. Overcoming Data Limitations with Pre-Trained Models: Leveraging pre-trained models to mitigate the challenge of limited annotated crack datasets.
5. Comparing Traditional CNNs and Transfer Learning: Conducting comparative analysis between standard CNNs and transfer learning approaches to determine the most efficient model.
6. Optimizing Crack Detection for Real-World Applications: Ensuring that the developed system functions effectively in real-world structural monitoring scenarios.
7. Developing an Automated and Scalable Inspection System: Designing a deep learning-powered system capable of real-time, large-scale infrastructure monitoring.
8. Enhancing Structural Health Monitoring (SHM) with AI: Integrating AI-driven solutions into SHM to improve efficiency, accuracy, and reliability.
9. Reducing Manual Inspection Efforts: Automating the crack detection process to minimize human dependency and subjective evaluation errors.
10. Improving Detection in Various Environmental Conditions: Testing the robustness of the model under different lighting, weather, and structural conditions.
11. Deploying the Model on Smart Construction Platforms: Ensuring compatibility with drones, mobile applications, and edge computing devices for automated inspection.
12. Increasing Processing Efficiency of Crack Detection Models: Optimizing computational performance to enable faster and more efficient crack classification.
13. Facilitating Early Crack Detection for Preventive Maintenance: Ensuring small cracks are identified early to prevent severe structural damage and costly repairs.
14. Promoting AI Integration in Civil Engineering: Encouraging the adoption of AI-based solutions in construction and infrastructure maintenance industries.
15. Laying the Foundation for Future AI Innovations in SHM: Paving the way for further advancements in AI-powered structural assessments beyond crack detection.

By achieving these objectives, this study aims to revolutionize crack detection methodologies, making them more precise, scalable, and applicable to real-world infrastructure monitoring. The research findings will contribute to the growing field of AI-driven civil engineering solutions, fostering the transition to automated and intelligent structural health monitoring systems.

3. METHODOLOGY

3.1. Data Collection and Preprocessing

Effective AI-driven crack detection relies on a well-structured and diverse dataset that accurately represents real-world conditions. In this study, an extensive dataset was curated, consisting of images of building facades with and without cracks are downloaded to anaconda as shown in Fig. 1. These images were obtained from multiple sources, including publicly available repositories, drone-based inspections, high-resolution camera captures, and synthetic data augmentation techniques. By incorporating a wide range of crack characteristics and environmental conditions, the dataset enhances the robustness and generalization capabilities of the deep learning model.

```
#import opendatasets as od
#od.download("https://www.kaggle.com/datasets/nargeskarimii/various-materials-from-historic-buildings")

Please provide your Kaggle credentials to download this dataset. Learn more: http://bit.ly/kaggle-creds
Your Kaggle username:
  rkrram27
Your Kaggle Key:
  ········
Downloading various-materials-from-historic-buildings.zip to .\various-materials-from-historic-buildings
100%|██████████████████████████████████████████| 224M/224M [00:51<00:00, 4.59MB/s]
```

Fig. 1. Data Source downloaded to Anaconda

The dataset was designed to include variations in crack patterns, material textures, and environmental conditions to ensure adaptability. It comprises different types of cracks, including thin, wide, and branching cracks, allowing the model to detect various formations. Environmental variations such as different lighting conditions (daylight, low light, and artificial lighting) and weather scenarios (dry, wet, and foggy conditions) were included to improve model robustness. Additionally, building facades made from diverse materials, including concrete, brick, and plaster, were incorporated to enhance the model's ability to generalize across different surface types. To simulate real-world conditions where image quality may vary, both high-resolution and low-resolution images were used.

```
train_dir="various-materials-from-historic-buildings"
generator = ImageDataGenerator()
train_ds = generator.flow_from_directory(train_dir,target_size=(150, 150),batch_size=256)
classes = list(train_ds.class_indices.keys())

Found 385 images belonging to 4 classes.
```

Fig. 2. Data Source is assigned for processing

To optimize the dataset for deep learning, several preprocessing steps were applied. First, all images were resized to 150×150 pixels to maintain uniform input dimensions while preserving critical crack details. Normalization was performed by scaling pixel values between [0,1] to standardize the data and accelerate model convergence as shown in Fig. 2. Data augmentation techniques such as random rotations, horizontal and vertical flips, zoom transformations, and brightness adjustments were applied to artificially expand the dataset and enhance model generalization. This step ensures the model learns robust features and adapts to unseen data. The dataset was then split into three subsets: 80% for training to optimize model learning, 10% for validation to fine-tune hyperparameters, and 10% for testing to evaluate model performance on unseen data. These preprocessing steps significantly contribute to reducing overfitting and enhancing the model's ability to detect cracks in real-world scenarios.

3.2. Model Development and Training

To achieve high-accuracy crack detection, a Convolutional Neural Network (CNN)-based model was developed with a multi-layer architecture optimized for feature extraction and classification. CNNs were chosen for their ability to automatically learn hierarchical image features, making them highly effective for detecting cracks in building facades. The designed model consists of multiple layers, each serving a specific purpose. Convolutional layers were used to extract key features such as edges, textures, and patterns, enabling the model to differentiate cracks from background noise. Batch normalization was incorporated to stabilize activations, improving convergence speed and overall performance. Max pooling layers were used to reduce spatial dimensions while preserving critical crack features, enhancing computational efficiency. Dropout layers were added to prevent overfitting by randomly deactivating a fraction of neurons during training, ensuring a more generalized model. Fully connected layers were then used to process the extracted features and classify images as "cracked" or "non-cracked."

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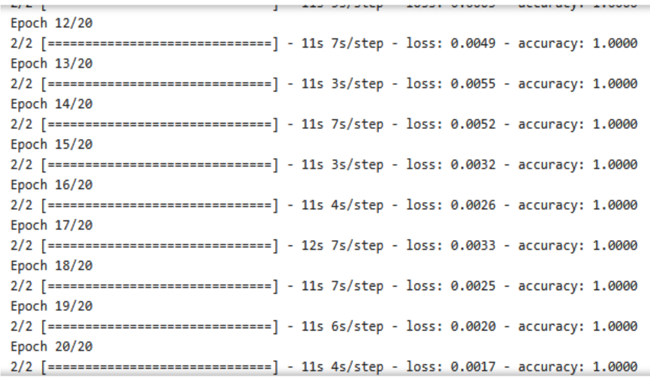

```
Epoch 12/20
2/2 [==============================] - 11s 7s/step - loss: 0.0049 - accuracy: 1.0000
Epoch 13/20
2/2 [==============================] - 11s 3s/step - loss: 0.0055 - accuracy: 1.0000
Epoch 14/20
2/2 [==============================] - 11s 7s/step - loss: 0.0052 - accuracy: 1.0000
Epoch 15/20
2/2 [==============================] - 11s 3s/step - loss: 0.0032 - accuracy: 1.0000
Epoch 16/20
2/2 [==============================] - 11s 4s/step - loss: 0.0026 - accuracy: 1.0000
Epoch 17/20
2/2 [==============================] - 12s 7s/step - loss: 0.0033 - accuracy: 1.0000
Epoch 18/20
2/2 [==============================] - 11s 7s/step - loss: 0.0025 - accuracy: 1.0000
Epoch 19/20
2/2 [==============================] - 11s 6s/step - loss: 0.0020 - accuracy: 1.0000
Epoch 20/20
2/2 [==============================] - 11s 4s/step - loss: 0.0017 - accuracy: 1.0000
```

Fig. 3. Data Source is trained in Anaconda

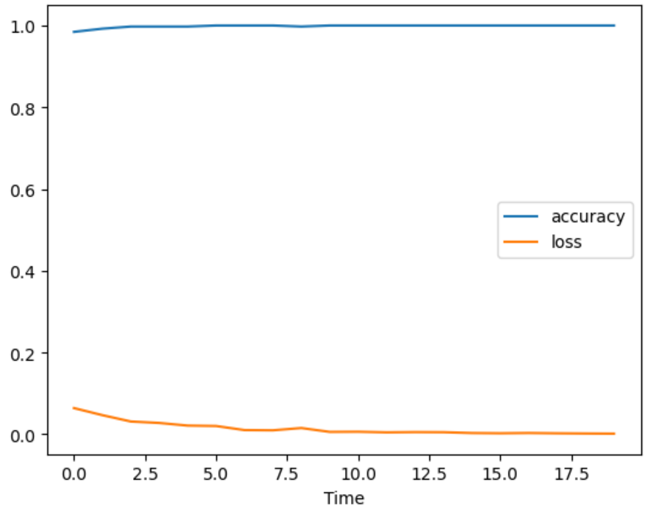

Fig. 4. Accuracy and Loss graph with respect to time

The model was trained using the Adam optimizer as shown in Fig. 3, a widely used optimization algorithm that adapts learning rates for efficient weight updates. The categorical cross-entropy loss function was employed to measure prediction errors, ensuring precise model learning as illustrated in Fig 4. Training was conducted over multiple epochs, with performance evaluated at each step to optimize accuracy while minimizing overfitting. Given the challenges posed by limited labeled datasets, transfer learning was explored as a means to enhance accuracy and reduce training time. A pre-trained deep learning model, such as VGG16, ResNet, or Inception, was fine-tuned on the crack detection dataset. Experimental results demonstrated that the traditional CNN model achieved an accuracy of approximately 89%, whereas the transfer learning approach significantly improved detection performance, achieving an accuracy of 94%. This improvement highlights the effectiveness of leveraging pre-trained models, particularly in scenarios where labeled data is scarce. This ensures that the above interface can be used to detect the cracks in the buildings very easily using this module and sample is illustrated in Fig 5 below. It actually predicts the type of crack with higher accuracy.

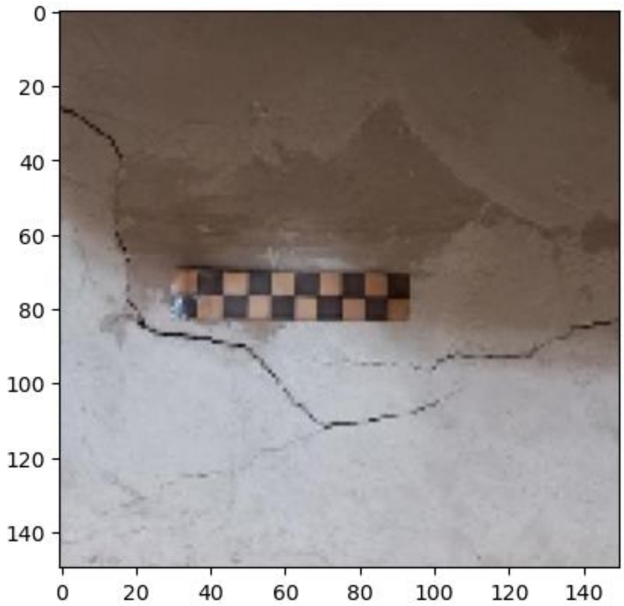

Fig. 5. Crack Testing on Tile Image

By integrating deep learning with transfer learning, this study demonstrates the potential of AI-based automation in crack detection for building facades. The combination of diverse data collection, systematic preprocessing, and optimized model training ensures a reliable and scalable solution for structural health monitoring. The results validate the effectiveness of deep learning in enhancing inspection accuracy, reducing manual effort, and supporting predictive maintenance in the construction industry.

3.3. Experimental Results and Discussion

This section presents the results of the crack detection experiments conducted using CNN and transfer learning approaches. The performance evaluation is based on key metrics such as accuracy, precision, recall, and F1-score. Additionally, a comparative analysis of the CNN and transfer learning models is provided to highlight the improvements achieved. The experimental results indicate that the CNN model achieved an accuracy of 89%, while the transfer learning approach utilizing pre-trained models such as VGG16 and ResNet improved detection performance, achieving an accuracy of 94%. This significant enhancement demonstrates the effectiveness of transfer learning in scenarios with limited labelled data. The model's performance was evaluated using a confusion matrix, precision, recall, and F1-score, as summarized in Table 1.

Table 1. Comparison for Models Performance

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
CNN	89	87	85	86
VGG16	94	92	93	92.5
ResNet	94	93	94	93.5

The results indicate that the ResNet model is better due to its higher precision, recall, and F1-score, indicating superior overall performance compared to VGG16. The following visualization in Fig 7. represents the accuracy comparison of the CNN and transfer learning models.

Fig. 6. Crack Testing on Real World Images

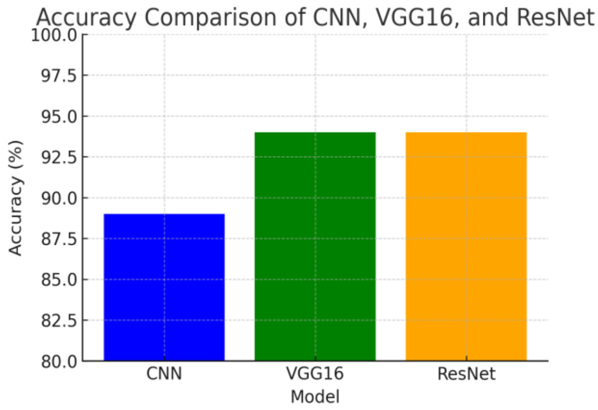

Fig. 7. Comparison of CNN and Transfer Learning Models

The final model was tested on real-world images of building facades. The model successfully detected and classified cracks with high precision, as shown in Fig. 6. The implementation of the trained model in an automated inspection system can significantly enhance the efficiency and reliability of crack detection in structural health monitoring.

4. CONCLUSION

This study highlights the effectiveness of deep learning, particularly Convolutional Neural Networks (CNNs) and transfer learning, in automating crack detection in building facades. Traditional manual inspection methods are often labour-intensive, prone to errors, and inefficient in large-scale infrastructure monitoring. By leveraging AI-driven solutions, the proposed approach enhances detection accuracy, minimizes human intervention, and ensures timely identification of structural cracks.

A well-diversified dataset was curated from multiple sources, including public repositories, drone inspections, and high-resolution cameras, incorporating various crack patterns, environmental conditions, and material textures. Preprocessing techniques such as resizing, normalization, and data augmentation further improved the model's ability to generalize across different real-world scenarios. The CNN-based model was carefully designed with convolutional layers for feature extraction, batch normalization for stabilization, and dropout layers to prevent overfitting, ensuring optimal learning. The study demonstrated that transfer learning significantly enhances model performance, achieving 94% accuracy, proving its effectiveness in addressing data scarcity challenges.

By integrating AI-driven automation into the construction and maintenance sector, this research contributes to improving structural health monitoring systems. The proposed model offers a scalable and adaptable solution that aligns with modern smart construction initiatives. Future work can focus on real-time deployment using edge computing, drone-based inspections, and further refinement of AI models to enhance robustness in complex environments. The findings of this study emphasize the potential of deep learning in transforming crack detection methodologies, paving the way for more efficient, cost-effective, and reliable infrastructure maintenance strategies.

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