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# A Comparative Study of CNN Models for Crack Classification in Buildings

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## Abstract

Background: Cracks serve as a vital indicator of a building's condition. Cracks may emerge due to various factors such as the age and design of the structure, soil properties beneath the building, or environmental impacts. For example, cracks caused by seismic activity pose significant risks to structural integrity and may lead to collapse if left unattended. Detecting and categorizing building cracks is critical for its effective maintenance and timely repairs.

Objective: The aim of this study is to evaluate and compare the use of CNN models for the detection and classification of the cracks.

Methods: In this study, cracks were categorized into four groups based on their severity. Four pre-trained models—VGG16, AlexNet, ResNet50, and a modified CNN model were used and their performance were assessed. Additionally, the combination of the models' outputs was also used for detecting and categorizing the cracks and the resulted accuracy was evaluated.

Results: The findings revealed that the ResNet50 model achieved the highest accuracy at 99.5%, while AlexNet produced the lowest accuracy at 88.2% and VGG16 98.3%. However, combining all four models together resulted in the accuracy rate of 91%.

Conclusion: The results demonstrated how quickly and accurately deep learning can detect and classify cracks.

**Keywords:** Convolutional Neural Network (CNN), VGG16, Alex net, Building Integrity Assessment, Structural Crack Analysis, Automated Inspection Techniques

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# 1. Introduction

In the field of civil engineering, early detection of defects, such as cracks, is crucial for effective maintenance and renovations on buildings. Early detection of cracks significantly enhances our ability to prolong the lifespan and improve the stability of concrete structures. Various factors contribute to the creation of different types of cracks. These includes soil shifting beneath the building, earthquake, and climate-based factors like temperature fluctuations and moisture penetration [1]. Some cracks also result from the advanced age of the building and its poor design and material. These cracks may lead to the deterioration of buildings if left unaddressed.

Various crack detection methods have been developed over time, beginning with traditional manual infrared and thermal testing, ultrasonic testing, laser testing, and radiographic testing [2]. The effectiveness of these methods depends mainly on the skill and experience of inspectors. However, these approaches require significant maintenance costs, time, and expertise to identify cracks effectively. To address these limitations, several automated methods have been introduced, based on computer vision techniques like edge detection, intensity thresholding, and filtering. Modern approaches use UAVs equipped with cameras that have thermal sensors, LiDAR technology, or 3D cameras with RGB sensors [3] to systematically scan structures for cracks. These methods are relatively effective in detecting cracks. However, their ability to handle image noise caused by brightness variations, shadows, or rough surfaces remains limited. To address these challenges, several advanced approaches have been introduced that offer highly accurate and fast crack detection. Among these, deep learning (DL) emerges as a leading method due to its ability to process large volumes of data, handle various forms of noise, and deliver robust accuracy. Commonly used DL architectures in crack detection research include RNN, DNN, and CNN [4].CNNs, in particular, are a deep learning framework capable of addressing fundamental computer vision tasks such as image classification, object recognition, localization, and segmentation. Comprising multiple layers like convolution and pooling layers, CNN models are designed to extract meaningful features from images effectively [5-7]. This study focuses on the application and comparison of four convolutional neural networks (CNNs) used for classifying different types of cracks in concrete.

In structural engineering, CNNs are increasingly used, particularly in Structural Health Monitoring (SHM), damage detection, vibration-based diagnostics, and condition assessment. One way CNNs contribute is by using UAVs with cameras for image-based inspection to identify surface defects through classification or localization [8-10].

(Li and Zhao (2019), Chow et al. (2020), Dais et al. (2021) and. Huang and Wu (2022) [11], in this work, researchers aim to develop an optimal model capable of handling diverse conditions, including small datasets, while maintaining high accuracy in crack multi-classification. They compare their work with models that strike a balance between accuracy, cost, and robustness, such as Alexnet. Additionally, residual connections in ResNet-50 are used to train deeper networks, alongside simpler architecture models like VGG16.

This paper is organized into five sections. The first section serves as an introduction. The second section reviews several studies that have used deep learning techniques for crack detection. The third section outlines the methodology used in this research. The final two sections present the results and compare them with the findings of other studies.

# 2. Literature Review

Deep learning has revolutionized the field of civil structure defect detection, providing substantial advancements over traditional inspection methods. Chow et al. (2020) highlighted the effectiveness of deep learning in identifying and categorizing building defects under varying environmental conditions, such as changes in lighting and camera angles [9]. They recommended further improvements to deep learning models to enhance accuracy. Liu et al. (2020) developed a technique that combines deep and conventional image analysis methods to identify rebars in Ground Penetrating Radar (GPR) data, achieving an accuracy of 99.60% ± 0.85%. They suggested that a larger database would further enhance the model's robustness [12]. Another study used a Convolutional Neural Network (CNN) to categorize Impact-Echo (IE) waveforms, achieving an accuracy between 45% and 81%. The researchers highlighted the need for further refinement of the CNN model. Lee et al. (2020) utilized deep learning to find cracks in railroad infrastructure, measuring the largest crack width with high accuracy through semantic segmentation within a deep CNN architecture [13]. C. Zhang et al. (2020) proposed a single-stage algorithm for the visual identification of defects in concrete bridges using the You Only Look Once (YOLOv3) real-time object detection technique [14]. Their improved algorithm achieved a detection precision of up to 80% and 47% at Intersection-over-Union (IoU) metrics of 0.5 and 0.75, respectively, outperforming the original YOLOv3 and Faster Region-based Convolutional Neural Network (Faster RCNN) with ResNet-101. Bae et al. (2021) introduced the crack network (SrcNet) to detect defects with an increased pixel resolution, improving the accuracy by 24% compared to traditional techniques [15]. Kim and Cho (2019) employed a Mask R-CNN for detecting and specifying crack widths on concrete buildings, achieving reliable detection for cracks equal to or wider than 0.3mm, but with more errors for widths less than 0.1mm [16]. Li et al. (2019) used a Fully Convolutional Network (FCN) to identify various forms of damage such as efflorescence, fractures, spalling, and holes [8]. Despite its effectiveness, the model struggled to determine the damage level. Liang (2019) enhanced a method for examining reinforced post-accident concrete using CNN layers for semantic segmentation, object identification, and image classification [17]. The study highlighted the need for real-time deterioration evaluation and detection. Ni et al. (2019) introduced a new technique, Convolutional feature fusion and pixel-level categorization (CDN), for automated crack detection at the pixel level, achieving high precision without the need for manually designed low-level features [18]. Ali et al. (2021) evaluated four deep learning techniques (ResNet-50, Inception V3, VGG-16, and VGG-19) across eight datasets, revealing the significant impact of dataset heterogeneity and size on model effectiveness [19]. Shatnawi (2018) suggested a 6-layer CNN structure for recognizing pavement surface cracks, validated with extensive datasets [20]. Cha et al. (2017) merged CNN with sliding window methods to identify building surface defects, recommending network training with over 10,000 images for improved accuracy [21]. Xu et al. (2019) created a 28-layer neural technique for detecting concrete bridge cracks, employing Atrous Spatial Pyramid Pooling (ASPP) and deep convolution to reduce model parameters [22]. Loprencipe (2020) proposed an automatic pavement crack recognition model using an ensemble of CNN models, which achieved a high crack probability score [23]. Pauly et al. (2017) developed three distinct CNN architectures for crack identification, positioning, and feature extraction in Ground Penetrating Radar (GPR) images [24]. Yang (2018) introduced a Fully Convolutional Network (FCN) for automatic crack detection and measurement, utilizing downsampling and upsampling techniques [25].

Table 1. A review of papers that use CNN algorithms to recognize cracks.

| Reference | Best model | Accuracy | Dataset |
|---|---|---|---|
| (Xu et al. 2019) [22] | CNN atrous convolution, Atrous Spatial Pyramid Pooling (ASPP) module and depthwise separable convolution. | 96.37% | 8272 |
| (Dais et al. 2021) [10] | U-net-MobileNet | 95.3٪ | 351 |
| (Islam et al. 2022) [33] | VGG16,ResNet18, DenseNet161, and AlexNet | 99.90%, 99.60%, 99.80%, and 99.90% | 20,000 |
| (Cha, Choi, and Büyüköztürk 2017) [21] | CNN with a sliding window | 98% | 332 |
| (Le, Nguyen, and Le 2021) [5] | CNN | 99.7% | 40,000 |
| (Silva and Lucena 2018) [2] | InceptionV3 | 0.9898% | 12,000 |
| (Silva and Lucena 2018) [2] | CNN | 92.27% | 3500 |
| (Peyman.Babaei 2023) [34] | Resnet50,MobileNetv2,VGG16 | 96.64%, 97.33%, 97.61% | 51839 |
| (S. M. Mousavi and Hosseini 2023) [35] | InceptionV3 | 96.943% | 10239 |
| (M. Mousavi and, Soodeh Hosseini, 2023) [35] | InceptionResNetV2, InceptionV3 | 99.366%, 96.943% | 10239 CT Scan, 5228 X-ray |

Li and Zhao (2019) modified AlexNet to detect cracks in concrete surfaces, achieving 99.09% accuracy despite noisy conditions [8]. A. Zhang et al. (2018) developed CrackNet II, addressing processing speed and detecting fine cracks in 3D road surfaces [26]. Transfer learning models, such as those by

Google and the Visual Geometry Group (VGG), have been shown to reduce training time while maintaining high accuracy [27-29]. Gopalakrishnan et al. (2017) used a pre-trained VGG16 model for crack detection, finding it more dependable and faster than traditional CNN models [30]. K. Zhang et al. (2018) utilized an ImageNet-based pre-trained model for crack recognition and sealing in surface images, with impressive results [31]. Sun and Wang (2018) combined UAV and pre-trained DL models for efficient infrastructure preservation [32], while Dais et al. (2021) enhanced Inception V3 for detecting building damage in concrete water pipes [10]. Huang and Wu (2022) used YOLOv5 to identify pavement cracks, achieving over 88.1% detection accuracy and quick identification times [11]. Finally, Table 1 shows a comparison between different researchers who depend on CNN for crack detection.

## 3. Methodology

In this study, the researcher applied several steps to the models before classifying the crack images, as illustrated in (Figure 1). The researchers initiated the compilation of a dataset containing various types of concrete images. The dataset was then cleaned and noise was removed to help improve the training ability. After that, the researchers modified four CNN models from Kaggle to classify images of cracks in concrete structures. We used four CNN models, including VGG16, Resnet50, Alex Net, and a modified model, for this purpose. The researchers trained these models to produce four image classes that were aligned with the requirements of our study. Finally, we used accuracy metrics as shown in (equation 1) to assess each model's accuracy and select the model with the highest accuracy.

$$\text{Accuracy} = \frac{(\text{TP}+\text{TN})}{\text{TP}+\text{TN}+\text{FP}+\text{FN2a}} \quad (1)$$

$$\text{Precision} = (\text{TP}) / (\text{TP}+\text{FP}) \quad (2)$$

$$\text{Recall} = (\text{TP}) / (\text{TP}+\text{FN}) \quad (3)$$

where:

TP (True Positives): The number of correctly predicted positive samples.

TN (True Negatives): The number of correctly predicted negative samples.

FP: (False Positives): The number of incorrectly predicted positive samples.

FN (False Negatives): The number of incorrectly predicted negative samples.

### 3.1. Model Architecture

CNN is generally considered a deep learning algorithm. It consists of multiple layers, such as convolution and pooling, responsible for feature extraction. Additionally, it applies a fully connected layer for image classification. However, CNN models have different sub-models, such as VGG16 and Resnet50. Each sub-model has a unique architecture, parameters, and training techniques that differ from each other (as appears in Table 3). For instance, the VGG16 model consists of 13 convolution layers and three fully connected layers with 3*3 kernels. VGG16 is the simplest and uses simple kernel convolution. Dropout layers help in regularizing the model by randomly setting a fraction of input units to zero during training, thereby preventing the co-adaptation of neurons. Hyper-parameters, such as the epoch values for all four models were standardized to 10 epochs each. This adjustment is aimed at achieving a uniform training regimen and evaluating model performance under consistent conditions.

### 3.2. Overall Framework

Figure 2 explains the structure of our work process from collecting the dataset to classifying the cracks. The proposed methodology consists of three main stages: data collection, pre-processing and training, and classification.

Dataset Description

A comprehensive dataset was created by collecting images of various types of cracks (The width of cracks varies significantly, with larger cracks (exceeding 1 cm) generally exerting detrimental effects, such as those associated with foundation or soil movement (e.g., Crack1). In contrast, smaller cracks, such as those arising from volumetric changes in materials like shrinkage cracks (e.g., Crack3 and Crack4), typically have a negligible structural impact. Meanwhile, cracks induced by bending and shear stresses (e.g., Crack2) are of particular concern but can be effectively remediated through established structural rehabilitation methods) from various Kaggle sources(https://www.kaggle.com/datasets/lakshaymiddha/crack-segmentation-dataset), consisting of 4977 images of crack 1 with a resolution of (227× 227), 211 images of crack 2 with a resolution of (384×544), 162 images of crack 3 with a resolution (544×384), and 221 images of crack 4 with a resolution (448×448) as shown in Figure(1). Images were scaled to a uniform resolution of 256 × 256 pixels using Python code, using 256×256 pixel images in deep learning models improves the ability to capture detailed images, which can improve output accuracy in tasks that need high visual precision. However, this comes with higher computational costs, increased GPU memory needs, and longer training times. Providing a robust foundation for model training.

Crack1 Crack2 Crack3 Crack4

Figure 1. The different type of cracks

### 3.3. Pre-processing and Training

Images were resized and augmented such as (rescale =1/255.0, rotation range=30, zoom range =0.4, horizontal _flip=True) to enhance the dataset's diversity and improve the model's generalization. The data was then split into training (60%), validation (20%), and testing (20%) groups. Data Standardization Images were transformed into arrays of pixel values and standardized to ensure consistent input data for the models. As mentioned before, various CNN architectures, including VGG16, ResNet50, and Alex Net, were used for model training. The modified CNN model was trained using convolutional layers to extract image features. The pooling layers were used to reduce the spatial dimensions of the feature maps, decreasing over fitting and reducing training time. However, an optimization algorithm like Adams was used to improve model performance by minimizing the loss function. Activation functions like ReLU were applied after each convolutional or fully connected layer to introduce non-linearity into the model.

Crack Classification

The final stage involved classifying the images into four categories (crack1, crack2, crack3, and crack4) based on the severity and their impact on the concrete structure. The proposed method aimed to achieve high accuracy in detecting and categorizing cracks while effectively handling large datasets and overcoming image noise. (Figure 2) shows the overall framework of the proposed method.

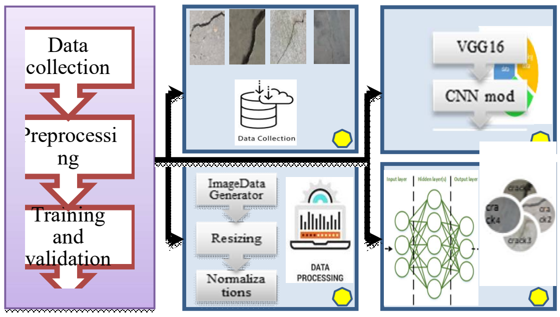



Figure 2. The overall framework of the proposed method.

Table 2. Matrices for models.

| Deep learning models | Accuracy (%) | Precision (%) | Recall (%) |
|---|---|---|---|
| Model 1 (CNN modification) | 89.32 | 95.2 | 87.9 |
| Model 2 (VGG16) | 98.32 | 97.5 | 98.3 |
| Model 3 (Alex Net) | 88.02 | 89.3 | 84 |
| Model 4 (Resnet50) | 99.5 | 99.5 | 99.4 |

In summary, this methodology leverages advanced CNN architectures and rigorous data preparation to develop a robust model for crack detection and classification in concrete structures. The proposed approach aims to provide accurate and efficient defect categorization, enhancing the maintenance and safety of civil infrastructures. Furthermore, this study demonstrates the merits of utilizing pre-trained models initially trained on large datasets and then retraining them on a smaller dataset, particularly for crack classification tasks. This approach enhances model performance by retaining the generalized features learned during pre-training while significantly reducing the computational time required for training.

## 4. Results

The study compared the performance of four different CNN models for concrete crack classification. Among them, Model 4 (Resnet50) performed the best with a training accuracy of 99.5% shown in (Table 2) and a low training loss of 0.01%. The validation accuracy for Model 4 was 97%, with a validation loss of 0.08%. The best-performing model 4 achieves this because it has wide support and sufficient depth, which doesn't require excessive resources. Additionally, residual connections assist in training deeper networks, offering a good balance between depths and training stability. The models were evaluated using the categorical cross-entropy loss function and precision metrics, confirming they did not suffer from over fitting. The improved model, created by combining all four models, achieved an accuracy score of 90.72% with a loss of 13.39%. Although this combined model provided high accuracy, it required 15.3 minutes to complete its task. While the results are promising, increasing the dataset size would be beneficial. Specifically, the number of images and the distribution of the different types of cracks in the dataset should be detailed. Providing more specific metrics used for model assessment would also enhance the clarity of the results.

Furthermore, the models were compiled utilizing the Adam optimizer, with a dropout rate of 0.5 before the ReLU activation function. The loss function was set to categorical cross entropy, and the training period was standardized to 10 epochs for all models to ensure quick execution.

Overall, our results demonstrate that deep learning is a promising approach for accurately categorizing cracks in concrete structures. By modifying and combining existing models, we achieved high accuracy without significant adjustments to network architecture. Future research could focus on expanding the dataset and exploring pixel-level data models for multi-classification tasks, potentially leading to more accurate and efficient manners for concrete crack detection and classification. This could significantly enhance the safety and longevity of structures.

## 5. Discussion

The objective of this research was to leverage deep learning for accurate categorization of cracks in concrete structures. Each of the four trained models was modified to optimize performance. For instance, Model 1 was enhanced with an additional layer and increased parameters. Model 2 (VGG16), which has the highest accuracy as shown in (Figure 3) with a low loss value, featured 13 Conv2D layers, 5 max-pooling layers, and 512 neurons per layer which are shown in (Table 3) The model's structure demonstrated enhanced stability and exhibited no issues with adding conventional layers. Model 4 (Resnet50) comprises 53 Conv2D layers and 6 max-pooling layers. Our findings show that increasing the number of convolutional layers and neurons generally improves model accuracy, with some challenges. One of these challenges is over fitting with a small training dataset, especially with unseen data. Other problems are that larger numbers of neurons lead to increased computational cost and longer training times. So, to get a suitable accuracy, the model must have a suitable number of convolutional layers, neurons, and hyper-parameters. Also, using appropriate techniques like data augmentation helps the model to be more robust and improves its performance. This technique involves rotation to assist the model to adapt to different orientations. In addition, scaling the dataset was useful for recognizing images at various scales. On the other hand, (Figure 4) shows that accuracy has increased with increased training epochs. Conversely, the loss decreases as the number of epochs increases. As appears in this figure, validation loss began with a 0.48 value until reaching 0.19, which confirms the model's capacity to achieve a high classification accuracy. This was evident when comparing our results to those of other studies, which employed different models for crack identification. By combining the four models, we developed a CNN model that achieved a balanced accuracy without extensive adjustments to network architecture or parameter counts as shown in (figure5). This combined approach effectively addressed the accuracy weaknesses of individual models. Furthermore, when our researcher is compared with others such as N. M., & Sarhan, A. M. (2021) [29] in multi-class classification, our researcher achieves higher accuracy results and Develop a novel model that corresponds better with the way we operate.

Table 3. Architectures layers for CNN models.

| Models | Conv2D | Max-pool | BN | Dense | Flatten | Dropout |
|---|---|---|---|---|---|---|
| Model1 (CNN modification) | 11 | 5 | 0 | 3 | 1 | 2 |
| Model2 (VGG16) | 13 | 5 | 0 | 1 | 1 | 0 |
| Model3 (Alex Net) | 5 | 3 | 9 | 4 | 1 | 3 |
| Model4 (Resnet50) | 53 | 6 | 45 | 0 | 0 | 0 |

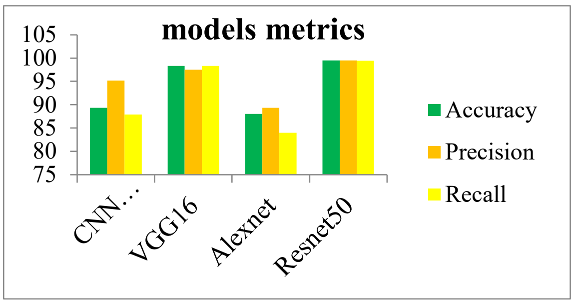
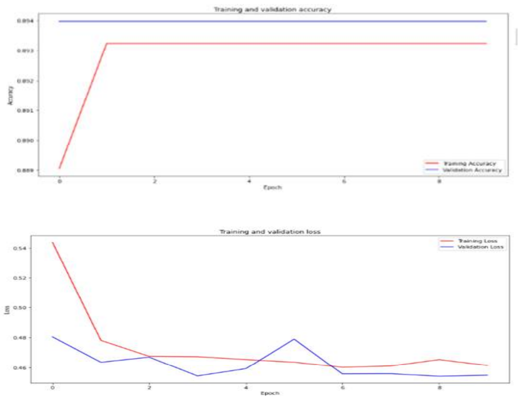
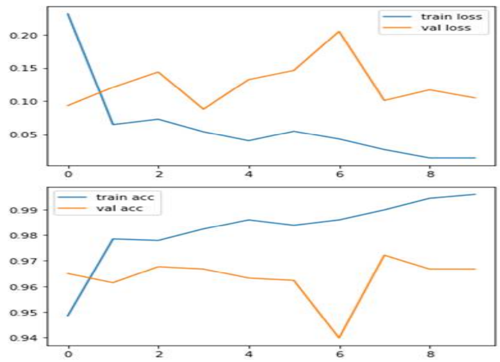


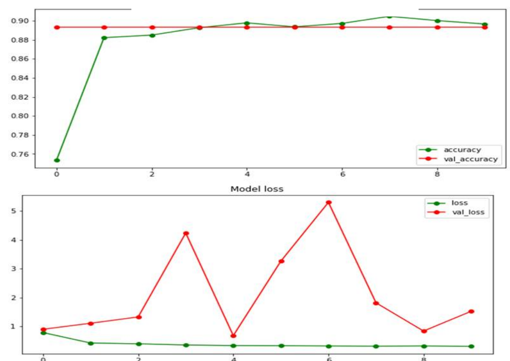
Figure 3. Model metrics (accuracy, precision, recall)



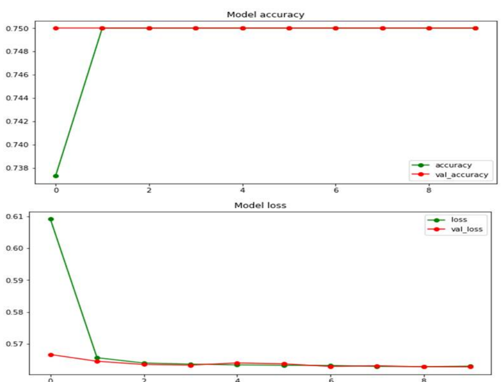

**Model 1**




**Model 2**




**Model 3**




**Model 4**

Figure 4. Accuracy and loss function of models

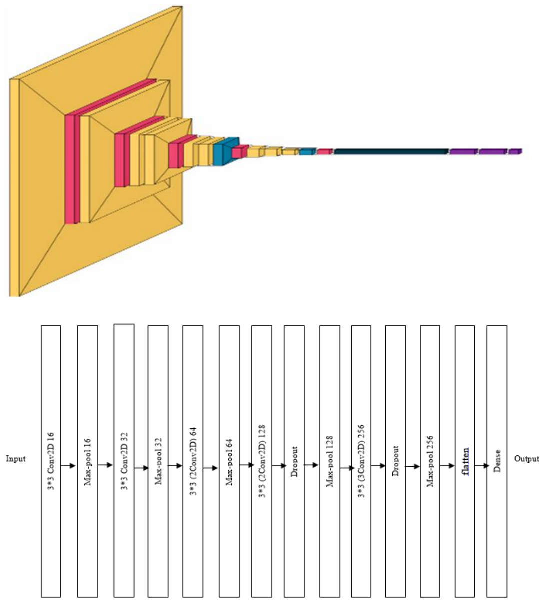



Figure 5. Architectures of (CNN) modification model

## 6. Conclusion

This study introduced a deep learning approach to classify crack images in concrete structures into four categories based on severity. By combining and modifying four pre-trained models—VGG16, AlexNet, and ResNet50—within a CNN framework, a notable accuracy rate of 91% was achieved. This demonstrates the potential of our model for early detection of concrete cracks, thereby preventing long-term damage to buildings. To enhance the robustness of our model, we employed data augmentation techniques, including rescaling, rotation, and horizontal flipping, which increased the variety and quantity of training samples. Additionally, sourcing diverse crack images from various online databases contributed to the improved performance. The results of this study suggest that further expanding the dataset and employing advanced modified models that operate on pixel-level data could lead to even higher accuracy rates. Future research should also explore integrating other deep-learning techniques and real-time data processing to enhance the models' efficiency and reliability. In summary, our work presents a significant step towards the development of more accurate and efficient methods for detecting and classifying concrete cracks. In the future, we recommend exploring this topic more extensively, including measuring crack dimensions or integrating deep learning with tools such as GIS to illustrate the locations and three-dimensional representations of the cracks in structures. In addition, UAVs can be used with deep learning to detect and classify cracks automatically. Replace the pre-trained model's final layers with new layers specific to them and utilise additional hyper parameters to enhance classification accuracy in models with lower performance.

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