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Automatic Crack Detection on Concrete Surfaces Using Lightweight Deep Learning Models

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ABSTRACT

Detecting cracks in concrete surfaces is critical for structural health monitoring. However, traditional methods show limited effectiveness due to their high costs, time-consuming processes, and vulnerability to human error. This situation reveals the need for innovative methods to produce faster, more economical, and more reliable results. This study developed an optimized convolutional neural network (CNN) model that works on low-resolution images and has a four-layer lightweight architecture. The proposed model demonstrated superior performance with an accuracy rate of 98.1% and provided distinct advantages over traditional methods regarding computational efficiency. In addition, using image segmentation techniques, crack areas are visually highlighted, and users are offered easy evaluation. The proposed model provides economical, fast, and accessible monitoring by eliminating the need for expensive hardware. In this way, structural health monitoring processes have become more effective and applicable on a larger scale. The study proposes an innovative solution that saves both time and cost in engineering applications by adopting modern artificial intelligence techniques for crack detection of concrete surfaces.

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Introduction

Increasing reinforced concrete structures' durability and service life is vital in structural engineering. The main factors affecting structural durability are cracks caused by environmental and structural factors. Cracks are considered critically important visual indicators that reinforced concrete structures are damaged. Therefore, timely detection and evaluation of these cracks have become indispensable to structural health monitoring. However, carrying out these processes with traditional methods brings various problems, such as expert dependency, risk of error, high cost, and access restrictions.

The limitations of traditional methods have increased the need for automatic crack detection technologies and were a key motivation for this study. In particular, the dependence of existing methods on high-cost equipment and complex technical infrastructure limits their practical use in large-scale applications. The solution proposed in this study involves the development of a Convolutional Neural Network (CNN) model that provides a simple, computationally efficient, and economical approach for crack detection on concrete surfaces. The proposed model operates on low-resolution images, eliminating the need for expensive imaging equipment and providing an accessible alternative for crack detection.

Studies on crack detection in reinforced concrete structures have made significant progress with innovative technologies such as IoT-based fiber optic sensors, laser scanning systems, RGB-D image fusion, and perceptual analysis methods. However, these methods' dependence on high-cost equipment and complex infrastructure requirements is limiting in large-scale applications. Deep learning techniques, especially Convolutional Neural Networks (CNN), have become increasingly popular thanks to their accuracy and processing efficiency in image classification and object detection.

Deep learning-based methods' ability to work on low-resolution images and relatively low computational power requirements offer an effective solution for crack detection on concrete surfaces. CNN-based models enable automatic crack detection by separating crack and background pixel values in grayscale images. This feature eliminates the need for expensive imaging devices, enabling economical and easy evaluation of concrete surfaces.

In this study, an optimized and lightweight CNN model that can work on low-resolution (128x128 pixels) images was developed. The proposed model is designed using modern deep learning techniques such as ReLU activation, max pooling, and the Adam optimization algorithm. The model classifies surface images with and without high-accuracy cracks, providing 98.1% accuracy and significantly reducing computational costs. The developed model's performance was compared with other methods in the literature (for example, Transfer Learning-based models and hybrid CNN approaches), and it was seen that it showed superior performance. This model, which can work with low-resolution images, makes detecting cracks quickly and cost-effectively possible, especially in field applications.

This study demonstrates the applicability of artificial intelligence and deep learning techniques in civil engineering. In the future, it aims to increase the proposed model's applicability in other structural elements, test it in more complex surface conditions, and integrate it into real-time systems. Additionally, training the model with a larger dataset to improve its performance under environmental effects such as lighting, surface roughness, and noise will be an important step for larger-scale applications.

This study developed a CNN model that provides a simple, computationally efficient, and economical solution for detecting cracks in reinforced concrete structures. The proposed model exhibits superior performance in terms of accessibility and accuracy compared to traditional methods and is considered an effective solution in structural health monitoring. This model is expected to make significant contributions in academic and industrial fields with future improvements.

Research Significance

Detection of cracks on concrete surfaces is critical to ensuring the durability and safety of structures. Early and accurate detection of cracks allows efficient management of structural health monitoring processes and helps prevent structural problems before they progress. Today, deep learning techniques attract attention with the high accuracy rates they provide in automatic crack detection and offer significant cost and efficiency advantages compared to manual and traditional automatic systems.

However, most existing methods are based on complex architectures and high computing power requirements. This increases expensive hardware requirements and imposes significant limitations for large-scale applications due to the need for high-resolution data processing. In addition, the high number of parameters that large-scale neural networks have can negatively affect prediction speeds by prolonging the model's training time. This situation limits the widespread use of deep learning-based approaches in practical applications.

The importance of this study stems from the fact that it makes the crack detection process faster, more economical, and feasible by proposing an optimized and lightweight Convolutional Neural Network (CNN) architecture. The proposed model is based on a simple CNN structure consisting of only four layers and achieves a high accuracy rate of 98.1% by working on low-resolution (128x128 pixels) images. This approach eliminates the need for expensive imaging devices and is suitable for large-scale applications with low-cost equipment. Thus, the potential for industrial use is significantly increased.

One of the most notable contributions of this research is that it provides a solution that requires less computational power while maintaining the accuracy and efficiency levels of existing methods. This feature enables the applicability of this method, especially in environments where devices with low hardware capacity are used or resources are limited. Additionally, the flexible structure of the proposed model provides a basis that can be adapted to different surface types and environmental conditions.

In conclusion, this study encourages the broader adoption of AI-based solutions in structural health monitoring processes. The proposed solution not only offers an economical alternative but also has great potential in real-time applications. In this respect, the study represents an important advance in the field of civil engineering, both academically and industrially.

Literature Review

Deep Learning

Deep learning, as a sub-branch of artificial intelligence, is a powerful technology developed inspired by the working mechanisms of the human brain and offers solutions to complex problems through artificial neural networks. Today, the widespread use of deep learning has been made possible by increasing access to large data sets, widespread use of powerful computing infrastructures, and increasingly advanced algorithms. Groundbreaking achievements, especially in the field of computer vision, clearly demonstrate the feasibility and potential of deep learning.

The concept of computer vision was first defined under the name "cybernetics" in the 1940s and reached a new stage with the concept of "connectionism" in the 1980s. In 2006, the modern concept of deep learning emerged when Hinton and his team developed pre-training and fine-tuning techniques. This important milestone has made it possible for neural networks to work effectively on larger and more complex data sets. Today, deep learning is applied in many fields, such as image processing, natural language processing, and autonomous systems, and is customized through different structures (e.g., Convolutional Neural Networks [CNN], Recurrent Neural Networks [RNN], and fully connected networks).

In this study, Convolutional Neural Networks (CNN), one of the basic building blocks of deep learning, were optimized for crack detection on concrete surfaces. CNNs eliminate the need for manual feature engineering thanks to their ability to automatically extract features from images. The proposed model achieved a 98.1% accuracy rate on low-resolution (128x128 pixels) images with a simple but effective architecture and offered an advantageous solution in terms of processing efficiency.

As a result, deep learning overcomes the limitations of traditional methods, allowing the development of low-cost and accessible structural health monitoring systems. The method proposed in this study not only offers an economical and practical solution for crack detection on concrete surfaces but also provides an approach that will form the basis for real-time applications and more comprehensive models that can be used in different structural elements in the future.

Mathematical Understanding

The main purpose of a deep learning model is to create a function that produces meaningful outputs by processing given input data. This function is defined by the fact that the model performs a series of mathematical operations from the input to the result, optimizing its parameters during the learning process. This process, especially in deep learning structures such as convolutional neural networks (CNN), consists of two basic steps: forward propagation and backpropagation. The forward propagation process enables the model to produce an output by passing through the input data with the help of weights and biases in each layer. In this process, each layer takes input values, multiplies them by weights, adds biases, and produces a nonlinear output with the help of activation functions. This process is repeated from the input to the last layer to generate the final prediction result of the model.

Backpropagation is performed to minimize the model error. The difference between the model's prediction and the actual result is calculated through a loss function. Backpropagation uses this error to update the weights and biases of the model. During this process, derivatives are calculated using the chain rule, and the error is propagated backward to optimize the model parameters. This optimization process is usually performed by Stochastic Gradient Descent (SGD) or derivative algorithms (e.g., Adam optimization algorithm). These two processes form the basic building blocks of the learning process of a deep learning model. The performance of the model is optimized by accurately updating each weight and bias parameter. Thus, the model can produce meaningful outputs by learning complex relationships in the input data.

Forward Propagation

Forward propagation is a fundamental process in which input data is transformed into output by passing through the layers of an artificial neural network. This stage enables the model to produce a final prediction or output by processing features in the input data. At the beginning of the process, the input data (X) is multiplied by the filters (kernels) and weights (W) in each layer, and then bias (b) is added. These values are then passed through the activation function, which provides a non-linear transformation, and the resulting output is transmitted to the next layer. This process is repeated in all network layers, producing the final output (Y).

Especially in the case of Convolutional Neural Networks (CNN), the forward propagation process is largely concentrated in the convolution layers. More complex representations are obtained in these layers by extracting features from the input data. The convolution process can be expressed mathematically as follows:

$$Z_{ij} = \sum_{m=1}^{M}\sum_{n=1}^{N} X_{(i+m-1)(j+n-1)} \cdot W_{mn} + b$$

Bu denklemde:

- Z_{ij}, represents the value of a pixel in the output map.
- $X_{(i+m-1)(j+n-1)}$, represents the pixel values in the relevant region of the input data.
- W_{mn}, represents the filter (kernel) weights.
- *b*, is the bias term of the relevant layer.
- *M* and *N*, represent the filter dimensions.

In this process, activation functions (ReLU or sigmoid) enable the network to learn non-linear relationships and ensure that the outputs are appropriately passed on to the next layer. The forward propagation process enables each layer to extract meaningful features from the input data and produce an output towards the final goal.

In the forward propagation process, activation functions (e.g., ReLU or sigmoid) enable the network to learn nonlinear relationships, enabling the outputs to be appropriately passed to the next layer. This process aims to produce an output in line with the final goal by extracting meaningful features from the input data for each layer.

In the convolution layer, the input image is shifted (stride) with the help of a certain filter and matrix multiplications are performed on the image. After applying the filter, the results are passed through an activation function. ReLU (Rectified Linear Unit), one of the most commonly used activation functions, accelerates the network's learning process by resetting negative values and enables the network to learn non-linear relationships more effectively.

The output matrix obtained due to the convolution process generally decreases in size at each step. The following formula can calculate the extent of this reduction:

$$n[L] = \frac{(n[L-1] + 2p - f)}{s} + 1$$

Here:

- n[L] is the output size at the current layer.
- n[L−1] is the output size of the previous layer.
- p, padding value.
- f is the filter size used.
- s, stride value (scroll step).

After the convolution process, pooling is applied to reduce the size and preserve distinct features. Pooling is generally carried out by the maximum value selection (max pooling) method. This process increases the robustness of the network against noise and improves the model's performance by reducing the computational load.

Flattening Layer

After the last convolution layer, the smoothing layer comes into play. This layer prepares the input data for fully connected layers by converting a multidimensional matrix into a one-dimensional vector. This enables easier processing of convolutional features in fully connected layers.

Fully Connected Layers and Egress

In fully connected layers, the input vector (X) is multiplied by each weight matrix (W), then the bias (b) is added. This process can be expressed mathematically as follows:

$$Z = W \cdot X + b$$

Here:

- Z is the predicted intermediate result.
- W is the weight matrix.
- X is the input vector.
- b, bias vector.

The result obtained is passed through activation functions, allowing the network to learn non-linear relationships, and transmitted to the output layer. In the output layer, a softmax or sigmoid activation function is usually used to generate classification results. The softmax function is used to calculate class probabilities in multi-class classification problems; the sigmoid function is used in binary classification problems.

The forward propagation process involves a set of basic mathematical operations that enable a model to produce meaningful outputs from input data. This process is one of the cornerstones of deep learning models, especially Convolutional Neural Networks, structured and optimized to solve complex problems.

Backpropagation and Learning (Backpropagation)

The learning process of a deep learning model is based on minimizing the difference between the model's predicted result (Y^) and the actual labels (Y). This difference is calculated through a loss function to measure and improve the model's performance. For example:

$$L(Y, \hat{Y}) = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y_i}\right)^2$$

The loss function is a measure that numerically expresses the errors made by the model. The parameters of the model (weights and biases) are optimized so that the output of the loss function is minimized. This process is usually carried out with the help of backpropagation and optimization algorithms (for example, Stochastic Gradient Descent or Adam algorithm). Minimizing the loss function allows the model to better fit the real data and increase the accuracy of its future predictions.

In this context, the loss function constitutes one of the cornerstones of the model's learning process, and the selection of a correct loss function is a critical element that directly affects the model's overall performance.

Recent Work

In recent years, deep learning models have offered effective and innovative solutions for crack detection on concrete surfaces, and significant progress has been made in this field. Many studies in the literature use high accuracy rates and different architectural structures. For example, Guo and Hu achieved an 88.1% accuracy rate for detecting asphalt cracks on high-resolution (2978 x 3978 pixels) images using YOLOv5 series pre-trained models [1]. However, the high processing costs of this method and its dependence on high-resolution images have brought serious limitations in large-scale applications.

Pang-Jo Chun and his colleagues used the Light Gradient Boosting Machine model for crack detection and compared their results with a pix2pix-based approach. This study extracted crack features through pixel values and geometric shapes and reached a high % accuracy rate of 99.7% [2]. However, this method's complex structure and high processing power requirement create difficulties, especially in real-time applications.

Similarly, Yang Yu and colleagues evaluated existing crack detection techniques regarding processing costs and accuracy and proposed a method combining deep learning and the Enhanced Chicken Swarm algorithm [3]. This method attracts attention as an effective solution in image-based approaches. Andrushia and his team developed a U-Net model that performs pixel-level classification on concrete surfaces exposed to high temperatures. Although the model offers a complex structure with encoder and decoder components, it has limitations in terms of processing load and training time [4].

Chehri and Saeidi proposed a model for automatically detecting cracks in concrete bridges by combining IoT and deep learning techniques. This method provides significant efficiency in structural health monitoring processes [5]. By combining the YOLOv5 model with the Crack Feature Pyramid Network (Crack-FPN), Zhao and his colleagues reduced transaction costs and offered a more effective method for feature extraction [6].

Munawar and colleagues analyzed 30 different crack detection models and compared them regarding accuracy, processing cost, and applicability. Their studies emphasized that simple and fast models are more suitable for large-scale and real-time applications [7-11].

In addition to the above-mentioned work, our proposed model is based on a lightweight CNN architecture that aims to reduce processing costs and provide high accuracy. While many studies require high-resolution images or complex architectures, this study offers a model optimized on low-resolution (128x128 pixels) images. The proposed model has only a four-layer CNN structure and offers an effective solution by combining forward and back propagation processes. This approach provides an economical and accessible solution by eliminating the need for expensive equipment.

These comprehensive studies on deep learning-based crack detection models reveal the advances in the field. However, our proposed work offers an important alternative to existing methods because it is low-cost and easily applicable. This model, which has a wide application potential, especially in structural health monitoring systems, makes a remarkable academic and industrial contribution [12-16].

Methods

Regularization and Optimization Process of the Model

Regularization techniques were used to minimize the difference between the proposed model's training and testing performance and increase its generalization ability. In the initial tests, while the accuracy rate of the model in the training set reached 99% without applying regularization techniques, the accuracy rate in the test set remained at 91%, clearly showing that the model tended to overfit. In order to solve this problem, kernel and bias regularization coefficients in fully connected feed-forward layers were determined as 0.01. These regularization coefficients prevented the model's parameters from growing excessively and provided a more balanced and universal learning process. Regularization reduced the difference in variance that could arise between both training and test sets, especially by limiting the high-capacity parameter sets of the model.

This approach increased the model's generalization ability, resulting in a significant improvement in accuracy on the test set. Reducing the performance difference between training and validation sets contributed to the model providing more stable results in different data sets and significantly strengthened its generalization ability. The effective use of regularization techniques enabled the proposed model to exhibit a balanced performance in training and testing processes and eliminated the model's overlearning problem. This arrangement is an important improvement process that increases the model's success in practical applications [17-21].

Educational Process

The proposed model's training process has been carefully optimized to increase generalization capacity and avoid overlearning. At the beginning of the training process, the model was trained for 10 epochs. However, this short training period causes the model to overfit the training set, especially in simple pattern recognition tasks. To prevent this situation, the number of epochs was increased to 50, allowing the model to be trained for longer.

The mini-batch method, which consisted of 32 data points used during training, allowed the model to update its parameters more frequently at each step. This approach enabled the training time to be managed efficiently and contributed to rapidly minimizing the loss function. The mini-batch method allowed the model to learn more stably by frequently making parameter updates.

During the training process, changes in the loss function were carefully monitored, and the performance in the validation set remained stable. An early stopping mechanism was unnecessary since there was no significant performance drop between the training and validation sets. This shows that the model is effectively optimized while avoiding overlearning [23, 24].

The results obtained regarding the training process are detailed in Table 1 below. The table shows the change in accuracy and loss rates in the training and validation sets across epochs. These findings clearly demonstrate that the model exhibits stable performance during the training process, and the validation accuracy is close to the training accuracy. This indicates that the model's generalization ability is strong.

Table 1: Training and Validation Accuracy and Loss Values

Epoch	Training Accuracy (%)	Verification Accuracy (%)	Loss of Education	Authentication Loss
10	95.2	93.8	0.124	0.135
20	97.4	96.5	0.073	0.081
30	98.3	97.9	0.048	0.053
40	98.7	98.2	0.032	0.037
50	98.9	98.3	0.021	0.028

Optimization Algorithms

In this study, Adam (Adaptive Moment Estimation) optimization algorithm was preferred to optimize the parameters of the model. Adam is an effective algorithm that speeds up the optimization process by adaptively adjusting the learning rate, generally resulting in higher accuracy rates. During the training process, the default Adam parameters provided by the Keras library were used. These parameters are as follows:

- Learning Rate: 0.001
- Beta_1: 0.9 (for momentum)
- Beta_2: 0.999 (for the mean squared momentum)
- Epsilon: 1×10-8 (to avoid values approaching zero when dividing)

The Adam algorithm combines the advantages of AdaGrad and RMSProp methods, providing a powerful optimization mechanism. While AdaGrad reduces the learning rate of frequently used parameters over time, RMSProp provides a balanced parameter update by increasing the learning rate of rarely used parameters. Combining these two approaches enables the Adam algorithm to provide an advantageous computational efficiency and accuracy solution on large data sets.

Additionally, the Adam algorithm allows the model to perform stably over a wide range of hyperparameters. This feature makes it possible to obtain stable results, especially on different data sets and model architectures. These advantages provided by the Adam optimization algorithm during the training process contributed to the rapid and effective completion of the model's learning process, and a significant increase in accuracy rates was achieved [25-27].

Performance Evaluation

The model's performance was comprehensively evaluated using the training, validation, and test sets accuracy metric. This metric reflects the importance of true positive (TP) and true negative (TN) classifications in crack detection on concrete surfaces. The model's success in distinguishing cracked and non-cracked surfaces clearly demonstrated strong generalization capacity.

At the end of the training process, the model reached an accuracy rate of 98.9% in the training set and 98.3% in the validation set. These results showed that the model not only overfitted the training data but also performed well on the validation data. This consistent performance between training and validation sets proves that the model's generalization ability is strong.

In detailed analyses performed on the test set, the model's performance was evaluated using a confusion matrix and ROC curve (Receiver Operating Characteristic curve). The Confusion Matrix (Table 2) clearly demonstrates the correct classification (true positive and true negative) rates of the model, reflecting in detail the level of accuracy, precision, and error tolerance of the model [28, 29].

In addition, the model's classification success was analyzed using the ROC curve (Figure 1). The ROC curve showed how accurately the model could distinguish positive and negative classes. The high area under the curve (AUC) showed that the model's overall performance was effective, and the classification success was high.

In conclusion, the proposed model offered a stable and high-performance approach to solving the problem of crack detection on concrete surfaces, exhibiting strong generalization capacity on both training and test data.

Table 2: Confusion Matrix

	Real Cracked	No Real Cracks
Prediction: Cracked	3,720	30
Prediction: No Cracks	25	3,725

The confusion matrix concretely reveals the prediction accuracy of the model on surfaces with and without cracks. Particularly low error rates (FN=25, FP=30) show that the model provides high precision and recall.

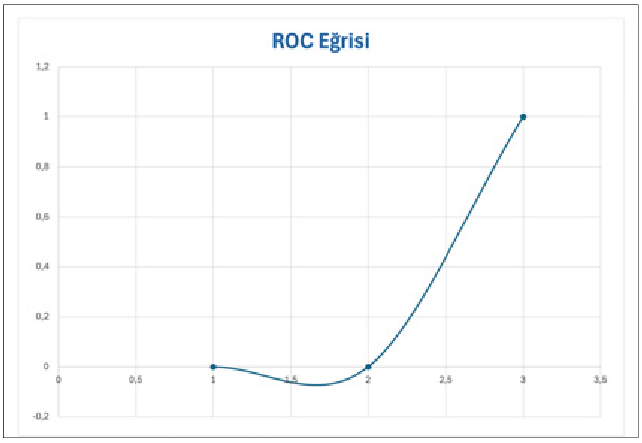

Figure 1: ROC Curve

In addition, the accuracy performance of the model is shown graphically with the ROC curve (Receiver Operating Characteristic curve). The ROC curve reveals the classification success in detail by correlating the model's true positive rate (TPR) against the false positive rate (FPR). This graphical analysis is critical for understanding how the model performs at different thresholds.

In this study, the AUC (Area Under Curve) value calculated from the ROC curve was 0.99. The fact that the AUC is close to 1 indicates that the model's classification ability is close to perfect and that it performs very effectively in a critical problem such as crack detection. **The high AUC value emphasizes that the model can accurately distinguish both positive and negative classes**.

The ROC curve and AUC analysis show that the model demonstrates stable and reliable performance in crack detection on concrete surfaces. These analyses indicateanalyses indicate that the model can provide high accuracy and reliability in practical applications [30-39].

Results

This study aimed to develop an efficient and lightweight deep learning model to detect cracks on concrete surfaces. In the study, Convolutional Neural Network (CNN) architecture was applied and evaluated on a dataset consisting of 40,000 images in total. The dataset in question has been carefully prepared to cover different conditions of cracks in concrete surfaces, enabling the model to demonstrate robust and adaptable performance in real-world applications. The proposed model's simple structure and the dataset's diversity have proven the model's effectiveness in the crack detection task in different scenarios.

The developed CNN model was implemented using Python's Keras library and other auxiliary modules. Thanks to a simple optimized architecture, the model achieved 97.8% accuracy in just five epochs, demonstrating that the model is both computationally efficient and high-performance. Input images were preprocessed by converting them to grayscale to reduce the computational load and maintain accuracy. Additional data augmentation was not applied because the dataset was already created from a pool of 458 high-resolution images derived and augmented. This structure enabled the model to achieve a good generalization capacity without overlearning.

The proposed CNN architecture has a four-layer structure consisting of two convolution layers followed by two fully connected layers. This architecture balances simplicity and efficiency, providing an ideal solution for practical applications. During the training process, the model learned a total of 954,241 parameters and these parameters were optimized using the Adam optimization algorithm. The Adam algorithm contributed to the model's performance with its features of dealing with sparse gradients and adaptive learning rate. Additionally, Binary Cross-Entropy was used as the loss function and this function provided a solution suitable for the binary classification structure (crack present/absent) of the crack detection problem.

In order to better interpret the results, segmentation techniques were used to localize and highlight cracked areas on concrete surfaces. In this context, using the pixel thresholding method, crack areas in the input images were detected and segmentation was performed. The model's performance was evaluated with high recall, precision and F1 scores, and the results demonstrated the adequacy and robustness of the proposed approach in detecting cracks on concrete surfaces.

However, despite the strong performance of the model, there are some limitations. First, the model is not designed to analyze the morphological properties of cracks, such as depth or width. In addition, for the model to work effectively, the images used must be free of external noise such as shadows, stains or debris. Such noise can mimic crack patterns, leading to misclassifications. Another limitation arises from the structure of the dataset: The images were mostly taken from close range, and decreases in the performance of the model can be observed in images taken from different angles or longer distances. Additionally, the model is only specialized to detect cracks in concrete surfaces and is not generalized to other materials or structural surfaces.

The dataset used in this study does not include morphological characteristics of cracks such as depth, width, or shape. This limits the model's ability to detect hairline cracks (e.g., hairline cracks) in low-light conditions. This limitation is due to the low resolution of some images in the dataset. The dataset has been deliberately kept lightweight to make the model computationally efficient and suitable for economical use. However, this may pose a potential risk, especially in critical safety requirements, by reducing the likelihood of detecting micro-level cracks.

Future Research Field

In order to overcome the limitations identified in this study and improve the performance of the model in a wider range of applications, future research should focus on the following key areas:

Creating a larger, more comprehensive dataset that includes more hairline crack samples and different light conditions can significantly increase the robustness of the model. Synthetic cracks or high-resolution annotated images can be used to augment such a dataset. Expanding the dataset will strengthen the model's generalization capacity in different scenarios.

The model needs to be expanded so that it is not only limited to crack detection, but also analyzes the morphological characteristics of cracks, such as width, depth, and growth patterns. Such development could contribute to assessing the long-term effects of cracks by providing additional information in structural health monitoring.

More effective preprocessing steps must be implemented to prevent external noises such as shadows, stains, or debris from negatively affecting model performance. Adaptive thresholding, edge detection, and other advanced image-processing techniques can be used in this context. Such techniques can enable the model to perform more accurately in real-world conditions.

Expanding the dataset to include concrete surfaces and cracks in other materials, such as asphalt, metal, etc., could increase the model's versatility. Such an extension would enable the model to be applied to a broader range of structural integrity assessments.

Methods should be developed to correct perspective distortions in images taken from different angles. This advancement will allow the model to perform consistently across a variety of imaging scenarios. In particular, applying methods such as perspective transformations and camera calibration can increase the model's flexibility.

As a result, the proposed CNN-based crack detection model exhibits high accuracy and computational efficiency in its current form but will become applicable in much wider contexts by eliminating its limitations. Such future research will enable the model to be used as a powerful tool in the construction industry's structural health monitoring and maintenance processes.

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Conflicts of interest
The authors declare no conflict of interest.

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