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Research Article

Automated Concrete Crack Detection Using Wavelet Transform and CNN with Multi-Objective Optimization

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Abstract

Detection of concrete cracks plays a vital role in structural health monitoring and maintenance. In this paper, an intelligent framework based on image processing and deep learning is proposed to automatically detect concrete cracks. Initially, two-dimensional wavelet transform (WT) is applied to the input images in order to enhance crack-related features and suppress noise or irrelevant patterns. The transformed images are then fed into a Convolutional Neural Network (CNN) for classification and detection purposes. To further improve the performance of the CNN, critical hyperparameters such as filter size and number of filters are optimized using the Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D). This optimization process seeks to achieve a trade-off between classification accuracy and computational complexity. Experimental results on benchmark datasets demonstrate that the proposed approach significantly outperforms conventional methods in terms of accuracy, robustness, and generalization ability. The integration of wavelet-based feature extraction, CNN learning capability, and evolutionary optimization makes this method a powerful tool for automated concrete crack detection in real-world scenarios.

Keywords: Concrete Crack Detection, Wavelet Transform, Convolutional Neural Network (CNN), Multi-Objective Optimization, MOEA/D Algorithm

Introduction

Concrete cracks are a significant concern in the field of civil engineering and structural health monitoring, as they can compromise the safety, stability, and longevity of concrete structures. Cracks in concrete can form due to a variety of reasons, including but not limited to thermal expansion, moisture fluctuations, loading stresses, and shrinkage. Over time, even small cracks can evolve into larger fissures, leading to more severe structural damage. The presence of cracks in concrete not only undermines the structural integrity but also poses potential risks for safety, especially in critical infrastructure such as bridges, dams, and buildings. Cracks can also allow the ingress of harmful substances, like water or chemicals, which can accelerate the deterioration of concrete through processes such as corrosion of reinforcement steel.

Detecting concrete cracks in a timely and accurate manner is crucial for ensuring the long-term durability of concrete structures and preventing costly repairs or catastrophic failures. Traditional methods of crack detection, such as visual inspections or manual monitoring, are time-consuming, labor-intensive, and subject to human error. Moreover, these methods may not be able to detect small or hidden cracks, which can go unnoticed until significant damage has occurred. With the advancement of technology, automated methods for crack detection using image processing and machine learning techniques have become increasingly popular [5-6]. These methods allow for faster, more accurate, and reliable identification of cracks, enabling engineers to monitor the health of structures in real-time and take necessary actions before significant damage occurs. Overall, the importance of concrete crack detection lies in its ability to prevent costly repairs, enhance the safety of structures, and prolong the life of infrastructure, ultimately ensuring that concrete structures continue to serve their intended purpose without compromising public safety.

Concrete crack detection faces several challenges, with the most significant being the diversity and complexity of crack behavior in concrete [7-8]. Concrete cracks can vary greatly in terms of size, depth, type, and location, which makes their accurate detection difficult. Some cracks may be very fine or hidden and may not be detected through regular visual inspections, yet they can cause serious long-term problems. Additionally, environmental and weather conditions have a significant impact on crack detection. Rain, humidity, temperature changes, and even dust can affect the concrete surface and cause cracks to be hidden or misidentified. Moreover, cracks may form in areas that are difficult to access, such as beneath structures or in regions with limited access, making their inspection and identification more complex. On the other hand, evaluating the impact of these cracks on the overall strength of the structure can also be problematic, as many cracks may initially appear small and harmless, while over time, they can lead to significant damage to the concrete structure. These issues highlight the need for the development of new methods and technologies to enable more accurate and effective crack detection and to assess their impact on the overall health of the structure.

Image processing plays a crucial role in concrete crack detection because these methods are capable of extracting accurate and efficient visual features from images of concrete structures [9-12]. One of the greatest advantages of image processing is its ability to analyze visual data automatically and with high precision. Techniques such as wavelet transform (WT), Gaussian filters, edge detection, and feature extraction can identify cracks and distinguish them from the background. Image processing can also improve low-quality images or images captured under unfavorable lighting conditions, highlighting crack-related features. Especially in large-scale structures where manual inspections are difficult and time-consuming, image processing techniques can significantly increase the speed and accuracy of structural monitoring. Moreover, these methods are effective in detecting small or hidden cracks that may go unnoticed by traditional methods.

Deep learning, especially Convolutional Neural Networks (CNNs), has revolutionized the field of concrete crack detection. These techniques can automatically extract complex, nonlinear features from images and, through multiple layers of the neural network, learn how to identify and classify cracks. In fact, CNNs are highly capable of processing visual data and can recognize complex crack patterns that might remain undetected using traditional methods. This learning process not only speeds up crack detection but also helps eliminate human errors that may occur with manual inspection methods. The use of deep learning in concrete crack detection also offers additional benefits such as high accuracy, scalability, and the ability to generalize across various datasets. Specifically, deep learning algorithms can be trained to detect concrete cracks in images with varying lighting conditions or from different angles, which is highly valuable in real-world and industrial applications. As a result, the combination of image processing and deep learning has become one of the most effective solutions for automatic and accurate concrete crack detection, particularly in large and complex structures that require continuous monitoring.

This paper is structured as follows: In Section 2, a comprehensive review of existing methods is presented. Section 3 provides a detailed explanation of the proposed methodology, including the multi-objective optimization framework, WT for feature extraction, CNN architecture for crack detection, and the optimization process for hyperparameter tuning. Section 4 discusses the datasets used, and the simulation results, comparing the performance of the proposed method with existing techniques. Finally, Section 5 concludes the paper by summarizing the key findings of the paper.

According to our present literature review on bio-removing ATR using growing fungi, a limited number of studies have been conducted [25, 26]. However, our current literature evaluation has no study about the application of growing *A. versicolor*, isolated from Turkey, for remediation of ATR contamination in water. This study aims to determine the ATR removal performance of a wild filamentous fungal strain biomass comparing bio-removal and bio-sorption mechanisms. In addition to this, the concentrations of ATR in aqueous solutions were determined by electrochemical methods in this study. In previous studies, high-performance liquid chromatography (HPLC) and gas chromatography (GC) methods were used for pesticide detection [27, 28]. Monitoring ATR bioremediation by fungus in aqueous solutions via electrochemical techniques is a new approach, which is applied in this study.

Existing Methods

The paper [8] proposes a semi-automatic, enhanced texture segmentation method for detecting and classifying surface damage on infrastructure elements. The approach accounts for variations in damage forms, lighting, angles, and image resolution by analyzing neighboring pixels in different color spaces. A feature vector is created using pixel intensity values and statistics from the Grey Level Co-occurrence Matrix. Non-linear Support Vector Machines, optimized for parameters, classify the feature vector. A Custom-Weighted Iterative model and a 4-Dimensional Input Space model are introduced, and Receiver Operating Characteristics are used to assess detection efficiency across different damage conditions. Surface cracks in concrete structures are critical indicators of damage and durability. Manual visual inspection, the most commonly used method, is inefficient in terms of cost, time, accuracy, and safety. A promising alternative is computer vision-based methods that can automatically extract crack information from images. Image binarization, developed for text detection, is suitable for crack identification due to the similarity between texts and cracks, both consisting of distinguishable lines and curves. However, standardizing crack identification using image binarization is challenging, as it depends on the method and associated parameters. The paper [9] investigates image binarization for crack identification, focusing on determining optimal parameters and conducting a comparative performance evaluation of five common binarization methods. Crack images are prepared to minimize errors in crack width estimation. A comparative analysis is then performed using crack images under different conditions based on three evaluation criteria: accuracy in crack width and length measurement and computation time.

Crack detection is essential for ensuring safety and cost-effective maintenance of concrete structures. Researchers have proposed various machine vision-based methods for identifying cracks on the bottom surface of concrete bridges. However, obtaining high-quality images and effective processing results is challenging due to the complex lighting and environmental conditions under bridges. In the paper [10], a new method for processing crack images in concrete bridge bottom inspections is introduced. A machine vision system based on this method is developed, capable of detecting cracks in real time. Experimental results show that the proposed method outperforms traditional methods in terms of efficiency and accuracy in complex bridge underpass environments. Automatic crack detection on roads is highly important for early maintenance, but factors such as complex backgrounds, class imbalance, and weak texture reduce its accuracy. The paper in [11] introduces the DEHF-Net, which accurately and effectively detects and segments cracks using a dual-path encoder and hierarchical fusion. By simultaneously extracting spatial and contextual information, enhancing features through attention and refinement blocks, reducing the semantic gap between the encoder and decoder, and better integrating texture and semantic information at multiple levels, the proposed model outperforms other state-of-the-art methods. However, the model's reliance on dual-path encoding and hierarchical fusion may make it more susceptible to overfitting

The paper [12] explores the use of Fourier-based image enhancement combined with CNNs for crack detection in concrete structures. Fourier enhancement improves image clarity and reduces noise, leading to better CNN performance in crack classification. Results show that this approach increases accuracy compared to non-enhanced images, achieving up to 95% accuracy in one dataset. Overall, the findings demonstrate the effectiveness of combining frequency-domain techniques with deep learning for structural health monitoring. One limitation of using the Fourier method in this study is its inability to accurately capture complex and local image features. The paper [13] presents a UAV-based crack assessment system combining hybrid image processing with distance measurement. Using a camera, ultrasonic sensor, and WiFi module, the system captures crack images and their distance from the target structure. A hybrid binarization method then accurately estimates crack width while preserving length information.

The paper [14] reviews automated crack detection techniques for infrastructure using image processing and machine learning. It highlights the challenges of manual inspection and the need for efficient, automated methods. The review analyzes some articles and comparing various techniques to identify the most promising approaches for crack detection. Machine learning techniques, especially CNN, have become the primary approach in crack detection research. Crack detection is essential for structural health monitoring but challenging due to low-level features and issues like inconsistent lighting. Convolutional Neural Networks (CNNs) offer high accuracy, and transfer learning allows customization without deep algorithm knowledge. The study [15] analyzes the performance of pretrained CNNs, considering factors like dataset size, network depth, and adaptability to different materials, providing insights for researchers on key considerations for effective crack detection.

Proposed Method

In the proposed method, three main techniques, including two-dimensional wavelet transform, CNN, and multi-objective evolutionary algorithm based on decomposition (MOEA/D), are employed. In this framework, the 2D wavelet transform is first used to extract important features and reduce noise from the input data. Then, the convolutional neural network, with its ability to learn complex and nonlinear features, performs the classification process on the extracted data. Finally, in order to simultaneously optimize multiple performance criteria and adjust the model parameters, the MOEA/D algorithm is utilized to enhance the efficiency and accuracy of the proposed method.

Two-dimensional Wavelet Transform

In the proposed method, three main techniques, including two-dimensional wavelet transform, CNN, and multi-objective evolutionary algorithm based on decomposition (MOEA/D), are employed. In this framework, the 2D wavelet transform is first used to extract important features and reduce noise from the input data. Then, the convolutional neural network, with its ability to learn complex and nonlinear features, performs the classification process on the extracted data. Finally, in order to simultaneously optimize multiple performance criteria and adjust the model parameters, the MOEA/D algorithm is utilized to enhance the efficiency and accuracy of the proposed method.

The 2D-WT is a powerful mathematical tool designed to analyze two-dimensional data, especially images. It is similar to the Fourier Transform but differs in that it provides a way to analyze data at multiple scales and positions, making it particularly useful for analyzing localized features in images. Unlike the Fourier Transform, which only captures frequency information, the Wavelet Transform offers a more flexible approach by allowing both time and frequency domain analysis simultaneously.

For a 2D image $f(x, y)$, the 2D Wavelet Transform is mathematically defined as [16-18]:

$$W_{\psi}(a, b) = \iint f(x, y)\, \psi_{a,b}(x, y) dxdy \quad (1)$$

Where $\psi_{a,b}(x, y)$ is the wavelet function scaled by a (scale) and translated by b, and $W_{\psi}(a, b)$ is the wavelet coefficient.

The steps of the 2D Wavelet Transform involve several key stages. Initially, the image is processed using low-pass and high-pass filters in both horizontal and vertical directions, which decomposes the image into different components, each with its own specific features. Then, the result of each wavelet transform stage is used as input for the next stage, and this process is repeated multiple times to extract features of the image at different scales. Finally, after the transform, the image with distinct features such as edges, cracks, or other patterns becomes recognizable, and these features can be used for various purposes, such as object recognition, pattern detection, and especially concrete crack detection. The application of the 2D Wavelet Transform in concrete crack detection is as follows:

1- Feature Extraction: Cracks in concrete usually appear as features with sudden spatial changes and scalable variations in the image. The 2D Wavelet Transform is capable of identifying these changes at various scales. These features can help in detecting and classifying cracks.

2- High Accuracy in Detection: Using the 2D Wavelet Transform, different characteristics of cracks can be detected from the image, leading to higher accuracy in crack identification. This method is especially effective when cracks have complex and diverse features.

3- Noise Removal: Concrete images may contain noise or disturbances that make it difficult to accurately detect cracks. The 2D Wavelet Transform can reduce the noise in the images and more clearly extract the true features of the cracks.

4- Detection at Multiple Scales: Cracks in concrete may appear at different scales in images. The 2D Wavelet Transform can identify cracks at various scales, which is particularly important for analyzing images with different resolutions or for detecting both large and small cracks.

Convolutional Neural Network

CNNs are one of the most advanced and successful architectures in deep learning, specifically designed for processing image data. These networks automatically extract important features from raw data, such as images, and use them for various machine learning tasks. Unlike classical models that require manually extracted features, convolutional networks can identify complex and higher-level features from input data, making them ideal for tasks like object recognition in images, face detection, and even video processing and simulation. CNNs have revolutionized fields such as computer vision, natural language processing, and even speech recognition due to their ability to process large amounts of high-dimensional data efficiently [19-22].

One of the key strengths of CNNs is their ability to reduce the dimensionality of data and extract meaningful features from images. The core layers of a CNN include convolutional layers, activation layers, pooling layers, and fully connected layers. The convolutional layers serve as the heart of the network, applying filters to the data to identify features such as edges, textures, patterns, and even more complex details like shapes or objects. These convolutional filters operate locally on sections of the image, performing a series of mathematical operations, such as convolutions, to extract specific features. The local receptive field in convolutional layers allows the network to detect spatial hierarchies within the image, meaning that the network is not limited by a global perspective but rather examines local patterns, leading to higher accuracy in object detection. Activation layers, such as ReLU (Rectified Linear Unit), are essential for introducing non-linearity into the network, preventing issues like vanishing gradients. These layers enable the network to learn more complex and abstract patterns from the input data, which is critical in understanding intricate structures within images.

After the convolutional and activation layers, pooling layers are used to reduce the dimensionality of the features and computational complexity, often through techniques like max pooling or average pooling. These layers extract the most significant features from the data, ensuring that the network can focus on the most relevant information while discarding less important details. Pooling layers also help in achieving invariance to translation, meaning the network can recognize objects regardless of their location within an image. This not only improves processing speed but also reduces memory usage, making CNNs more efficient and scalable for large datasets. Finally, after feature extraction, the network uses fully connected layers for final processing and performing tasks like classification or prediction. These layers combine the data extracted from earlier layers and use it to make decisions based on the learned features. This structure allows CNNs to classify objects, recognize faces, detect anomalies, or predict outcomes based on the data in a highly accurate manner. The fully connected layers are crucial for understanding the global relationships between the learned features, integrating them for more abstract and meaningful outputs.

Convolutional neural networks have become a powerful tool in many fields due to their high performance in processing and analyzing images. Some of their most common applications include disease detection in medical images, such as identifying tumors or abnormalities in X-rays or MRI scans, object recognition in images for applications like security surveillance or autonomous vehicles, and face recognition for applications in biometrics and social media. CNNs have also been instrumental in image classification tasks, categorizing large datasets of images into different classes, such as distinguishing between different animal species or classifying satellite imagery. In autonomous vehicle driving, CNNs are used to process live camera feeds to detect obstacles, pedestrians, and road signs in real-time, enabling self-driving cars to navigate their environment safely. These networks, by learning key features from input data and automatically detecting complex patterns, are extremely useful and versatile in real-world applications, especially in tasks involving image and video data. As deep learning continues to evolve, CNNs are likely to remain a fundamental tool in various fields, pushing the boundaries of what can be achieved in image recognition, natural language processing, and beyond.

Multi-objective Evolutionary Algorithm based on Decomposition

The MOEA/D is one of the widely used algorithms in the field of multi-objective optimization, aiming to find a set of Pareto-optimal solutions for complex problems. In this algorithm, instead of directly solving a multi-objective problem, the original problem is decomposed into a number of simpler single-objective subproblems. Each subproblem considers a specific combination of objective functions using techniques such as the weighted sum method or the Chebyshev method. This decomposition enables the algorithm to perform a more effective search in the solution space by leveraging the collaboration among subproblems and covering different regions of the Pareto front [23-25].

One of the important applications of MOEA/D is hyperparameter optimization in deep learning models such as CNNs. Proper tuning of hyperparameters, such as learning rate, number of layers, number of filters, and filter sizes, plays a vital role in improving the accuracy and performance of the model. Hyperparameter search is inherently a multi-objective problem, as a balance must be maintained between various criteria such as accuracy, computational complexity, and learning speed. In this regard, the MOEA/D algorithm can simultaneously search for multiple objectives and find optimal values of CNN hyperparameters that not only ensure desirable accuracy but also maintain computational cost and model complexity at an acceptable level.

By using the MOEA/D algorithm, the multi-objective problem can be formulated in different ways. For this purpose, the weighted sum method and the Chebyshev method are utilized. The weighted sum method is formulated as follows:

$$\min \ g^{ws}(x|\lambda) = \sum_{j=1}^{m} \lambda_j f_j(x) \tag{2}$$

In these equations, $f(x)$ represents the objective function, and $\vec{\lambda}$ denotes the weight parameters. The Chebyshev method is formulated as follows:

$$min \quad g^{te}(x|\lambda, Z^*, p) = ||f(x) - Z^*||_{p,\lambda}$$
$$= \sqrt[p]{\sum_{i=1}^{m} \lambda_i |f_i(x) - Z_i^*|^p} \tag{3}$$

In the above equation, Z^* represents the ideal point.

Concrete Crack Detection Procedure

The architecture of the CNN-MOEA/D is shown in Figure 1. The main steps of the proposed method are as follows:

Based on your abstract, here’s the revised version of the steps in English:

1. In the first step, a 2D WT is applied to the input images. This transform is used to enhance crack-related features and suppress noise or irrelevant patterns. One of the key advantages of this method is that the wavelet transform can extract information at various scales with high resolution. This is particularly useful for concrete crack detection, as cracks may appear at different scales and with varying characteristics. The wavelet transform allows for the separation of crack-specific features from the background and noise, significantly improving the accuracy of crack detection.

2. Defining the CNN Architecture: Initially, the architecture of the CNN is explicitly defined. This architecture consists of a sequence of layers including imageInputLayer, convolution2dLayer, batchNormalizationLayer, reluLayer, dropoutLayer, maxPooling1dLayer, fullyConnectedLayer, softmaxLayer, and classificationLayer. Each of these layers plays a crucial role in processing the input data and performing the classification and detection of concrete cracks.

3. Determining Key Parameters for the Convolution Layer: In this step, the key parameters for the convolution layer, such as filterSize and numFilters, are determined. These parameters significantly influence the network's performance. In the proposed method, the goal is to optimize these parameters to achieve a balance between classification accuracy and computational complexity, ensuring the network operates efficiently and quickly.

4. Optimizing Parameters Using MOEA/D: To further enhance the network's performance, the optimal values for filterSize and numFilters are determined using the MOEA/D. This algorithm evaluates the trade-off between multiple objectives, allowing for the identification of the best combination of parameters that leads to the optimal network configuration.

5. Evaluating Accuracy and Inference Time: Both the accuracy of the CNN and the inference time are simultaneously evaluated. The MOEA/D algorithm iteratively updates these parameters to ensure that the final model provides the highest accuracy while maintaining minimal inference time. This is particularly crucial for real-time applications that require high speed.

6. Stopping Criterion for the Optimization Algorithm: The optimization process halts once the maximum allowed number of iterations is reached. If this condition is not met, the algorithm continues to generate new solutions and refines its search for optimal parameters. This iterative process ensures that the solution converges to the best possible outcome within the computational constraints.

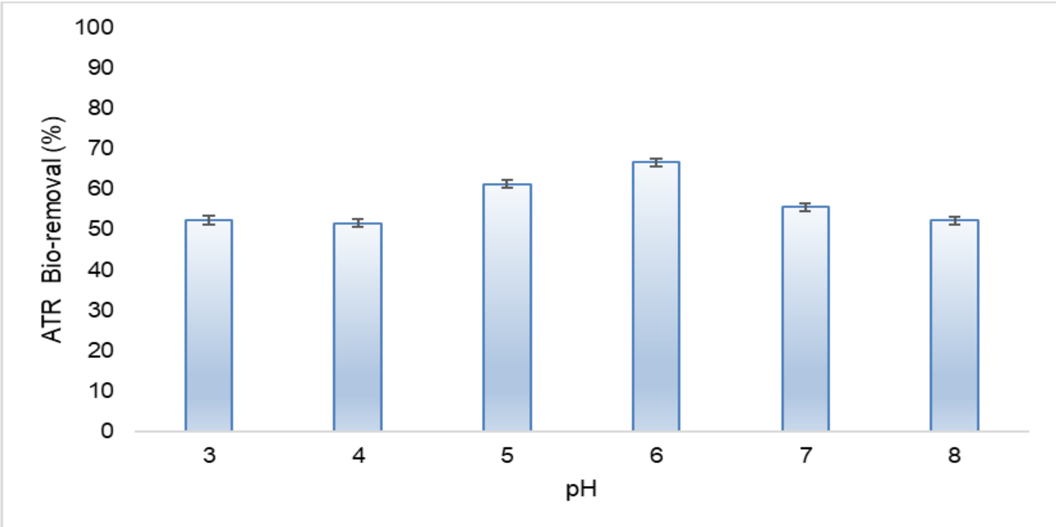

Figure 1. *CNN-based Concrete Crack Detection*

Simulation Results

The proposed algorithm and the existing method have been implemented using MATLAB software from MathWorks. The processor used is an Intel(R) core^{TM} i5-4460 CPU @ 3.2 GHz with 16 GB of RAM. MOEA/D is run with a population size of 100 individuals over 100 iterations.

The dataset consists of concrete images that contain cracks, collected from various buildings on the METU Campus. It is divided into two categories for image classification: positive (cracked) and negative (non-cracked) images. Each category contains 20,000 images, resulting in a total of 40,000 images, each with a resolution of 227 x 227 pixels and RGB channels. The dataset is derived from 458 high-resolution images (4032 x 3024 pixels) using the method proposed by Zhang et al. (2016). These high-resolution images exhibit variability in surface finish and lighting conditions [26].

Examples of crack-free images and images containing cracks from the dataset are clearly shown in Figures 2 and 3. Figure 2 displays images representing concrete surfaces without cracks, which exhibit smooth and uniform surfaces with no visible damage or cracks. In contrast, Figure 3 showcases images containing cracks in the concrete. These images display cracks appearing on the concrete surface, which are crucial for crack detection. The visualization of these images helps to clearly distinguish between crack-free and cracked images, ultimately aiding in improving the accuracy of crack classification and detection models.

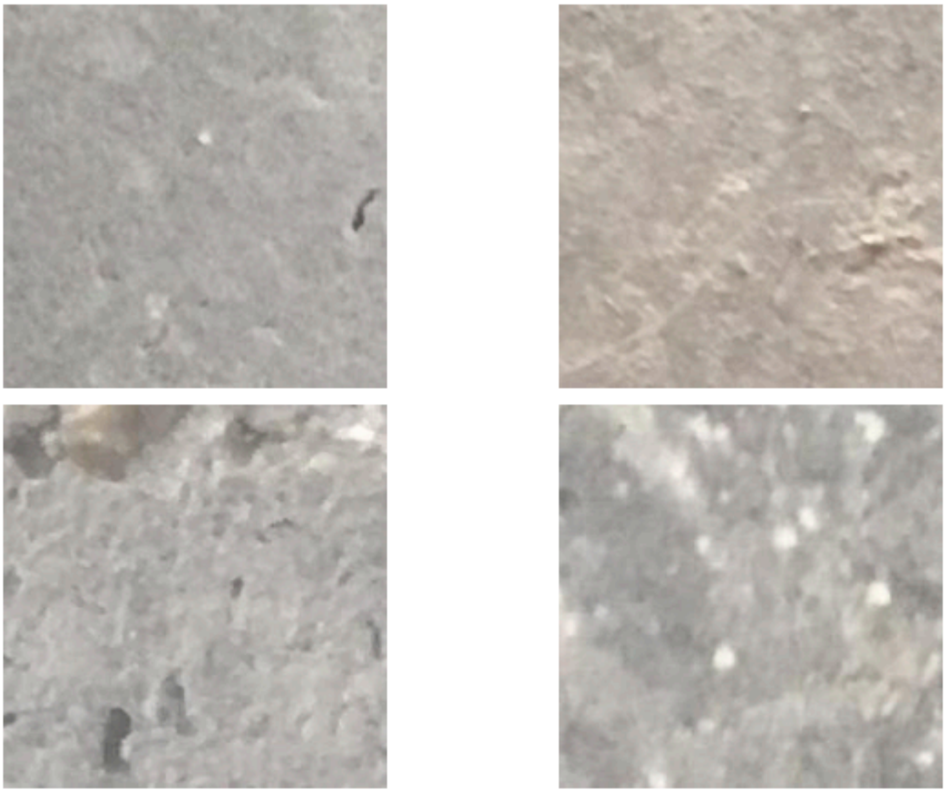

Figure 2. *Concrete images without cracks*

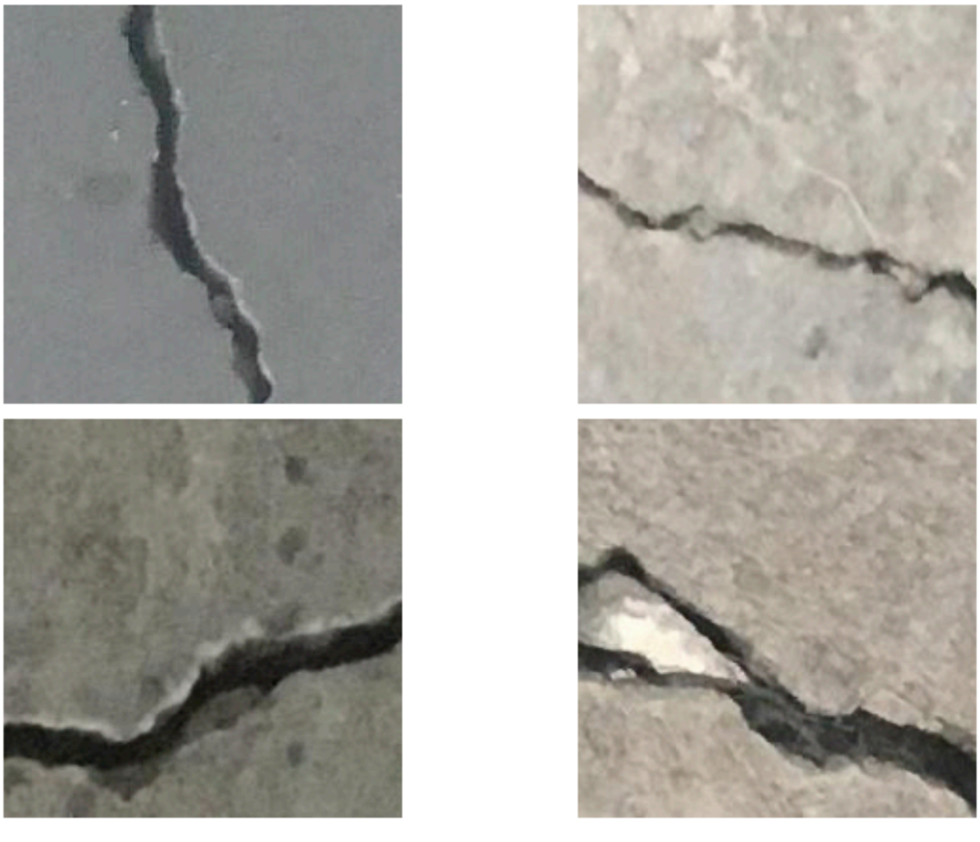

Figure 3. *Concrete images with cracks*

An example of a crack-free image along with its two-dimensional wavelet transform components, including approximation, vertical, horizontal, and diagonal details, is illustrated in Figure 4. Similarly, an example of a cracked image and its corresponding two-dimensional wavelet transform components are presented in Figure 5. Figure 6 illustrates an example of the training process of the proposed network, which integrates CNN and MOEA/D over 100 iterations. As can be observed, the classification accuracy of the model gradually increases and eventually reaches 100%, indicating the excellent learning capability of the proposed framework. In addition, the loss value steadily decreases during the training process and ultimately approaches zero, which reflects the effective optimization of network parameters and the proper fitting of the model to the training data. The accuracy and precision curves for comparing the proposed method with existing methods are illustrated in Figures 7 and 8, respectively. The results clearly demonstrate the superior performance of the proposed method over the existing approaches.

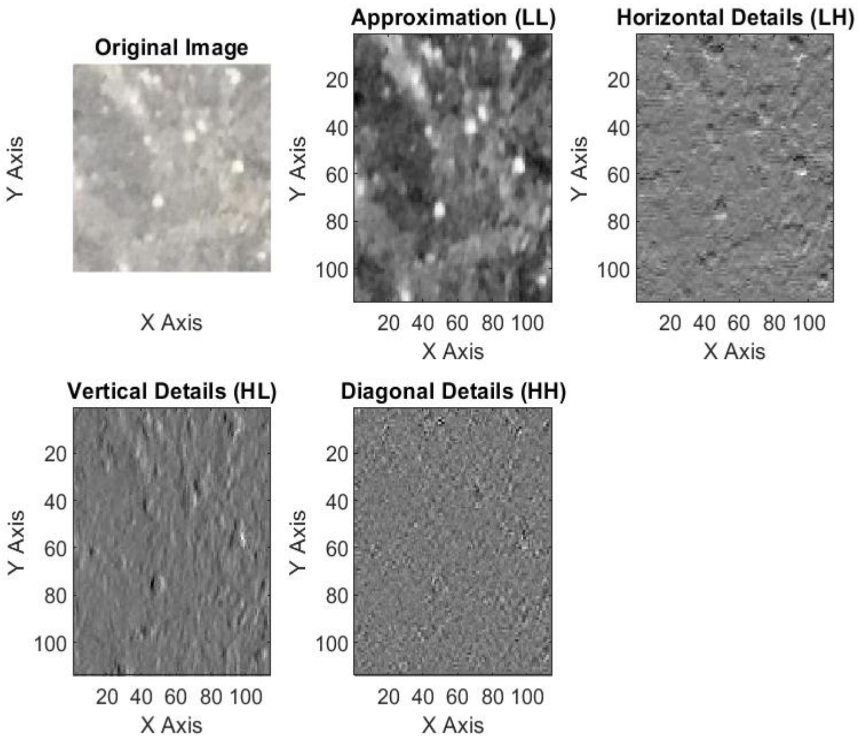

Figure 4. *Two-dimensional wavelet transform components (Approximation, Vertical, Horizontal, and Diagonal) of a crack-free concrete image.*

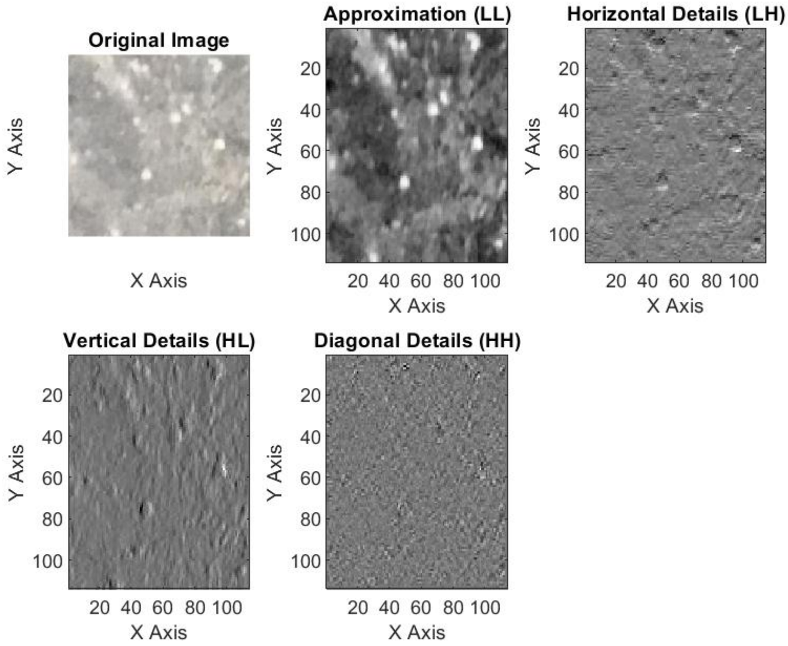

Figure 5. *Two-dimensional wavelet transform components (Approximation, Vertical, Horizontal, and Diagonal) of a concrete image with cracks.*

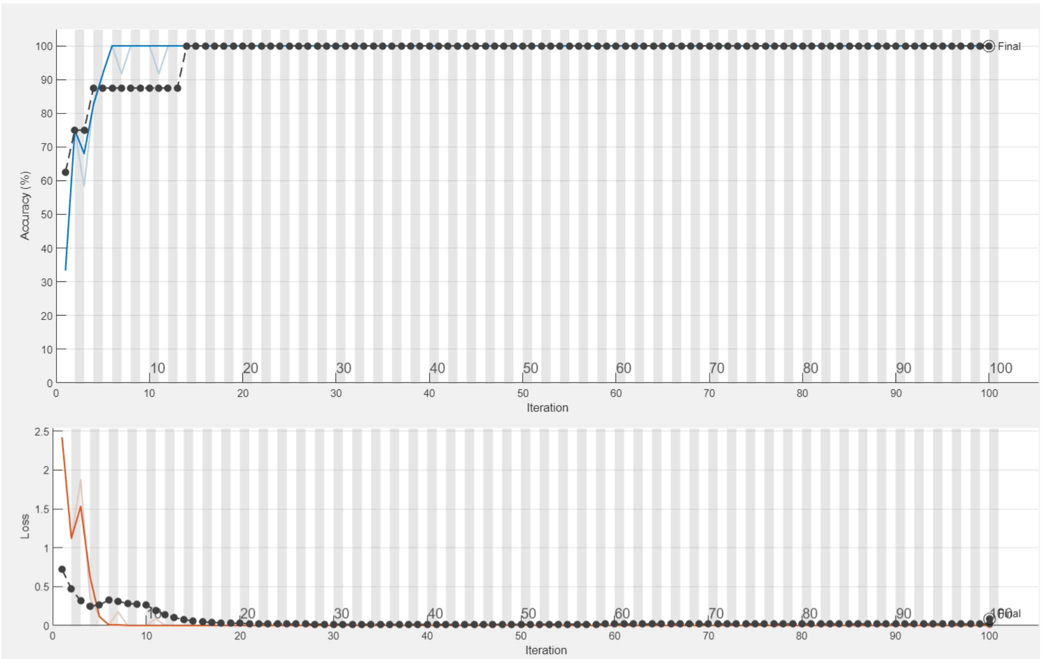

Figure 6. *Training process of the proposed CNN and MOEA/D-based network: accuracy and loss.*

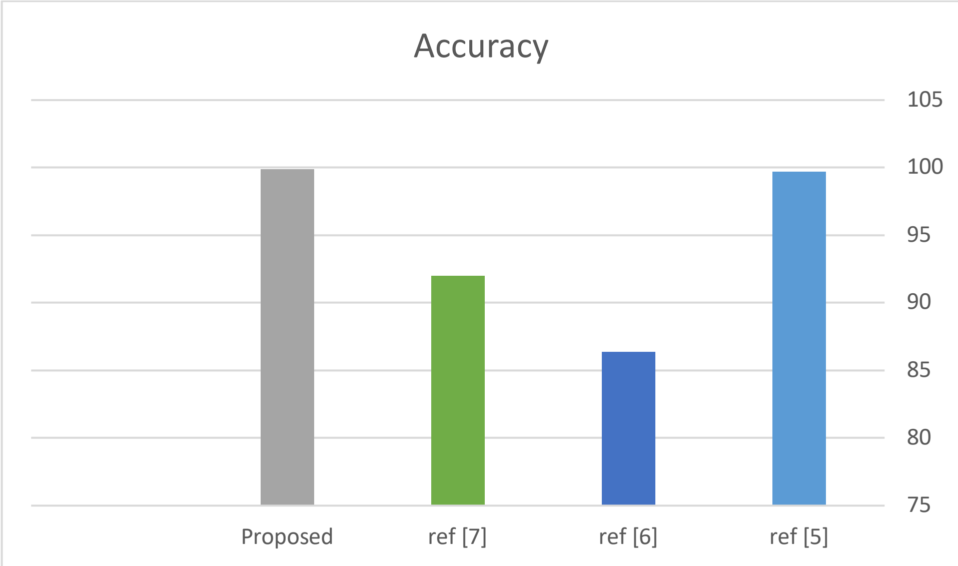

Figure 7. *Comparison of the Accuracy between the Proposed Method and Existing Methods.*

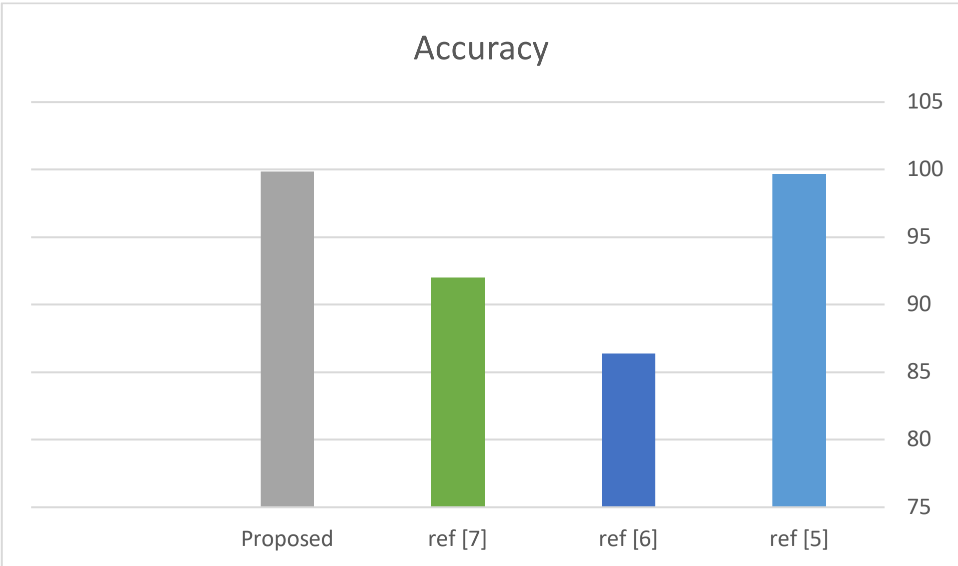

Figure 8. *Comparison of the Precision between the Proposed Method and Existing Methods.*

Conclusion

In this study, an intelligent and automated framework was presented for concrete crack detection based on the integration of two-dimensional wavelet transform, convolutional neural network, and multi-objective evolutionary algorithm based on decomposition. The wavelet transform effectively enhanced the crack-related features while suppressing noise and irrelevant patterns, leading to improved feature extraction. Furthermore, the optimization of key CNN hyperparameters, including filter size and the number of filters, using MOEA/D enabled an effective trade-off between classification accuracy and computational complexity. Experimental evaluations conducted on benchmark datasets demonstrated the superior performance of the proposed method compared to existing approaches. The proposed model achieved a remarkable classification accuracy of 99.7% and a precision of 99.82%, indicating its high capability in distinguishing between cracked and non-cracked concrete images. These results highlight the robustness, efficiency, and generalization ability of the proposed framework, making it a promising solution for real-world structural health monitoring and maintenance applications.

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