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Integrated Machine Learning and Region Growing Algorithms for Enhanced Concrete Crack Detection: A Novel Approach

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Abstract: In the field of construction engineering, the cracking of concrete structures is a common engineering problem, which has a great impact on the overall stability and service life of the engineered structure. During structural repair, crack detection is the most critical step. Automatic detection significantly reduces the engineering cost and human factor error compared with manual detection. However, due to the changeable environment of the project site and different image specifications, using a single algorithm makes it difficult to balance high efficiency and high accuracy. In this study, we designed a combined recognition method including the region growth algorithm and machine learning regression that can achieve a tradeoff between accuracy and efficiency. Firstly, the regression method learns the image features of the dataset and the specific region growth threshold, and the regression function is trained by using the open-source dataset to determine the region growth threshold using the characteristics of the images included in the tests. The region growth algorithm is used to expand the threshold from the seed points of the image to obtain the crack recognition results. The results show that this method improves the accuracy of SSIM by 7% compared with the traditional region growth algorithm, and does not significantly increase the computational cost, with an increase of 0.78 s per photo process. Compared with the deep learning method, the recognition accuracy of SSIM is decreased by 5.96%, but it takes less resources and has high efficiency.

Keywords: structure cracks; regional growth; machine learning; regression analysis; crack detection

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Citation: Yao, W.; Li, H.; Li, Y. Integrated Machine Learning and Region Growing Algorithms for Enhanced Concrete Crack Detection: A Novel Approach. *Appl. Sci.* **2024**, *14*, 9745. https://doi.org/10.3390/app14219745

Academic Editors: Paulo Santos and Syed Minhaj Saleem Kazmi

Received: 1 August 2024
Revised: 16 October 2024
Accepted: 20 October 2024
Published: 25 October 2024

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1. Introduction

Crack detection is crucial in construction engineering, as it directly relates to the safety and stability of the structure. By detecting and analyzing cracks in a timely manner, engineers can assess the degree of structural damage, prevent potential safety hazards, ensure that project quality meets the necessary standards, and protect the safety of personnel and property. This is a key link in improving building reliability and durability.

In this paper, a novel combined detection method for concrete cracks, assisted by machine learning, is proposed that not only improves the efficiency of the region growth detection method for concrete crack areas, but also ensures the high accuracy of detection. In the first section, this article introduces the previous research progress on crack detection; the second section introduces the theory and implementation of regional growth recognition methods; the third section provides a detailed introduction to the experimental process and results; the fourth section discusses the experimental results; and the fifth section draws conclusions and looks toward future work.

2. Background

In construction projects, due to varied conditions such as temperature, humidity, geological environment, groundwater, external force, and technical problems, cracks in

concrete structures have become a common issue in these projects that affects the normal operation of engineering facilities [1]. The efficient and accurate detection of cracks in concrete structures is a challenging key problem. The earliest method of crack recognition was manual patrol, where inspectors moved through the facility, detected crack positions with the naked eye [2], marked and took photos after discovery, and prepared for maintenance. However, the method of manual inspection highly depends on the professional ability of inspectors, and is affected by subjective factors. When the project site conditions are poor, it increases the difficulty of this work. Therefore, in recent years, crack detection has gradually shifted to a human–machine collaboration approach. This method involves using instruments on-site to collect acoustic or image information, which is then further analyzed and assessed. Compared with acoustic recognition, image recognition has fewer controllable variables and is more suitable for fast-moving recognition equipment, as it is not affected by the Doppler effect. This means that image information can more efficiently and accurately reflect the distribution of concrete cracks. However, in practical engineering, the time requirements for image acquisition, analysis, and judgment are more stringent, and a large range of cracks need to be detected with high precision in a short time. If using deep learning methods such as U-Net, there are higher hardware requirements such as GPUs. At the same time, the timeliness of calculation is insufficient. In other words, while there are still challenges in image-based concrete crack detection, the high precision, accuracy, and ease of implementation of image recognition make exploring effective methods for detecting cracks in concrete structures a pressing need in the field of structural detection.

Currently, some researchers have conducted studies on crack detection in images using single algorithms. These algorithms are mainly divided into two categories: region growing algorithms and machine learning algorithms. Wenming Cao conducted a comprehensive review of various methods for detecting pavement defects, particularly focusing on crack detection [3]. The review reported that the region growing method is particularly useful for outlining the internal characteristics of cracks, which edge detection algorithms may not fully capture. The selection of seed pixels is crucial in this method, as it significantly impacts the accuracy of image segmentation. The review also emphasized that machine learning techniques can analyze deeper features of the data compared to traditional image processing methods, which often only capture superficial characteristics. The authors mentioned that deep learning, in particular, has greatly improved the accuracy of pavement crack detection.

The region growing method is an image segmentation technique that expands the region in all directions from a point that meets the detection criteria through pixel aggregation [4]. This method is based on similarity measurement, adding boundary pixels to the current region to ensure that their gray level is the highest within the region, thereby guiding the region to grow towards higher gray pixel levels. While researching concrete crack detection using the region growing algorithm, Kong Deming proposed the application of the region growth model in image recognition [5]. According to the characteristics of the complex point cloud model, a complex point cloud model segmentation method based on multi view region growth was proposed. At the same time, Wang Li proposed an algorithm using region growth in the field of crack detection [6]. Further, Zhou Yuxian applied the regional growth algorithm in the field of building crack detection [7]. This practice shows that when the crack width is greater than 0.15 mm and there is no water stain and non-destructive interference, the detection accuracy can reach 90%. Another approach to using regional growth in crack detection starts with Region of Belief (ROB) seeds, determining the search scope based on specially devised rules, and merging ROBs with different regions following a similarity criterion that considers various cues [8]. The process includes extracting the orientation and length of each ROB, starting from the ROB with the largest length as the seed, generating a set of growing regions based on matching criteria, merging ROBs with regions in the set based on spatial relationships, and repeating the process until all ROBs are grown. Noise regions not involved in growth are removed. Overall, the region growing algorithm appears to be highly accurate and efficient in the

field of concrete crack detection. However, the aforementioned research results do not consider the issue of recognition accuracy under interference conditions. When multiple factors interfere on-site, the accuracy of the region growing algorithm often significantly decreases because it cannot handle disturbances such as dust and water stains. Compared with machine learning methods, the region growth algorithm can solve the problem faster, but will cause serious over-segmentation and under-segmentation.

To address the interference imposed by construction site environments on recognition algorithms, numerous scholars have resorted to using machine learning algorithms for the detection of concrete cracks. Raza Ali compared various CNN methods in their review, specifically highlighting different architectures and their performance in crack detection [9]. They mainly compared the architectures of CNN, datasets, training methods, loss functions, performance metrics, and computational efficiency. Among these methods, R-CNN and U-NET were found to be more suitable for crack detection. U-Net has the advantage of data efficiency and R-CNN is good at distinguishing different types of cracks. Therefore, we have mainly surveyed these two kinds of machine learning methods.

Gong Qimin introduced an enhanced Cascade R-CNN for recognizing tunnel targets, which sharpens crack details, facilitating the detection of smaller cracks and the classification of tunnel defects [10]. However, this method necessitates the configuration of intricate hardware parameters, such as focusing and sub-frequency conversion modules. Wang Yadong proposed a crack recognition approach that integrates digital image processing and structured light recognition [2]. This involves capturing numerous images of the target object, extracting pixel position information, converting it to real-world spatial dimensions, and then performing a series of image processing tasks to achieve target recognition and positioning. Ramiro and his team utilized U-Net, a convolutional neural network architecture introduced by Ronneberger in 2015 for swift and precise image segmentation [9,10]. Its speed and support for multi-channel feature maps make it suitable for rapid crack detection. This team also designed a crack detection dataset for training and testing, which comprises 10,100 images, resulting in a training duration of nearly 10 h and a test time of approximately 3 s per image. In this study, the U-Net method served as a control, highlighting the substantial improvement in concrete crack detection accuracy achieved through machine learning algorithms. Another improved method for detecting cracks involves the Swin Transformer module, which enhances the network's ability to focus on and express crack features, thereby improving detection accuracy [11]. However, implementing these algorithms is often very complex, difficult, and costly. In practical engineering, there is a need to balance high efficiency, high accuracy, and low cost. Therefore, the adoption of machine learning-based concrete crack detection methods faces considerable resistance in practical engineering applications.

We have summarized the methods mentioned above in Table 1 for comparison.

Table 1. Detection method comparison.

Reference Notation	Experiment Dataset	Base Method	Machine Learning
[2]	Crack images collected from simulated tunnel environments	Sobel operator edge detection	×
[4]	Medical images of mammograms	Region growing	×
[5]	Selected model dataset	Multi-view region growing	×
[6]	Concrete crack images from specific reservoir	Region growing and grayscale image segmentation	×
[7]	Digital images of building structure	Region growing	×
[8]	Field-captured images and public benchmark dataset	Coarse-to-fine region growing	×
[10]	Six types of tunnel targets including cracks and water leakage	Cascade R-CNN	√
[12]	167 different images of cracked ceramics	U-Net	√
[13]	Electron microscopic stacks, transmitted light microscopy images, and DIC-HeLa dataset	U-Net	√
[11]	Concrete crack dataset that was constructed from 840 original images	Swin Transformer U-Net	√

To sum up, the traditional region growth algorithm cannot deal with the interference of dirt and water stains, and its accuracy is low, while the deep learning method is more complex and inefficient. To balance the conflict between efficiency and accuracy, this paper proposes a combined recognition method that integrates machine learning and region growing algorithms. This new combined algorithm ensures high accuracy in concrete crack detection while improving detection efficiency and applicability in construction sites. It is a highly practical algorithm with significant application value.

3. Recognition Methods and Their Implementation

The combined recognition algorithm based on region growth includes three parts: the region growth algorithm, regression analysis, and image feature extraction. Image feature extraction can calculate quantized image features, regression analysis uses these features to decide how to grow the threshold, and finally, the region grows, using the threshold to recognize cracks.

3.1. Region Growing Algorithm

The process of the region growth algorithm includes the selection of seed points and growth. The first step of regional growth is to select a group of seed points, which is based on the need to identify cracks. Because cracks are often dark areas in the image, seed points are selected based on grayscale in this study. Firstly, search all pixels to find the lowest gray point of the whole picture, and then find the pixels whose gray level is close to the lowest point in each image block, and put them into the seed point set.

After obtaining the seed point set, compare the gray values of eight adjacent pixels from each seed point. If a value is lower than the threshold, it will be added to the tail of the seed point set. The region growth pseudo code is shown in Pseudo Code.

The region growing algorithm has the advantages of fast image segmentation, clear edges, and a simple theory. However, it is sensitive to noise and the threshold needs to be provided manually. The noise problem can be solved by image preprocessing, and the threshold problem will be solved by regression analysis in the next part.

The Region Growth method could be surmised by pseudo code of Algorithm 1 below.

Algorithm 1: Region Growth

```
Input: image A
Output: image with growing result
For each pixel P∈A
If P.Grayscale>origin_threshold
Add P->Seeds
For each pixel K∈Seeds
If K.surrounding.grayscale-K.grayscale < growing_threshold and K.surrounding ∉ Seeds
Add K.surrounding->Seeds.tail
```

For the detailed procedure of the algorithm, refer to the steps below.

1. Load the image dataset containing concrete structure crack images.
2. Preprocess the images:
   Perform image equalization;
   Calculate the central pixel average;
   Apply the median filter.
3. Extract the image features:
   Calculate the grayscale mean and variance for each image;
   Implement the feature recognition algorithm BRIEF.
4. Train the regression function using the extracted image features:
   Use the regression method to learn the image features and determine the region growth threshold;
   Train the regression function on the open-source dataset.

5. Implement the region growth algorithm:
   Initialize the seed points for crack recognition;
   Expand the threshold from seed points using the region growth algorithm.
6. Evaluate the crack recognition results:
   Compare the results with the traditional region growth algorithm;
   Measure the accuracy improvement and computational cost.
7. Experiment and analyze the algorithm:
   Use the OpenCV toolkit for image processing and feature extraction;
   Utilize the RegionGrow toolkit for the region growth algorithm;
   Apply the sklearn toolkit for regression analysis.
8. Display the experimental results:
   Present the experimental environment details (processor, memory, GPU);
   Show the crack detection dataset and subsets used.
9. Repeat steps 2–8 for each image in the dataset.
10. Output the final crack recognition results and performance metrics.

3.2. Regression Analysis Algorithm

The main reason for using regression analysis in this article is based on the significant linear characteristics exhibited by the selected variables. Meanwhile, the dependent variable 'regional growth threshold' is presented in a concise and clear numerical form, making the application of regression analysis highly feasible. In addition, the calculation process of regression analysis is relatively simple and does not require additional GPU acceleration processing. In the previous step, the growth threshold regulates the results of regional growth. Different growth thresholds should be selected for pictures with different characteristics. In this part, the regression method is used in machine learning to obtain the relationship between image features and growth threshold. Firstly, it is assumed that the relationship between a growth threshold y and image feature x is

$$y = \sum_{i=1}^{N} f(\omega x_i + b) \tag{1}$$

in which case the MSE loss function is

$$L(\omega, b) = \frac{1}{N}\sum_{i=1}^{N}(y_i - f(\omega x_i + b))^2 \tag{2}$$

where L is the loss function and $\boldsymbol{\omega}$ is the parameter matrix of the relationship. At this point, the gradient descent algorithm is used to find the gradient of a certain point $\frac{\boldsymbol{dL}}{\boldsymbol{d\omega}}$, and let $\boldsymbol{\omega}$ move in the descending direction of the gradient; the update of the gradient can be expressed as

$$\omega_{i+1} = \omega_i - \alpha\frac{dL}{d\omega} \tag{3}$$

where $\boldsymbol{\alpha}$ is the learning rate. Equation (3) will loop until the loss function converges. Deviation b can be handled in a similar way.

3.3. Image Feature Extraction Algorithm

The BRIEF algorithm generates binary descriptors by comparing local pixel pairs and has lower computational complexity. This means that during the process of image processing, BRIEF can quickly extract feature points and generate their descriptors. The region growing algorithm relies on certain feature points as seeds or reference points, and the efficiency of BRIEF helps improve the speed of preprocessing for region growth. In regression analysis, the dependent variable used is the threshold size of regional growth, which is obtained by artificial experience. The independent variable is the input image's features.

In the process of crack detection, common factors affecting the detection include water stains, dirt, uneven lighting, and so on. They are reflected on the grayscale map by changes in grayscale mean and variance. So in this study, the mean and variance of the grayscale

image are used as two features. In addition to these two simple mathematical features, the study needed to consider the grayscale relationships of random point pairs in the local image neighborhood. So SURF [14], FAST [15], BRIEF [16], and other feature recognition algorithms were discussed. These common image feature analysis algorithms have been studied and compared before [17]. SURF has high computational complexity and low operation efficiency; FAST has no directionality and shows scale invariance; the BRIEF (Binary Robust Independent Basic Features) method can retain direction invariance while calculating quickly, and uses binary sequences to describe features. The value of each binary sequence depends on the comparison between the intensity values of two points in the image partition centered on the currently described feature. If the strength value of the first point of a given point pair is higher than the strength value of the second point, the bit corresponding to the point pair is assigned, otherwise the bit is reset. BRIEF is faster and consumes less CPU memory than other methods. However, due to its sensitivity to noise, the algorithm needs to smooth the image before calculation.

The calculation steps of BRIEF are as follows.

First, select Nd pairs of pixels in the S × S area around the feature point; these pixels shall be selected randomly. Then take the grayscale value of each pair of pixels and compare the size:

$$\tau(p;x,y) := \begin{cases} 1 \; if \; p(x) < p(y) \\ 0 \; otherwise \end{cases}. \tag{4}$$

Then each bit of the descriptor, which is composed of X and y pixels, can be calculated and the τ Function gives the following:

$$f_{n_d}(p) := \sum_{1 \le i \le n_d} 2^{i-1} \tau(p;x_i,y_i) \tag{5}$$

In this study, the BRIEF method is used as the third image feature, together with the gray mean and variance as independent variables, to input the regression function.

3.4. Implementation of Combined Method

This study uses the OpenCV 4.9.0 toolkit to carry out the processes of image preprocessing and image feature extraction. Image preprocessing includes equalization, central pixel average, and median filter. Then the RegionGrow toolkit (access the toolkit in https://github.com/wwbweibo/RoudDetect in 30 June 2024) is used to implement the region growth algorithm, and the sklearn 1.5.2 toolkit is used to implement regression analysis. The flow of the overall algorithm is shown in Figure 1.

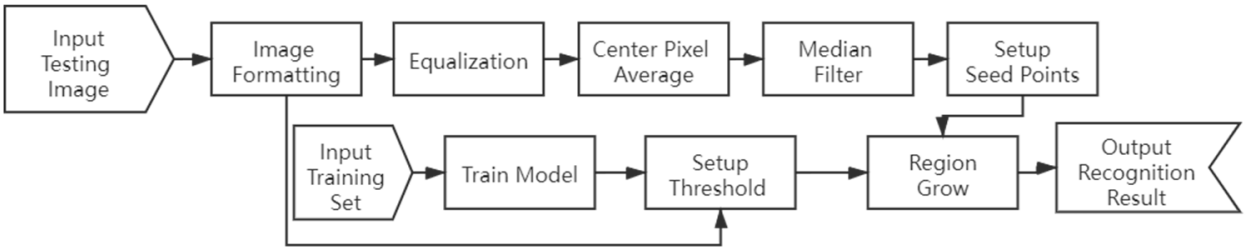


Figure 1. Algorithm flow chart.

4. Experimental Analysis

4.1. Experiment Scheme

The configuration used in this experiment is shown in Table 2.

Table 2. Experimental environment.

Equipment	Parameter
Processor	AMD Ryzen 7 5800 H (Santa Clara, CA, USA)
CPU memory	16 GB (DDR4 3200 MHz)
Graphics card	NVIDIA GeForce RTX 3060 (Santa Clara, CA, USA)
GPU memory	6 GB

The dataset used in this experiment is the online open-source crack detection dataset collected by Ramiro Daniel's team [18]. The training set and testing set are subsets of the dataset. The training set includes 160 photos of three different scenes (cement, brick wall, and cell membrane), as shown in Figure 2. The testing dataset we used includes 10 photos of different types of concrete cracks. The test dataset is shown in Figure 3.

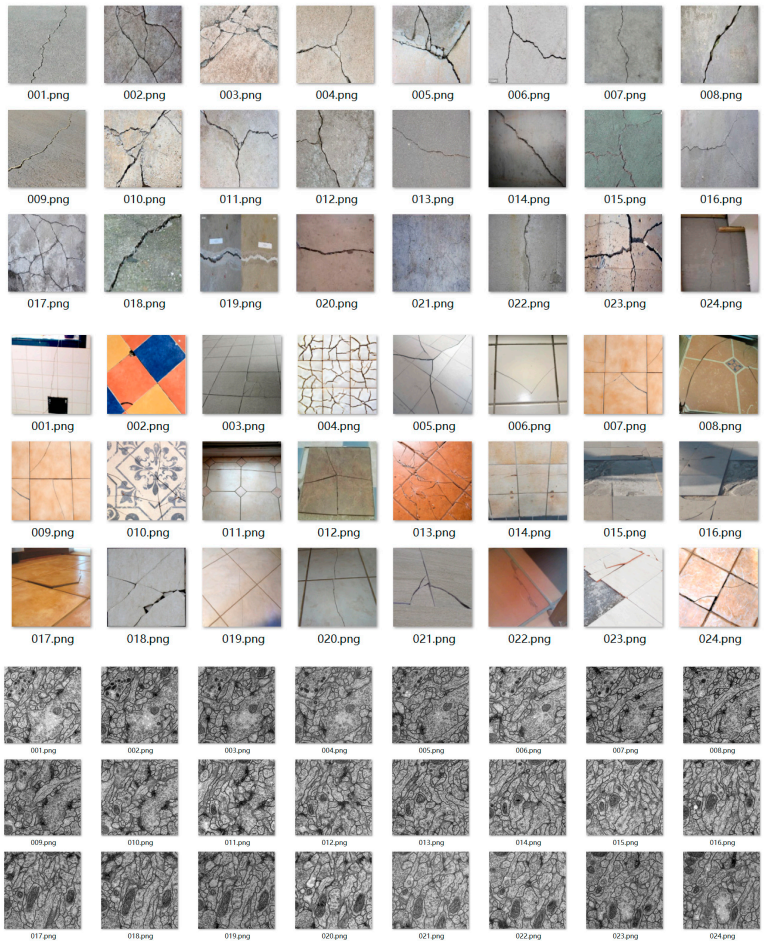


Figure 2. Training set display.

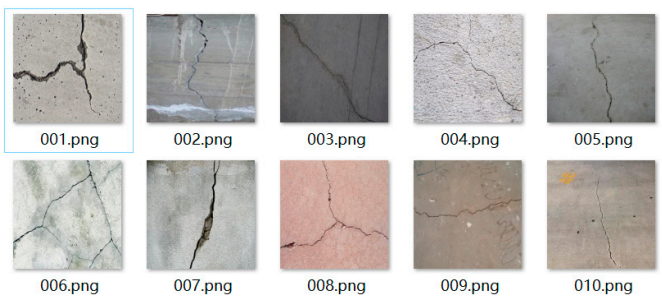


Figure 3. Testing set display.

In this study, a total of three control experiments were carried out involving the traditional region growth algorithm, the combined method of the region growth algorithm and threshold regression analysis, and the U-Net deep learning method.

4.2. Experiment Results

Finally, the recognition accuracy and operation resource loss are shown in Table 3. In crack recognition, the accuracy of the recognition algorithm can be evaluated by comparing the SSIM values of the recognition results with the reference image (i.e., the actual crack image). The closer the SSIM value is to 1, the more similar the recognition result is to the manually labeled image—that is, the higher the accuracy of crack recognition.

Table 3. Experimental results.

Method	Accuracy	Time Consumption	CPU Occupancy	GPU Occupancy
Region growth	81.30%	0.43 s/photo	2.4%	0%
Region growth + regression	88.29%	1.21 s/photo	4.6%	0%
U-Net	94.25%	2.37 s/photo	8%	49.1%

According to Table 3, it is obvious that the recognition accuracy of the combined method of region growth and regression analysis is approximately 7% higher than that of the traditional region growth algorithm, and its calculation cost is not significantly increased. Compared with the U-Net method, the recognition accuracy of the combined method is decreased by 5.96%, but its CPU resource usage is only half of that of the deep learning method, and GPU resources are not used. A comparison of the methods' recognition of cracks in pictures of typical concrete structures is shown in Figure 4.

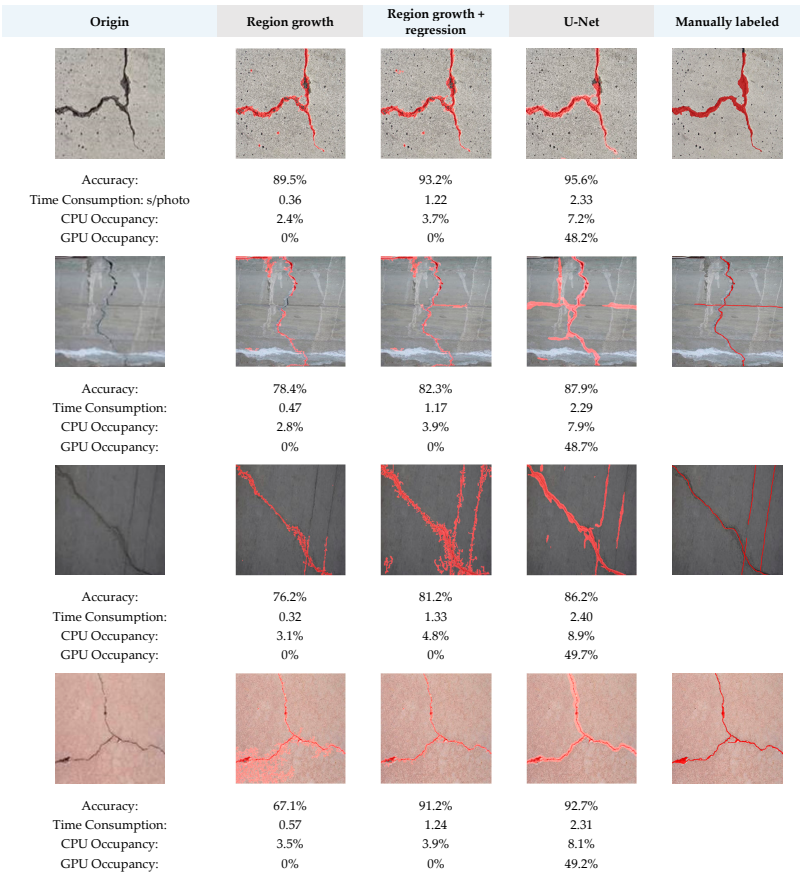


Figure 4. Display of test comparison results.

As we can see in Figure 5, the combination algorithm identifies smaller cracks in A2 compared to the region growing algorithm in A1, while the over-detection of cracks is avoided in B2, unlike B1. Our combination algorithm has a performance similar to U-Net's in A3 and B3 when detecting small cracks and interfering textures.

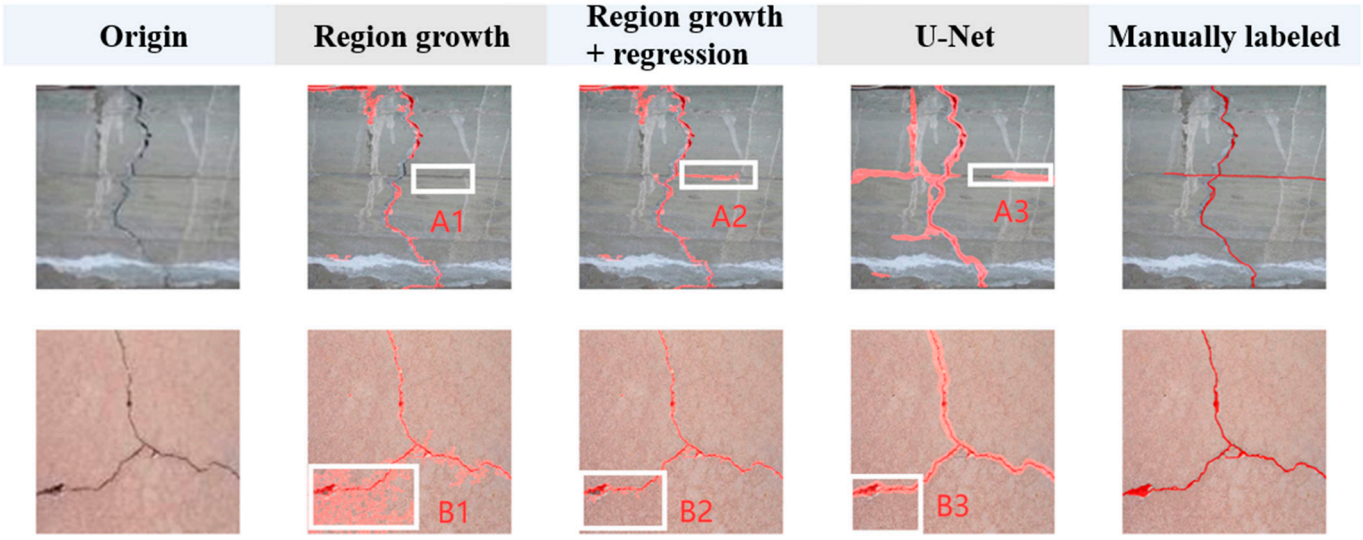


Figure 5. Display of test comparison results in detail. A2 and A3 show that our metod (Region growth + regression) and U-Net are better at detect narrow cracks compare with A1 with Region growth only. As well as B2 and B3 show that our methods and U-Net can avoid over detect some random texture as crack than B1's Region growth.

5. Discussion

From the experiment conducted in this study on the combined recognition of concrete structure cracks based on the region growth algorithm, several key learnings can be derived.

The experiment demonstrates the effectiveness of combining the region growth algorithm with machine learning regression for crack detection in concrete structures. The results show a significant improvement in accuracy compared to traditional methods. The experiment also highlights the tradeoff between accuracy and efficiency in crack detection. While the combined method may have a slightly lower accuracy compared to deep learning methods, it offers higher efficiency and lower resource consumption.

In addition, the experiment showcases the importance of image preprocessing techniques such as equalization, central pixel averaging, and median filtering in enhancing the quality of input images for crack detection. The experiment underscores the significance of regression analysis in learning image features and determining the region growth threshold for crack recognition, leading to improved accuracy in detecting cracks.

The experiment provides insights into the computational costs associated with the combined method, demonstrating that it offers a more resource-efficient solution compared to deep learning methods like U-Net. The experiment validates the applicability of the combined method in practical scenarios that require the efficient and accurate detection of concrete structure cracks, showcasing its potential for cost-saving benefits and reduced human error in maintenance processes.

6. Conclusions

Based on the region growing algorithm and a machine learning method, a combined method for crack detection in concrete structures is proposed in this paper. When dealing with complex images of water stains and dust, the method in this paper still has good recognition accuracy that is stronger than the traditional region growth algorithm. Compared with deep learning image recognition methods like U-Net, this method consumes fewer

computing resources and provides a good solution for the efficient and accurate detection of concrete structure cracks.

It should be emphasized that during the process of regional growth, in order to ensure the connectivity of detected cracks, the growth threshold is often increased, resulting in over-segmentation—that is, the detected crack picture is larger than the actual picture. Kong Deming and others proposed the use of the vector offset angle and distance measurement of each point of the grid to constrain the growth threshold [5], so as to avoid the phenomenon of over-segmentation. At the same time, it can also be prevented by improving image preprocessing, reducing noise interference, and passivating the split texture in the image. In addition, regression analysis is a relatively simple algorithm in machine learning, and fewer image features are used in this paper. In order to further improve the applicability of the growth threshold, more efficient and accurate machine learning methods and more image features should be used.

Author Contributions: Methodology, W.Y.; Software, W.Y.; Validation, W.Y. and H.L.; Formal analysis, Y.L.; Investigation, H.L.; Data curation, W.Y. and Y.L.; Writing—original draft, W.Y.; Writing—review & editing, H.L. and Y.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

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