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Research paper

Improved SOM algorithm for damage characterization based on visual sensing

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Abstract: In the field of concrete structure health monitoring, accurately and swiftly identifying damage characteristics stands as a pivotal task. To enhance the accuracy and efficiency of concrete damage identification, this research proposes an improved Self-Organizing Map algorithm based on visual sensing. By optimizing feature extraction and representation methods, introducing novel learning strategies, and incorporating spatial attention mechanisms, the model becomes adept at capturing and identifying concrete damage features more effectively. Additionally, employing stochastic gradient descent as an optimization algorithm enhances the model training efficiency. Experimental results showcase that the model exhibits a detection time of merely 0.8 seconds, while demonstrating outstanding fitting and clustering performance, achieving an actual accuracy of 98.2%. Compared to methods based on digital image monitoring and deep learning detection, it shows an improvement of 12.7% and 31.8%, respectively. The proposed enhanced model significantly augments the accuracy and efficiency of concrete damage identification, providing an effective solution for the health monitoring of concrete structures, particularly in scenarios requiring large-scale and real-time monitoring. This advancement elevates the practicality and convenience of concrete damage detection, propelling progress in the field of building safety.

Keywords: computer vision, damage detection, self-organizing map algorithm, attention mechanism

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1. Introduction

In engineering practice, concrete, as a widely utilized construction material, holds paramount importance in terms of safety and durability [1, 2]. With the increasing complexity of engineering structures and the harshness of operating environments, the development of concrete damage identification and detection technologies has become an urgent necessity [3]. However, in the current concrete damage identification, there is a lack of detection methods from the computer perspective, and the detection accuracy and efficiency need to be improved [4]. To address the issue of concrete damage identification and enhance its detection accuracy and efficiency, this study utilizes Deep Convolutional Neural Networks (DCNNs) combined with an attention mechanism for image preprocessing to extract crucial features related to concrete damage. Subsequently, a Self-Organizing Map (SOM) algorithm coupled with Support Vector Machines (SVMs) is employed for training, leveraging machine learning to enhance the precision of concrete damage identification. In terms of innovation, this research combines DCNNs with an attention mechanism, proposing a novel image preprocessing method. Concurrently, the integration of SOM with SVM constructs a novel model for concrete damage identification. This model can handle large-scale concrete image data while pinpointing minute damages within concrete structures. In terms of contributions and significance, the outcomes of this study are poised to enhance the safety and durability of concrete structures. Furthermore, they can offer scientific foundations for the design, construction, and maintenance of concrete structures, exerting a profound impact on the construction industry. Simultaneously, the methods and models developed in this study can be applied and extended to other domains, such as damage identification in metallic materials and monitoring soil erosion, promising extensive applications. In conclusion, this research aims to achieve efficient identification of concrete damage, offering new research insights and experimental methods for related fields. Moreover, it aspires to witness the widespread application of its findings, propelling technological advancements and societal development in relevant domains. The study is divided into four parts: a summary of computer vision and structural damage identification, implementation of the proposed methods, validation and testing of the methods, and a comprehensive conclusion of the research.

2. Related works

Computer vision is a discipline that encompasses both theory and technology, aiming to enable computers to "see" and understand their surroundings by mimicking the capabilities of human vision. It involves the comprehension and analysis of image and video data [5]. The primary objective is to empower computers to recognize and understand images or videos from the real world, extracting valuable information from them. The applications of computer vision are diverse and include image recognition, object detection, image segmentation, 3D model reconstruction, autonomous vehicles, medical image analysis, augmented reality, among others. Sheykhmousa et al. conducted a meta-analysis of the current state of research on remote sensing image classification. The study demonstrated the excellent performance of the random forest algorithm and SVM in remote sensing image recognition [6]. Zhu et al. addressed challenges in image label data recognition, proposing the use of a deep subdomain adaptation network. Experimental results indicated significant improvements in object recognition and digital classification tasks using this model [7]. Sun et al. tackled the difficulties in designing convolutional neural network structures for image classification tasks. They introduced a method that utilizes genetic algorithms for automatic structure design. The research validated the algorithm using widely adopted image classification benchmark datasets, showing its superiority in terms of classification accuracy, parameter count, and computational resource efficiency compared to existing methods [8].

In the field of engineering, damage identification is typically a part of structural health monitoring, used to assess the safety and reliability of structures such as buildings, bridges, aircraft, and roads. Damage identification technologies offer timely alerts to prevent structural failures and catastrophic accidents. Techniques for damage identification include visual detection, ultrasonic testing, electronic interference measurements, and infrared thermography. In recent years, with the development of computer science and artificial intelligence, the application of computer vision and machine learning technologies in the field of damage identification has become increasingly widespread. Aiming at the accurate rate of concrete damage detection, Yuan et al. proposed an intelligent inspection robot with deep stereoscopic vision based on the three-dimensional perspective, and the research proved that it could effectively identify and quantify damage [9]. Aiming at the problem of damage detection of bent concrete, Burud and Kishen proposed a wavelet entropy method using acoustic emission waveform, and proved that this method can effectively identify damage [10]. Zhang et al. proposed an improved deep network algorithm to improve the accuracy of concrete crack detection, and the research proved that the algorithm effectively improved the crack identification accuracy [11].

In summary, the current field of concrete damage identification still holds significant potential for development, with a need for further application of new technologies. Consequently, a concrete damage characteristic recognition model based on an improved SOM algorithm was proposed for research. Leveraging the power of deep learning and machine learning, this method not only enhances accuracy in identification but also strengthens the ability to handle complex data. Additionally, improving the effective handling of large-scale data and enhancing computational efficiency are crucial directions for future research. Anticipating the demonstration of greater potential in concrete damage identification and the emergence of broader applications, including in the recognition of damage in other materials and even in medical image analysis.

3. The construction of concrete damage characteristics recognition model

The study initially utilizes a DCNNs and attention mechanism to extract key features of concrete damage, aiming to preprocess concrete damage images. Subsequently, employing the SOM algorithm combined with the SVM model facilitates the model training, ultimately achieving recognition of concrete damage characteristics.

3.1. Preprocessing of concrete damage images

To enable computers to handle concrete damage issues, it is essential to abstractly address the concrete damage problem. Specifically, the concrete damage detection problem can be formalized as shown in Formula (3.1).

$$y = \delta\,(w * x + b) \tag{3.1}$$

In Formula (3.1), y represents the predicted matrix of damage detection probability. x signifies the probability. w represents the weight matrix with values to be determined, while b indicates the bias matrix. $*$ denotes convolution operation, and $\delta\,(\cdot)$ signifies the logical function. Within this, w and b can be represented as shown in Formula (3.2).

$$y = g_L\,(g_{L-1}\,(\cdots(g_l\,(x)))) = G\,(x;(w,b)) \tag{3.2}$$

In Formula (3.2), g_L represents non-linear modularized operations, L signifies the number of layers in non-linear modularized operations, and (w, b) denotes the corresponding parameters of the convolutional neural network. By introducing channel attention and spatial attention, Formula (3.2) can be rewritten as in Formula (3.3).

$$\begin{cases} y = g'_L\left(g'_{L-1}\left(\cdots\left(g'_l\,(x)\right)\right)\right) = G'\,(x;(w,b)) \\ g'_l\,(x) = g_l\,(\beta_l\,(\alpha_l\,(x))) \end{cases} \tag{3.3}$$

In Formula (3.3), α represents channel attention, while β signifies spatial attention. To more effectively process concrete damage images and extract critical damage features, the research introduces a novel preprocessing model architecture. DCNN is a robust model capable of processing complex image data and effectively extracting meaningful features [12]. In order to process concrete damage images more effectively and extract key damage features, a new preprocessing model architecture is introduced. The architecture uniquely integrates DCNNs and attention mechanisms, providing new possibilities for image preprocessing. In the pre-processing of concrete damage images, DCNN extracts multi-scale and multi-level features from original images through hierarchical convolution and nonlinear transformation [13]. These characteristics can better reflect the damage status of concrete and provide strong support for the subsequent identification task. At the same time, the introduction of attention mechanism further enhances the preprocessing ability of the model. The attention mechanism simulates human visual attention, so that the model pays more attention to the key parts of the image during image processing [14]. As shown in Figure 1, this is the schematic diagram of the proposed DCNN mixed attention mechanism image preprocessing.

To further enhance the detailed feature extraction capability of the architecture, a channel attention module is introduced into the basic convolutional module. By incorporating the channel attention module into the architecture, it becomes more adept at capturing microscopic changes in concrete damage images, extracting more representative features, thereby improving the architecture's effectiveness in handling concrete damage images. As depicted in Figure 2, this is the schematic diagram of the introduced effective channel attention module architecture.

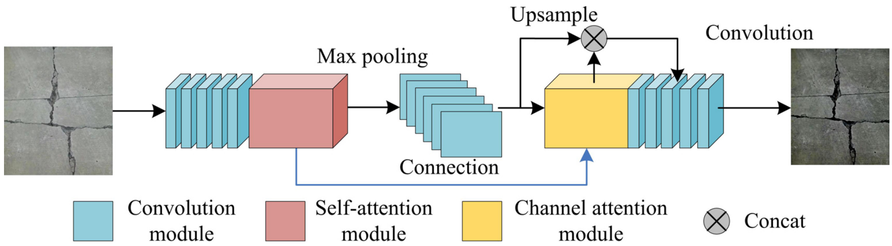


Fig. 1. Schematic diagram of image preprocessing architecture of DCNN hybrid attention mechanism

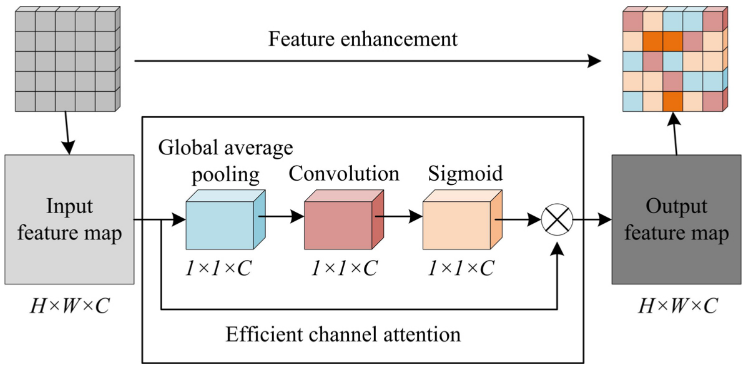


Fig. 2. Efficient channel attention module architecture diagram

The introduction of the channel attention mechanism module can to some extent strengthen the architecture's feature extraction capability for input images, thereby further enhancing the overall performance of the model, with the computation detailed in Formula (3.4).

$$\begin{cases} \alpha = \sigma_S \left(W_k * \left(P\left(y_{l-1}\right)\right) + b_y\right) \\ y_l = \alpha\left(y_{l-1}\right) \end{cases} \tag{3.4}$$

In Formula (3.4), σ_S represents the activation function, W_k represents the convolutional kernel, $*$ represents the convolution operation, P represents global average pooling, and b_y represents the bias term. The study further introduces a spatial attention module, which mainly includes convolutional layers, batch normalization layers, and activation function layers. The calculations of these three layers are detailed in Formula (3.5).

$$\begin{cases} q = \sigma_R \left(B\left(W_k * x_{l-1} + b_x\right) + B\left(W_k * y_{l-1} + b_y\right)\right) \\ \beta = \sigma_S \left(B\left(W_k * q + b_q\right)\right) \\ y_l = \beta\left(x_{l-1}, y_{l-1}\right) \end{cases} \tag{3.5}$$

In Formula (3.5), q represents the convolutional layer operation. β represents batch normalization operation. y_l represents the activation function layer operation. y_{l-1} represents the input feature map. x_{l-1} represents the encoder feature map. σ_R represents the ReLU activation function. b_q and b_xY represent the corresponding bias terms. In the actual computational process, the problem of vanishing or exploding gradients often occurs in deep learning networks, a phenomenon particularly common during the iterative training of deep learning models. To address this issue, the study adopts a strategy of incorporating the residual structure from MobileNetV2. MobileNetV2 is a lightweight deep learning network known for introducing residual and inverted residual structures to address information loss in deep networks. The introduction of the residual structure effectively resolves the vanishing gradient problem caused by small convolutional kernel dimensions, further enhancing the training stability and model performance of deep learning networks. As depicted in Figure 3, the schematic diagram illustrates the introduced residual structure.

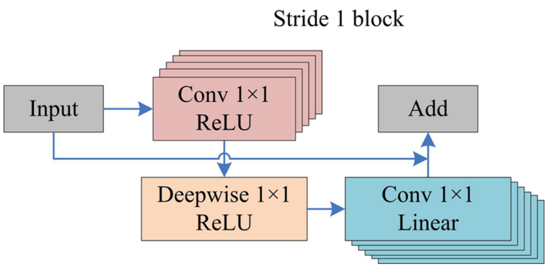


Fig. 3. Schematic representation of the residual structure

In this architecture, binary cross-entropy loss function is chosen as the loss function, specifically Formulated as shown in Formula (3.6).

$$L_{\text{loss}} = \frac{1}{N}\sum_i \left[P_i \cdot \log\left(y_i\right) + \left(1 - P_i\right) \cdot \log\left(1 - y_i\right)\right] \tag{3.6}$$

In Formula (3.6), N representational sample count, P_i represents the label value, and y_i represents the predicted image value. To improve the efficiency of model training and avoid falling into local optima, the study employs the stochastic gradient descent method as the optimization algorithm, as outlined in Formula (3.7).

$$\text{Gradient descent} = W_l + \lambda \frac{\partial L}{\partial W} \tag{3.7}$$

In Formula (3.7), W_l denotes the weights of the layer, and λ represents the initial learning rate. In traditional gradient descent, each iteration requires calculating the average gradient of all samples, which can be computationally inefficient when dealing with a large number of samples. On the other hand, stochastic gradient descent randomly selects a single sample to compute the gradient during each iteration, significantly improving computational speed.

3.2. Construction of SOM model for concrete damage characteristics identification

The SOM model is essentially an unsupervised learning neural network, distinguished from other neural networks by its lack of hidden layers. The input layer receives data, while the output layer is responsible for clustering and mapping the input data. Each neuron on the output layer has a fixed position during the training process, while the neuron's weights adjust continuously with training. The most notable feature of the SOM model is its ability to preserve the topological structure of input data on the output layer, making it widely applicable in areas such as clustering and visualization [15]. As shown in Figure 4, this is a schematic diagram of the SOM model structure.

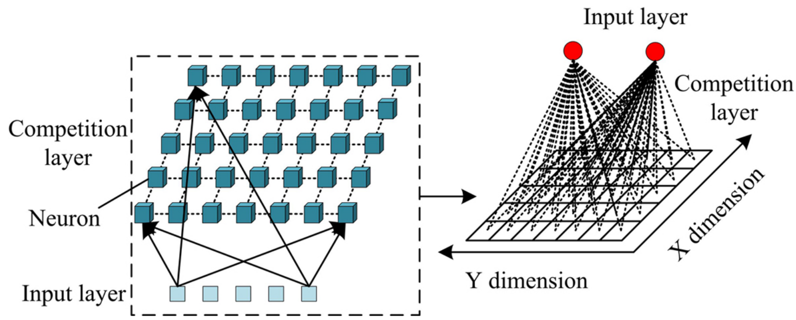


Fig. 4. Structure diagram of SOM model

The learning process of the SOM model mainly consists of two stages: competitive learning and cooperative learning. In the competitive learning stage, each neuron compares itself with the input vector, and the winner is the neuron with the closest distance to the input vector. In the cooperative learning stage, the weights of the winning neuron and its neighboring neurons are adjusted to be closer to the input vector [16]. When using SVM for model training, the optimal classification hyperplane is first determined based on known training data, and then this hyperplane is used for classifying and predicting new data. The training data may be features extracted by the SOM model, raw data, or other processed data. By utilizing SVM, the model's predictive ability is enhanced while retaining the topological characteristics of the SOM model. This allows the model to more accurately identify characteristics of concrete damage, thereby improving the efficiency and accuracy of concrete damage identification, as depicted in Figure 5, which illustrates the training process using SVM.

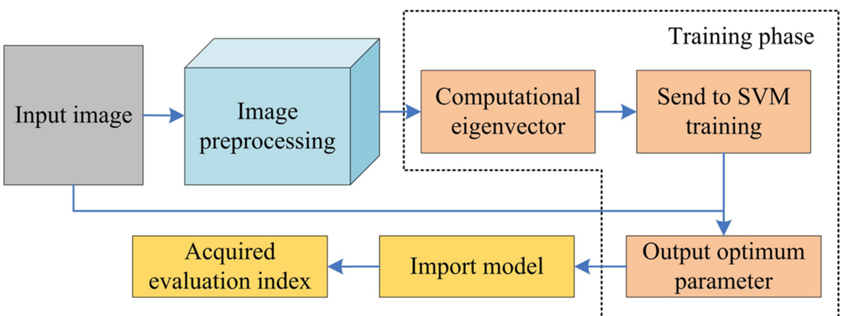


Fig. 5. Schematic diagram of SVM training model process

In practical usage, the process involves sending a request from a lower-level machine to the server, prompting it to input the images to be detected into the model. After completing the detection, the results are sent back to the server, which responds to the lower-level machine, completing the concrete crack detection process. The detailed flowchart for this process is illustrated in Figure 6.

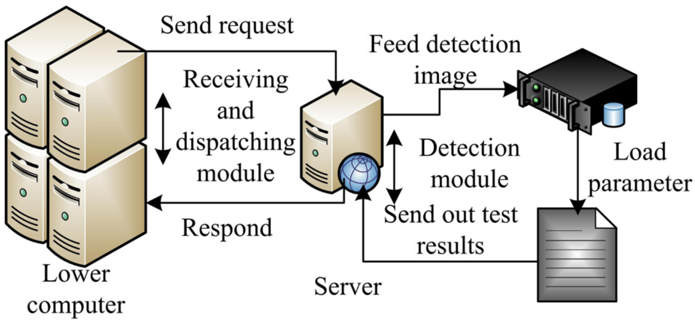


Fig. 6. Schematic diagram of concrete crack detection process

As shown in Figure 6, the framework flowchart of the concrete crack detection model is presented. Upon receiving the server's response, the lower-level machine can display the crack detection results to the user or proceed with further processing. For instance, it may mark the crack locations on the original image or record crack information in a database for subsequent analysis and processing. Through this process, automated detection of concrete cracks is achieved, improving detection efficiency and accuracy while also reducing the workload and error rate associated with manual detection.

4. Verification and testing of concrete damage characteristics identification model

4.1. Test environment

The study conducted validation and testing of a concrete damage identification model. The research utilized the Concrete Crack Images for Classification (CCIC) dataset, a collaborative effort between the National Research Council of Canada and the University of Winnipeg. This dataset, designed for concrete crack detection and classification tasks, consists of a substantial number of concrete surface crack images. The CCIC dataset comprises 20,000 images with cracks and 20,000 images without cracks, all with a resolution of 227×227 pixels. To construct the training and testing sets, 80% of the images were randomly allocated for training, while the remaining 20% constituted the test set. To mitigate performance limitations during testing, the study opted for a cloud server platform. The specific hardware and software configurations, along with experimental parameter settings, are detailed in Table 1. The study further evaluated the performance of three models: the Canny method based on digital image processing, a deep learning (DL) approach, and the proposed Improved Self-Organizing Map (IM-SOM) model. Canny algorithm is mainly suitable for identifying the clear outline of cracks, which has a certain resistance to noise and can effectively detect small and intermittent crack lines, but it is limited for complex or low-contrast crack detection [17]. Deep learning methods can process and identify cracks of various sizes, shapes and orientations, and adapt to different lighting and background conditions, but their detection effect depends greatly on the training effect [18].

Table 1. Details of hardware and software configuration and experimental parameter settings

<table>
<tr><th colspan="2">Hardware</th><th colspan="4">Software</th></tr>
<tr><th>Name</th><th>Detail</th><th>Name</th><th>Detail</th><th colspan="2">Version</th></tr>
<tr><td>Supplier</td><td>Amazon Web Services</td><td>Operating system</td><td>Ubuntu Server</td><td colspan="2">20.04 LTS</td></tr>
<tr><td>Server model</td><td>Amazon Elastic Compute Cloud (EC2)</td><td>Deep learning framework</td><td>TensorFlow</td><td colspan="2">2.7.0</td></tr>
<tr><td>Instance type</td><td>p3.2× large</td><td>Python environment</td><td>Python</td><td colspan="2">3.8.10</td></tr>
<tr><td>CPU</td><td>Intel Xeon E5-2686 v4 (Broadwell)</td><td rowspan="4">Python libraries and tools</td><td>NumPy</td><td colspan="2">1.21.2</td></tr>
<tr><td>RAM</td><td>61Gb</td><td>Pandas</td><td colspan="2">1.3.3</td></tr>
<tr><td>MEM</td><td>EBS</td><td>Scikit-learn</td><td colspan="2">1.0</td></tr>
<tr><td>GPU</td><td>NVIDIA Tesla V100</td><td>OpenCV</td><td colspan="2">4.5.3</td></tr>
<tr><td>Network performance</td><td>High</td><td>Server software</td><td>Gunicorn</td><td colspan="2">20.1.0</td></tr>
<tr><th colspan="6">Parameter setting</th></tr>
<tr><th>Name</th><th>Detail</th><th>Name</th><th>Detail</th><th>Name</th><th>Detail</th></tr>
<tr><td>Input layer size</td><td>227 × 227 × 3</td><td>Optimizer</td><td>Stochastic gradient descent, SGD</td><td>Kernel parameter</td><td>1/3</td></tr>
<tr><td>Learning rate</td><td>0.001</td><td>Loss function</td><td>Cross-entropy loss</td><td>SGD learning rate</td><td>0.01</td></tr>
<tr><td>Lot size</td><td>32</td><td>Kernel function</td><td>Radial basis function</td><td>SGD momentum</td><td>0.9</td></tr>
<tr><td>Epoch</td><td>100</td><td>Penalty parameter</td><td>1.0</td><td>SGD weight decay</td><td>0.0005</td></tr>
</table>

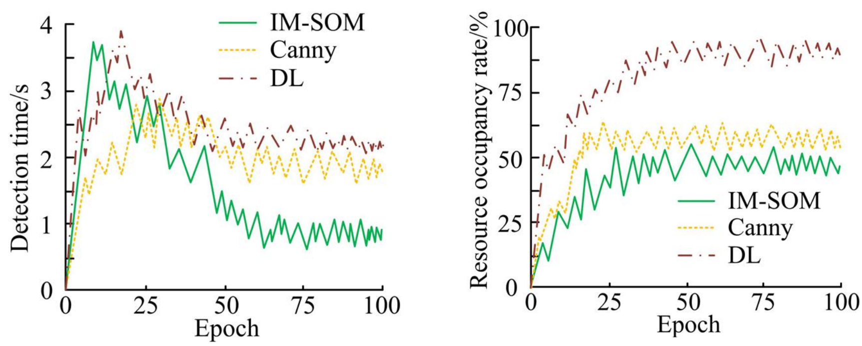
4.2. Basic performance index test

Comprehensive performance metrics for the three models were tested, with all models trained on the same dataset until optimal states were achieved. To minimize errors' impact on performance testing, each model underwent three rounds of testing. In Table 2, MAE represents the average absolute error; MSE stands for mean square error; R^2 is the coefficient of determination; NRMSE stands for normalized root mean square error; MAPE represents the mean absolute percentage error. The results are presented in Table 2, indicating that the proposed method outperformed the other two models across all performance metrics.

Table 2. Multiple performance test results for three models

	IM-SOM			**Canny**			**DL**		
	1	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
MAE	1723.457	1764.124	1822.342	1823.783	1923.435	1912.589	1997.563	2031.384	2197.589
MRMSE	2384.941	2475.329	2510.374	2867.562	2943.832	2941.925	2998.768	3074.269	3017.591
R^2	0.9548	0.9653	0.9631	0.8156	0.8293	0.8940	0.6241	0.6734	0.6987
NRMSE	17.677	18.236	18.697	15.824	16.284	16.905	14.256	14.349	15.029
MAPE	13.789	13.642	14.562	12.189	12.275	12.903	11.219	10.121	11.648

The study also conducted tests on the damage detection speed and relative resource utilization of the three models, as illustrated in Figure 7. From Figure 7(a), it is evident that IM-SOM exhibited superior detection speed, with the best detection time recorded at 0.8 seconds. Figure 7(b) demonstrates that IM-SOM showcased the best resource utilization, reducing resource consumption by 11.2% and 47.6% compared to Canny and DL, respectively.



(a) Detecting time (b) Resource occupancy

Fig. 7. The detection speed and resource occupancy test results of the three models

Testing was conducted on the fitting degree of damage detection for three models to assess their practicality and usability. The test results are shown in Figure 8. The damage grade is used to assess the severity of the crack, and the development trend is used to assess the future safety of the crack. Figure 8(a) represents the test for the fitting degree of damage prediction by the models, indicating that the proposed method from the research institute has the highest matching degree with real-world scenarios. As shown in Figure 8(b), the test for its ability to predict damage development reveals that the proposed method possesses the optimal fitting degree.

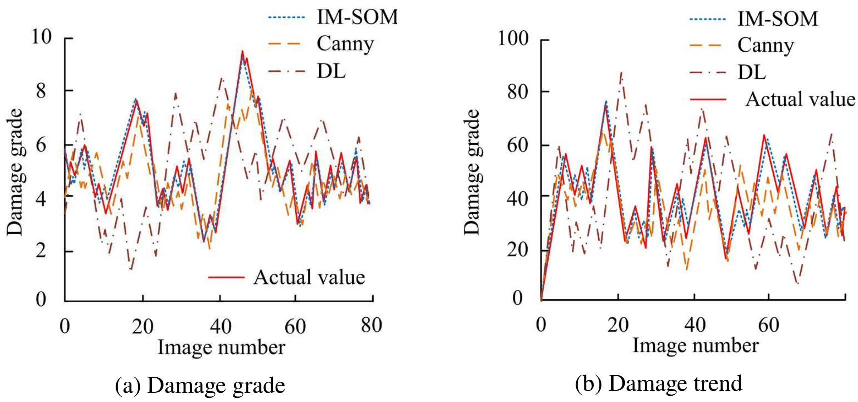


Fig. 8. Damage detection fitting test of three models

The clustering effects of the three models were tested, and the results are depicted in Figure 9. The different symbols in Figure 9 indicate different types of concrete cracks. From Figure 9, it is evident that the method proposed by the research institute exhibits the best clustering effect for predicting concrete cracks, allowing more precise detection of concrete damage.

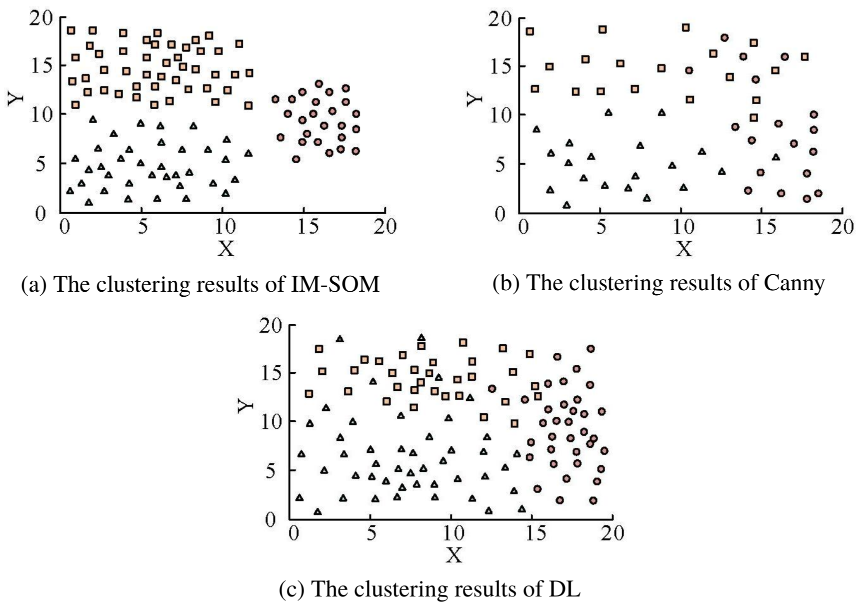


Fig. 9. The clustering effect test of three models

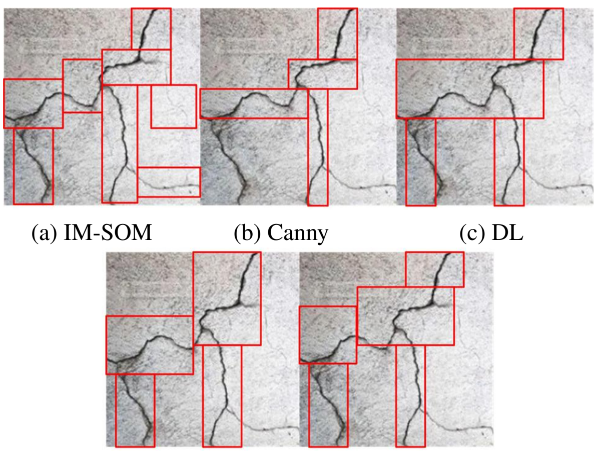
4.3. Practical application test

The practical image prediction capabilities of the three models were tested, and the results are presented in Table 3. The actual/predicted quantity mainly refers to the actual crack rating and the predicted crack rating. From Table 3, it can be observed that the IM-SOM proposed by the research institute has the best detection accuracy, achieving an actual accuracy of 98.2%, a 12.7% improvement over Canny, and a 31.8% improvement over DL.

Table 3. Actual damage detection results of three models

Graphic	Concrete damage type	Actual quantity	Predicted quantity		
			IM-SOM	Canny	DL
1	Crack	2	2	1	1
	Honeycomb	4	4	3	2
	Hole	1	1	0	1
2	Crack	1	1	0	2
	Honeycomb	0	1	1	1
	Hole	3	3	2	3
3	Crack	0	0	1	0
	Honeycomb	2	2	1	2
	Hole	1	1	1	1

Furthermore, YOVO algorithm [19] and U-Net crack detection method [20] are introduced, and a concrete crack image is selected to detect it, so as to evaluate the practical application effect of the research algorithm. The test results are shown in Figure 10. As can be seen from Figure 10, the proposed method has the best concrete crack detection effect, which can not only detect large obvious cracks, but also realize the accurate detection of minor cracks.



(a) IM-SOM (b) Canny (c) DL

(d) YOLO (e) U-Net

Fig. 10. Test of concrete crack detection effect of five models

In conclusion, the proposed IM-SOM is more effective in detecting concrete damage. Through improvements and optimizations to the SOM algorithm, Im-SOM demonstrates high performance in accuracy, efficiency, and practicality in concrete damage detection. Experimental results also indicate its potential application in the field of concrete damage detection.

5. Conclusions

In the field of health monitoring for concrete structures, accurate identification of damage characteristics is crucial. To enhance the accuracy and efficiency of existing methods in concrete damage identification, the research proposes an improved SOM algorithm based on visual sensing. Experimental results demonstrate the excellent performance of this method in concrete damage identification. Specifically, the optimal detection time is 0.8 seconds, with the best resource utilization performance, reducing resource usage by 11.2% and 47.6% compared to Canny and DL, respectively. The model shows excellent fitting degree and clustering effects. The actual accuracy reaches 98.2%, a 12.7% improvement over Canny and a 31.8% improvement over DL. The research not only enhances the accuracy of concrete damage identification but also improves detection efficiency. This is of significant practical value for the health monitoring of concrete structures, especially in large-scale and real-time monitoring scenarios. However, the research model mainly focuses on identifying concrete damage characteristics such as cracks, leaving room for further study on other types of damage characteristics, such as spalling. Future research should strive to improve the model's recognition of various concrete damage features while further optimizing its performance and accuracy.

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