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Research Article

Crack Detection of Concrete Surfaces with A Combination of Feature Extraction and Image-Based Backpropagation Artificial Neural Networks

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Abstract

Concrete surface imperfections can signify a structure undergoing severe degradation. It deteriorates when concrete is exposed to elemental reactions such as fire, chemicals, physical damage, and calcium leaching. Due to its structural degradation, concrete deterioration poses a risk to the surrounding environment. Structural buildings can collapse due to severe concrete decline. To prevent concrete cracks early, it is imperative to identify the concrete surface. This requires the development of a technique for detecting the image-based concrete surface. One way to detect concrete surfaces is to create artificial neural networks. The purpose of this study is to combine feature extraction and artificial neural networks to detect cracks in concrete surfaces. The data used is concrete surface image data divided into two classes, namely cracked class and uncracked class. The total data is 600 data points, 300 data points, and 300 data points. The technique used is feature extraction from GLCM and Backpropagation Artificial Neural Network. Test results using epoch five show 95% accuracy, epoch 10 shows 95% results, epoch 100 shows 83% accuracy, and epoch 250 shows 73% results. The test results that have been carried out show a decrease in lower accuracy results when the epoch is determined to be higher. The results of this study epoch that shows the highest accuracy results are epoch 5 with 95% accuracy and epoch 10 with 95% accuracy.

Keywords: Artificial Neural Network; Backpropagation; Concrete Crack Detection; Disaster; Feature Extraction.

Introduction

The automatic detection of image-based concrete surface issues, such as cracks, is crucial to a vision-based structural health monitoring system and civil infrastructure status evaluation. Concrete surface imperfections can signify a structure undergoing severe degradation [1]–[5]. It deteriorates when concrete is exposed to elemental reactions such as fire, chemicals, physical damage, and calcium leaching. Due to its structural degradation, concrete deterioration poses a risk to the surrounding environment. Structural buildings can collapse due to severe concrete decline [6]. Many approaches to measuring concrete degradation require considering concrete pH, solution concentration, physical conditions, and temperature charge level, among other characteristics [7]. In terms of constructing bridges, buildings, stadiums, dams, and other structures of economic and social significance, concrete is an essential material in the civil construction industry [8], [9]. As with different materials, concrete can undergo physical changes due to various circumstances, including increased structural strength, water-related wear, corrosion of internal metal structures, and others [10], [11]. One of the most visible signs of a concrete structure failing due to these causes is the appearance of cracks, usually visible from the structure's surface. Finding these cracks is, therefore, an essential part of maintaining concrete structures preventively [12], [13]. To prevent concrete cracks early, it is necessary to detect the concrete surface. A method that can detect the concrete surface based on images needs to be developed. One way to detect concrete surfaces is to create artificial neural networks.

Research on the same topic [14] used machine learning to classify cracks and non-cracks on concrete surfaces. The method proposed in this study helps determine the presence and location of cracks from images of concrete surfaces. The proposed approach is designed to classify cracked and uncracked patterns on concrete surfaces. This research produced a system that can automatically classify concrete cracks. Research [15] used artificial intelligence

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to detect and assess cracks in concrete based on visual inspection images. One thousand nine hundred photos of non-damaged and cracked concrete surfaces were used to train the artificial intelligence system. For system testing and validation, an additional 1100 photos were employed.

Regarding distinguishing between cracked pictures and those that weren't, protocol testing revealed that the AI model was 99.6% accurate. Developing a comprehensive AI system to assist with the inspection and upkeep of RC structures is promising in light of these results. In [16], this research classifies cracks in concrete based on transformers; this research applies Deep Learning, feature extraction, and other methods. Existing artificial neural networks could be more efficient and computationally expensive for concrete crack identification. As a result, Cross Swin transformer-skip (CSW-S) is a new idea to categorize cracks in concrete.

Based on the experimental results, the enhanced CSW-S network can recognize cracks more accurately because it has a broader range of image data. Without pre-training, the trained CSW-S has a detection accuracy of 96.92%. Compared to the Convolutional Neural Network (CNN) model and transformer model, the enhanced model shows better recognition accuracy and efficiency. Research [17] used a CNN to detect cracks on concrete surfaces automatically; the suggested approach uses pixel-level information to predict and identify photos showing cracks on concrete surfaces and images that do not. With the proposed CNN model, the final accuracy generated was 97.8%. In [18], this research uses a CNN to detect defects and cracks in concrete by implementing an integrated module; there are 3650 different types of concrete defects in the image dataset used, including concrete without cracks, delamination, spalling, and surface cracks. This research aims to build an automated image-based concrete condition detection technique to classify multivariate defects, including surface cracking, delamination, and spalling, and categorize non-defective concrete as defective. The trained model has an accuracy of 98.8% in detecting defects. Research [19] used artificial neural networks and Clustering to detect and analyze cracks in concrete structures. This research aims to study and develop an automatic concrete detection system based on artificial neural networks that can recognize cracks and utilize this knowledge to determine the proportion of cracks. Experimental results show that the trained model has a classification accuracy of 99.9% for concrete cracks. Research [20] uses an IoT-Based Intelligent System to detect cracks inside a building; this research proposes a tool to detect cracks in a building and display the results on an LCD [21]. This study compares R-CNN and Mask R-CNN to detect cracks in concrete. The results show that the joint training strategy is very effective, and it is confirmed that Faster R-CNN and Mask R-CNN can detect cracks when trained with 130+ images and outperform YOLOv3.

Based on the research that has been done, researchers use various methods to classify cracks in concrete and get different results. Some previous studies used machine learning methods, such as CNN [22], image processing, feature extraction in images, artificial neural networks, computer vision, and others. Based on previous research, no research combines feature extraction and artificial neural networks on concrete surface cracks. This research aims to combine feature extraction from Gray Level Co-occurrence Matrix (GLCM) and Artificial Neural Networks to detect concrete surface cracks; the data is taken from the dataset-sharing website Kaggle.com. The feature extraction method used in this research is the GLCM; GLCM is a feature extraction method that can provide good extraction [23], [24]. The classification method used is Artificial Neural Network, Artificial Neural Network can provide good detection results [16], [25], [26] of concrete surface cracks.

Method

A. Literature Study

A literature study is a step in the research process to locate pertinent references related to the studied issues, such as artificial neural networks, feature extraction, and detection. A literature review covering scientific journals published between 2018 and 2024 was conducted.

B. Data used

The data used in the research is data sourced from a free data-sharing website, kaggle.com. The data used is in the form of image data from the concrete surface, which is divided into two classes, namely, cracked class and non-cracked class [1], [17], [27]. The total data used is 600, with 300 cracked and 300 non-cracked data details. The data used in more detail can be seen in **Table 1**. Before the data is trained and tested, the image data is cropped from the original size of 1280×800 pixels to 227×227 pixels. Cropping is done to make computing more accessible. The data used as training data is 80% of the total data of both cracked and uncracked images, while the data used as testing data is 20% of the total data of both cracked and uncracked images. **Figure 1** is an example of a cracked and uncracked concrete surface image.

Table 1. Research Data

No	***The data used***	***Format***	***Amount of data***
1	Crack	JPG	300
2	Non-Crack	JPG	300

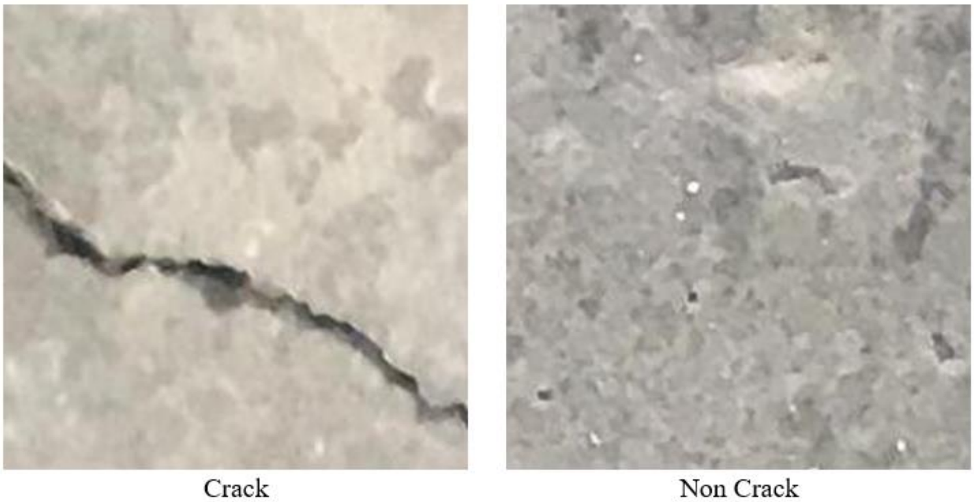

Figure 1. Example of a drawing of the concrete surface used

C. Image Feature Extraction Implementation

The feature extraction technique employed is the GLCM, which yields high-quality picture extraction results [26], [28]. In this study, the features used are contrast, correlation, energy, and homogeneity [29]. **Figure 2** shows the direction of the rotation of the computation in GLCM [23]. Grayscale conversion is performed on the RGB image before the classification stage is executed. **Figure 3** shows an example of how to convert an RGB image to a grayscale.

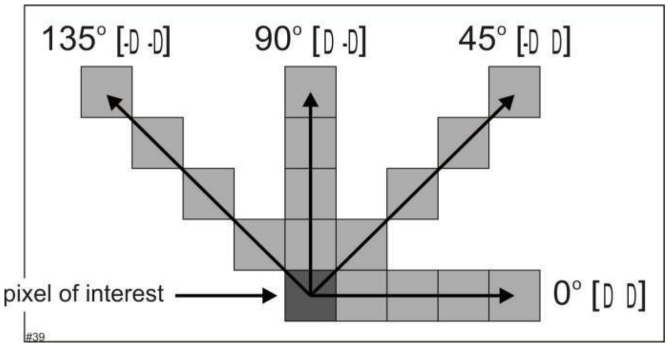

Figure 2. GLCM calculation

Figure 3. RGB to Grayscale Image

The GLCM feature extraction formula used is as follows [26]:

$$\text{Correlation} \quad \sum_{i}^{k} = 1 \sum_{j}^{k} = 1 \ \frac{(i - m_r)\,(j - m_c)\,p_{ij}}{\vartheta_r\,\delta_c} \tag{1}$$

$$\text{Contrast} \quad \sum_{i}^{k} = 1 \sum_{j}^{k} = 1 \ (i - j)^2\,P_{ij} \tag{2}$$

$$\text{Homogeneity} \quad \sum_{i}^{k} = 1 \sum_{j}^{k} = 1 \ P_{ij}^2 \tag{3}$$

$$\text{Energy} \quad \sum_{i}^{k} = 1 \sum_{j}^{k} = 1 \ \frac{P_{ij}}{1 + [i - j]} \tag{3}$$

D. Backpropagation Artificial Neural Network

An artificial neural network is the detection technique employed in the study; numerous studies report that this technique can effectively and highly accurately recognize objects in photos [26]. This study used a backpropagation artificial condition network with two hidden layers, one output, and several layers. GLCM was initially used in this investigation to extract the 600 total images that needed to be classed. The stages that will be carried out in this study are the training and testing stages; at the training stage, the epochs used are epoch 5, epoch 10, epoch 50, epoch 100, and epoch 250. The neurons used are 100, and the learning rate is 0.1.

Results and Discussion

A. Process Training

In the training stage, the data used is 240 images, or 80% of the total data; the data used has an image size of 227×227 pixels. The epochs used are epoch 5, epoch 10, epoch 100, and epoch 250 until maximum results are reached. In this training process, we use 100 neurons and a learning rate of 0.1 in each training process. The activation function in the hidden layer uses a binary sigmoid; in the output layer, the activation function is linear. From the results of training conducted using epoch 5, with a learning rate of 0.1, the accuracy obtained is 96.8%. From the results of epoch 5, the number of correct data is 465, and the number of incorrect ones is 15. The training results were conducted using epoch 10, with a learning rate of 0.1, and the accuracy obtained was 98.3%. From the results of epoch 10, the number of correct data is 472, and the number of wrong ones is 8. The training results were conducted using epoch 100, with a learning rate of 0.1, and the accuracy result obtained was 98.5%. From the results of this 100 epoch, the number of correct data is 473, and the number of wrong ones is 7. The training results were conducted using epoch 250, with a learning rate of 0.1, and the accuracy result obtained was 98.9%. From the results of this 250 epoch, the number of correct data is 475, and the number of incorrect 5 for the overall training results can be seen in **Table 2**.

Table 2. Overall training results

No	Epoch	Iteration	Time elapsed	Number of incorrect data	Accuracy
1	5	5	00.00.00	15	96.8%
2	10	10	00.00.00	8	98.3%
3	100	100	00.00.01	7	98.5%
4	250	250	00.00.03	5	98.9%

B. Testing and Evaluation of Results

In the testing stage, the image used is 20% of the total data, namely 120 images; the epochs used are epoch 5, epoch 10, epoch 100, and epoch 250. While the learning rate used is 0.1 and 100 neurons. The test results were conducted using epoch 5; the accuracy results obtained are 95%; using epoch 10 gets an accuracy result of 95%, and using epoch 100 gets an accuracy result of 83%, while using epoch 250 gets an accuracy result of 73%. In this study, the higher the epoch used when testing, the lower the results' accuracy. The overall testing results can be seen in **Table 3**.

Table 3. Overall classification results

No	Epoch	Classification result
1	5	95%
2	10	95%
3	100	83%
4	250	73%

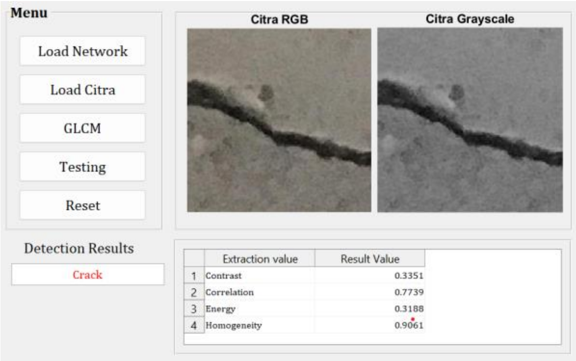

Figure 4. Classification results that were successfully detected

Figure 4 is one of the results of image-based classification of concrete surfaces. In this study, we tested 240 image data individually and then noted whether the system could detect it. **Figure 4** is an example of the classification results successfully detected by the system.

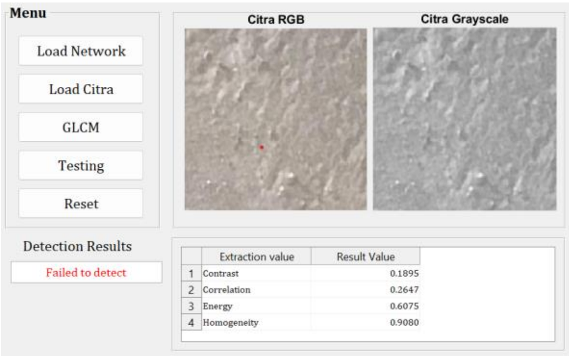

Figure 5. Example of a classification result that could not be detected

Figure 5 is an example of a classification result that failed. Upon closer inspection, we discovered that the primary reason for the detection failure was the unclear nature of the image used. The extraction results displayed a negative number at the extraction time. In the future, the image utilized should be pre-processed using specific techniques to eliminate noise, clean the image, and enable the system to execute extraction and detection correctly before the classification stage is completed.

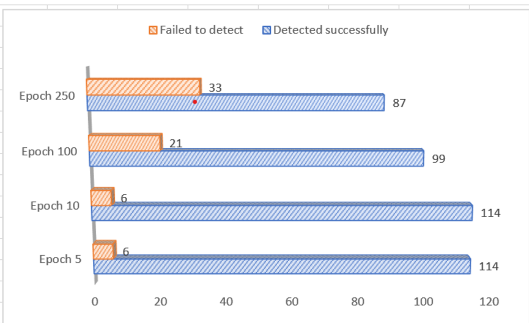

Figure 6. Successful and unclassified concrete surface images

Figure 6 is a graph showing the images that were successfully classified and those that failed to be classified. Using epoch 5, the image successfully detected was 114, and the image that failed detection was 6, while for epoch

10, the image successfully detected was 114. The image that failed detection was 6. For using epoch 100, the image that was successfully detected was 99, and the image that failed detection was 21, while using epoch 250, the image that was successfully detected was 87, and the image that failed detection was 33.

C. Discussion

In this study, by using epochs 5, 10, 100, and 250, with a learning rate of 0.1, we managed to get the highest accuracy results at epochs 5 and 10 with an accuracy value of 95% each. We have experimented by adding more significant epochs at 400, 500, 1000, and even 2000 epochs and different learning rates, but we need higher accuracy results. In this study, the accuracy results obtained were up to 99% when we did the training process. Since the experimental results show that more significant epochs show lower accuracy results, we did not include them in the detection results table. This research only samples epochs that produce high accuracy values. In this study, we experimented by adding higher epochs, but the accuracy results during testing became lower because the neurons used were the same.

In addition, **Table 4** shows other research that discusses the same topic, namely concrete surface damage detection, as a comparison result.

Table 4. Comparison of the proposed concrete surface detection method with concrete surface detection using different techniques.

No	Comparison Table With Other Studies	
	Method	***Accuracy %***
1	Convolutional Neural Network dengan arsitektur VGG [1]	94%
2	Convolutional Neural Network and Artificial Neural Neural [7]	CNN: 80.7% ANN: 98.1%
3	Random forest [12]	94%
4	Neural Network and Exhaustive Search Technique [13]	99.06%
5	Deep Learning, CNN [10]	96.5%
6	CSW-S network [16]	96.92%
7	Machine Learning [14]	Classification model A Precision: 0.51 Recall: 0.49 F1 score: 0.50 Accuracy: 0.84 Classification model B Precision: 0.24 Recall: 1.00 F1 score: 0.38 Accuracy: 0.47 Classification model C Precision: 0.94 Recall: 0.96 F1 score: 0.95 Accuracy: 0.98
8	Artificial Intelligence [15]	99.6%
9	Convolutional Neural Network [17]	97.8%
10	Convolutional Neural Network + Integrated Pooling Module [18]	98.8%
11	Image processing + deep learning [27]	95.19%
12	Neural Network + Clustering [19]	99.9%
13	Deep Learning [30]	Grayscale models: F1 score for 10 epochs: 99.331%, 20 epochs: 99.549% RGB models : F1 score for 10 epochs: 99.432%, 20 epochs: 99.533%
14	Deep Learning-Based Multiresolution Analysis + CNN [31]	90%

15	Our method (Feature Extraction GLCM + Backpropagation Artificial Neural Networks)	Epoch : 5 : 95% 10 : 95% 100 : 83% 250 : 73%

Conclusion

This study employs a backpropagation artificial neural network and the feature extraction method of GLCM to identify surface cracks in concrete; the data used is image data of cracks rather than surface data. The stages in this study are training and testing; for the training stage, the epochs used are epoch 5, epoch 10, epoch 100, and epoch 250. The learning rate used during training is 0.1. The training results indicate that the accuracy for epochs 5 through 250 is 90%, epochs 10 through 250 are 90%, epochs 100 through 250 are 90%, and so on. Test results using epoch five show 95% accuracy, epoch 10 shows 95% results, epoch 100 shows 83% accuracy, and epoch 250 shows 73% results. The test results that have been carried out show a decrease in lower accuracy results when the epoch is determined to be higher. The results of this study epochs that show the highest accuracy are epoch five and epoch 10, with 95% and 95% accuracy.

Suggestions that can be made in the future are to use different feature extractions and more datasets. The dataset should be pre-processed first to reduce noise in the image used.

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