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IMPROVEMENT OF ROAD CRACK DETECTION PROCESSES BASED ON IMAGE PROCESSING TECHNOLOGIES IN KOREA

Yunjung Shin and Dongsoo Kim*

Department of Industrial and Information Systems Engineering
Soongsil University
369 Sangdo-Ro, Dongjak-Gu, Seoul 06978, Korea
tlsdbswnd@soongsil.ac.kr; *Corresponding author: dskim@ssu.ac.kr

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Abstract. *This paper presents a framework for detecting road cracks using image processing techniques. Currently, the road crack detection process in Korea is manual and labor-intensive. A special vehicle equipped with a dedicated camera acquires road image data. Workers then manually examine the image data to identify road cracks and classify the crack types. We propose an automated framework for analyzing image data in order to minimize costs and errors due to the manual process. This research explores the applicability of existing methodologies in the aforementioned domestic environments. When the methodology was applied to Korea, limitations caused by environmental differences have been identified. In this regard, we propose an improved and extended framework to complement them. The proposed framework contributes to minimizing time, cost and errors by replacing the manual process.*
Keywords: Road crack detection, Image processing, Automated detection, Process improvement

1. **Introduction.** Cracks on the road can be caused by natural factors such as seasonal temperature differences and by accidental factors such as traffic accidents. If cracks occur, the cracks rapidly deteriorate over time so they must be identified and repaired quickly. The cracks on the road can directly touch the tire, which can adversely affect the ride quality and can even cause serious accidents.

Currently, a vehicle equipped with a special camera is used to collect road images in Korea. Many workers inspect the collected image data by eyes to detect cracks and classify their type and severity. That is, the current system requires a lot of manpower, because cracks in the image are identified manually. Therefore, this study aims to improve the existing road image analysis process. The proposed framework enables the system to automatically check and identify cracks, in the domestic environments by applying image processing technologies.

The improved and automated system can reduce labor and work time by replacing the manual process. In addition, human errors can be reduced. If we can get the results of the system used to maintain the road conditions quickly and accurately, it can be the basis for building a near-road repair system in real time.

The rest of the paper is organized as follows. Section 2 describes previous studies on crack detection. Section 3 explains the process of the current crack detection system in Korea and discusses the problems of applying the existing method. Section 4 presents the proposed framework for solving the problems and describes the results of prototype implementation. Finally, Section 5 offers conclusions and describes future work.

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2. **Related Work.** This section discusses previous studies on road crack detection using image processing. We consider various methods for crack detection and introduce an automation system to the process of domestic manual crack detection system through the following previous studies. Crack detection analyzes the intensity of the pixels contained in the image. Crack pixels are characterized by low intensity because they are darker than non-crack pixels. Therefore, the location of the crack pixels included in the classified crack images is identified and the crack types are classified again according to their types.

Chambon et al. used multiscale detection based on Markov Random Field for segment of 2D cracks [1]. On the other hand, Zalama et al. applied the Gabor Filter technique to extracting the features of longitudinal and transverse cracks, then trained the classification model, and applied the AdaBoost algorithm to improving the performance of the classifier [2]. They classified various types of cracks using filters.

Oliveira and Correia applied a block-based method of dividing an image into grid-like blocks and performed a preliminary labeling binary matrix (plb) step of giving crack or non-crack preliminary information using pixel intensities included in each block [3,4]. By introducing this step, cracks and non-cracks became more discriminative. And, Gavilán et al. separately set up features to identify non-cracks [5]. As a result, they reduced the false-positive rate and increased the precision of crack identification.

Zhang et al. performed crack detection based on deep convolutional neural networks (CNN) [6]. To effectively learn CNN with a small number of image data, they rotated and replicated crack patches of images. Images were collected with low-cost equipment such as smart phones, reducing the cost of data collection.

In this paper, the images collected for crack detection are used as it is. However, the images contain many obstacles such as afterimages, manhole covers, and white lanes, unlike images used in previous studies. Because of these obstacles, the performance when applying existing toolboxes has been reduced significantly. Therefore, we propose additional processes in order to achieve performance improvements in the domestic environments. The additional processes deal with the obstacles, by eliminating the causes of those obstacles. Specifically, the toolbox utilizes low average and high deviation of crack pixels as features. Therefore, obstacles that are not cracks but may be classified as cracks can be removed in advance.

3. **Current System and Problems.** This section explores the possibility of applying existing automation methodologies and toolboxes to the Korean manual crack detection system [4]. In the toolbox, the crack classification model is trained as preprocessed data, and the type and severity of each crack are categorized by analysis of the detected cracks. However, when the toolbox is applied to the Korean image data directly, the performance has dropped significantly. Therefore, we identify the causes of the problems.

3.1. **Current crack detection system in Korea.** This section reviews the existing crack detection system implemented in Korea and defines the processes to be automated. Special vehicles with dedicated cameras collect standardized images of the road surface. Many workers use dedicated tools to mark the cracks and provide information on the type of cracks. Based on the marked region and the crack types, information about the severity and location of the cracks contained in the image is generated and summarized in the appropriate indicators. The results of location, type, and severity are used as the basis for road maintenance. In the automation target process shown in Figure 1, a large number of workers manually examine the collected images to identify crack regions. The crack area is very small compared with the image size, so it takes a long time to determine the correct crack. In addition, because it is performed manually, there is a high probability that a human error may occur. Therefore, we propose a framework that minimizes labor costs and human errors by automating the crack detection and classification process.

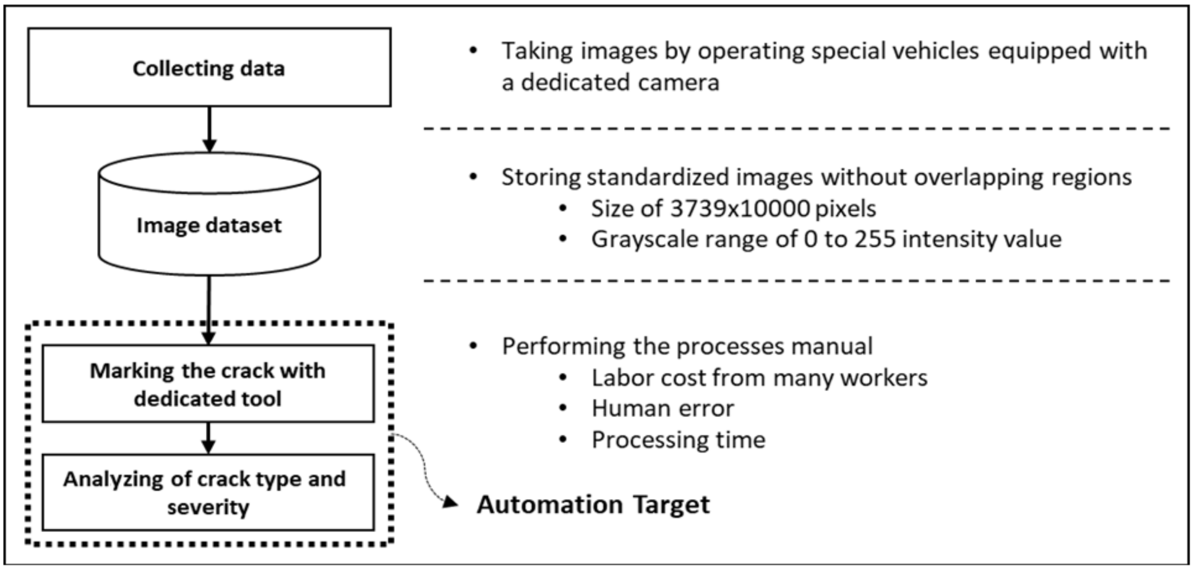
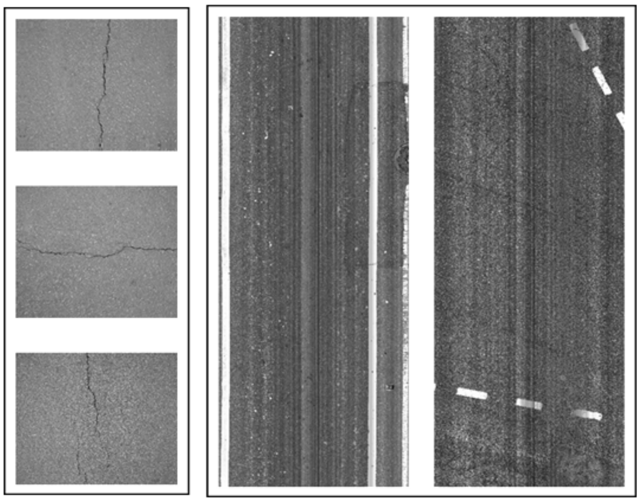


Figure 1. Present crack detection system in Korea

Table 1. Main processes of CrackIT-toolbox

Main Process	Description
Preliminary labeling binary matrix	• Binary matrix of crack or non-crack divided by grid • 75 × 75 sized block and intensity range of 0-255 • Mean and std computed by intensities contained each block
Pre-processing	• Intensity normalization and pixel saturation • Feature extraction and feature normalization
System training & Crack detection	• Clustering and one-class classification • Images featured as mean and std of matrix by block
Crack types labeling	• 2-D features of std by row and column • Label among longitudinal, transversal or miscellaneous
Crack severity level assignment	• Crack pixels selected by Otsu method • Crack width computed with connected component of pixels

3.2. **Problems of applying existing methods in Korea.** This section describes the existing methods of the CrackIT-toolbox proposed by Oliveira and Correia [3,4]. The limitations of applying CrackIT-toolbox to the domestic environments are presented in detail. The toolbox consists of five main processes as shown in Table 1, and uses Figure 2(a) as the input data. In the preliminary labeling binary matrix (plb), the mean and standard deviation (std) are computed for each block then binary values are assigned to determine whether or not a crack is included in each block according to the conditional expression. This conditional expression is based on the characteristic that the crack pixels are darker and have lower intensity than the surrounding non-cracks. After that, the pre-processing is performed for each of the blocks having the preliminary value, and the classification model is trained by the mean matrix and the std matrix, which are the features extracted from the preprocessing. For model training, clustering techniques and one-class classification strategies are used as learning algorithms. The blocks contained in the image are summarized by the points of the plot as mean and standard deviation, 2-dimensionally. Unlike many non-crack blocks, crack block points have lower mean and higher std, so they are used as the features to classify points into crack or non-crack according to the decision boundary. After the cracks are detected, the row and column std of each block are plotted in the 2D feature space, and the types are classified according



(a) (b)

Figure 2. Samples used in CrackIT-toolbox (a) and images collected in Korea (b)

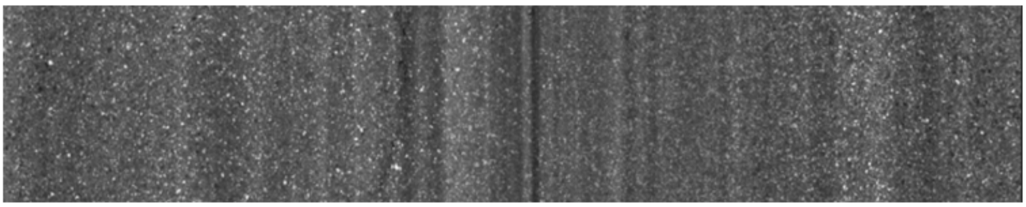


Figure 3. A part of an image without any object

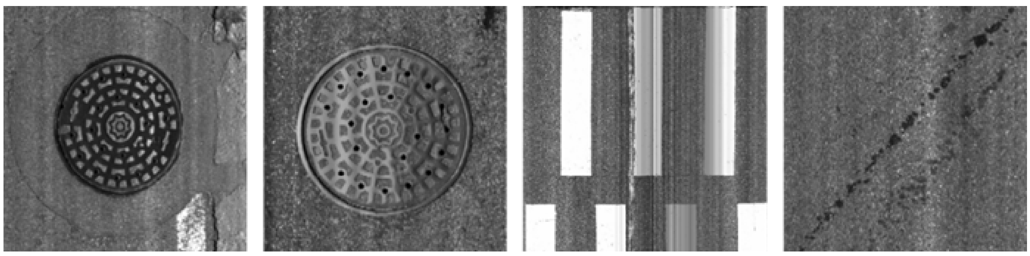


Figure 4. Various objects on the road

to the distance from the axis and the bisector. Finally, pixel-based Otsu method is applied to identifying darker pixels as crack pixels and average width of connected components is calculated to determine the severity of cracks.

The two images in Figure 2(b), collected in Korea, differ from the images 2(a) used in the CrackIT-toolbox. Therefore, preprocessing in the toolbox is not appropriate and training on classification algorithms is not effective. Crack types classification and severity assignment are the same. As a result, it shows remarkably low performance.

First of all, as shown in Figure 3, there are afterimages in the collected images. The system proposed in this paper analyzes the intensity of each pixel and uses it as a feature. Since unnecessary intensity variations interfere the analysis process, it should be prioritized that the afterimages are normalized.

Second, the objects in Figure 4 contained in the image were not processed properly. Various objects on the road (white lanes, manhole covers, oil stains, etc.) may interfere with accurate crack detection and should be excluded in advance.

Third, repaired surfaces shown in Figure 5, should be processed. There are the road surfaces repackaged (left) and sealed cracks (right). This repaired surface has darker intensity like a crack, and can be misclassified as a crack.

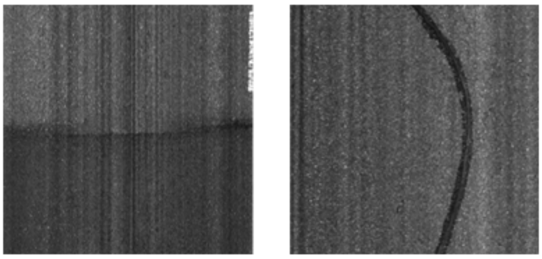


Figure 5. Repaired surface samples

4. **Proposed Framework.** Figure 6 shows the proposed framework with the additional processes in Table 2 to solve the problems described in the previous section. The added processes are expected to reduce the differences in the images shown in Figure 2 and improve the performance of the system.

Table 2. Additional processes for improving

Additional Process	**Description**
Afterimage normalization	• Processing the afterimage by normalizing • Discriminating the intensity of cracks
Region of interest (ROI) analysis	• Identifying region of interest • Excluding objects excepting road surfaces
Repaired surface processing	• Processing the repackaged road • Preventing misclassification due to road sealing material

4.1. **Overview of framework.** This section presents the overall framework of the proposed system and explains the three added improvement processes briefly. First, vertical normalization should be performed in order to remove the effect of the afterimage of each image. It is expected that the intensity variation can be eliminated and crack pixels can be classified more discriminately. Next, we need to clarify the analysis area of the automation system by adding the region of interest (ROI) analysis process to exclude objects of non-interest. In addition, the repaired surfaces have possibility being misclassified and appropriate processing should be performed. Figure 6 shows the overall framework with these processes added.

4.2. **Prototype of implementation.** This section describes the results of prototype implementation of the proposed processes to solve the problem described in Section 3.2. The graph in Figure 8 shows the vertical average of images that do not contain the objects such as Figure 7(a). As shown in the graph in Figure 8, there is the same pattern change in all images. That is, a change in intensity occurs at the same index of all images. To eliminate this unnecessary intensity variation, we obtain the difference from the mean of the change at each index to the global mean value (horizontal line on the graph in Figure 9). The calculated difference for each column index is applied to each pixel of the image, eliminating the variation between the columns, and eliminating the afterimage as shown in Figure 7(b). As a result, crack detection performance was improved as shown in Figure 10.

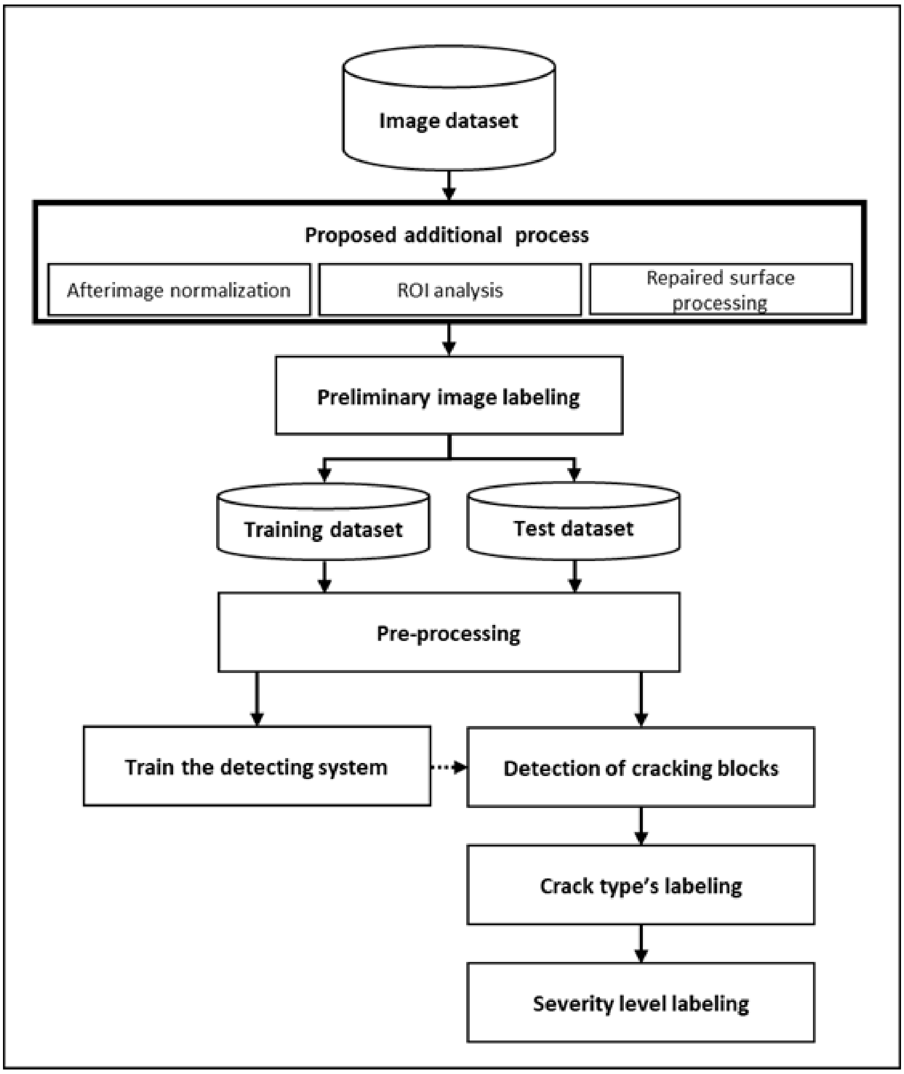


FIGURE 6. Proposed framework for detection of road cracks in Korea

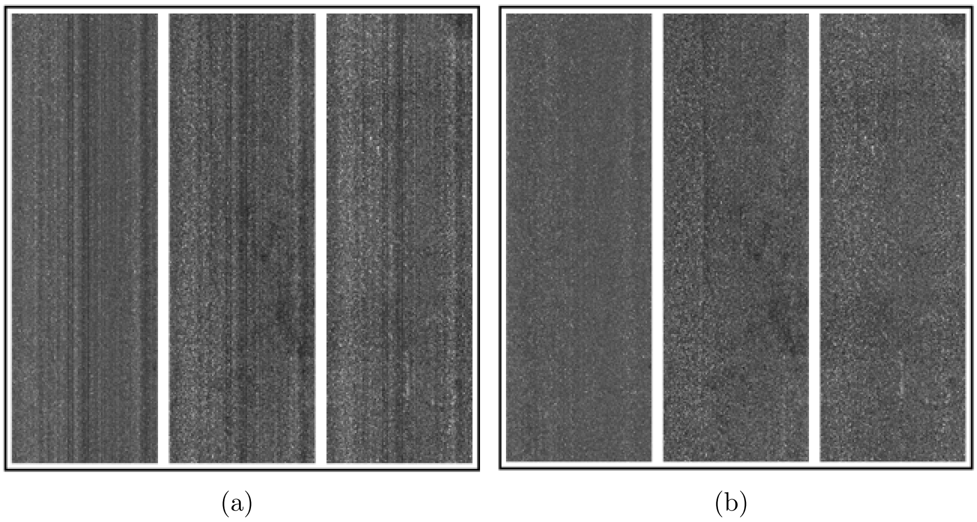


FIGURE 7. Image samples before (a) and after (b) the afterimage normalization process is applied

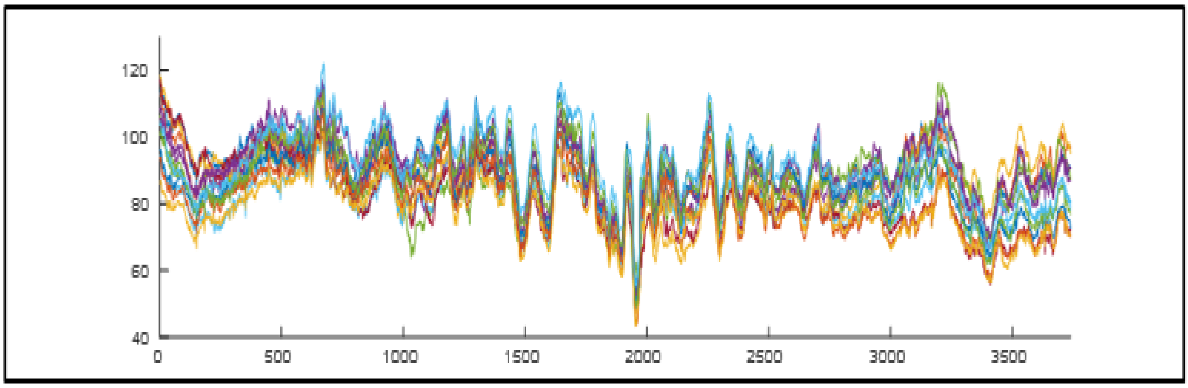


Figure 8. Vertical means of all images containing no objects

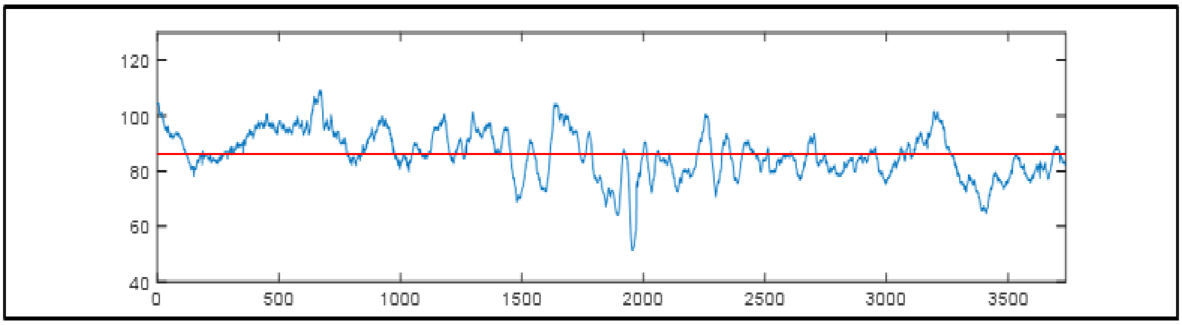
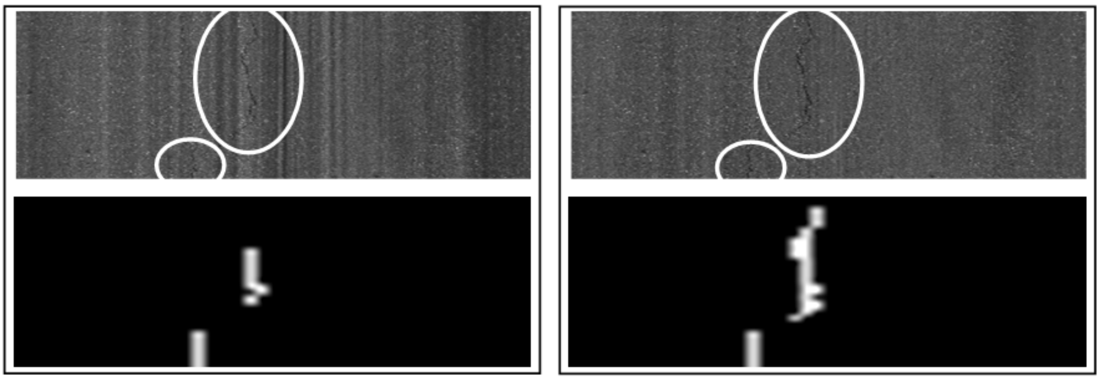


Figure 9. Average of intensity variation



(a) Without normalization (b) With normalization

Figure 10. Results of road crack detection with afterimage normalization

5. **Conclusions.** In this study, we researched for a framework for automating crack detection and classification processes performed manually in Korea and proposed the improved framework of Figure 6. In the proposed framework, three additional processes have been included to overcome the limitations due to differences in input images. Each additional process corresponds to process afterimage normalization, ROI process and repaired surface processing.

At first, we checked the possibility of application of the CrackIT methodology in the domestic environments. However, we determined that there was a need for another method because of the significant drop in performance. Although we proposed several processes for solving the problems in this paper, it has not yet been implemented as a complete system. In the future, we will utilize CNN method to pre-classify complex images and apply each additional process proposed in this paper according to the pre-classified image. Also, it is necessary to verify the effectiveness and evaluate the performance of the proposed framework.

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