Detection of Structural Damages for Petroglyphs of Bangudae Terrace using Edge Extraction based on Deep Learning

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Abstract

We will deal with a case of applying Deep Learning technology to the conservation and management of the Petroglyphs of Bangudae Terrace in Daegok-ri, Ulju that were designated as national treasures. They were also selected as UNESCO World Heritage priority candidates, but have been continuously under threat of damage due to various environmental factors. In this paper, we attempted displacement detection using three Deep Learning models for efficient protection of the petroglyphs. The experimental results showed that the average processing times of the DexiNed and PiDiNet models were 6.43 and 20.87 seconds, respectively, which were effective for fast displacement detection, and the DeepCrack model was 114.19 seconds, which was suitable for large-scale data set analysis. In addition, the displacement detection results of the DeepCrack model confirmed that the joint area significantly changed when the temperature changed rapidly.

CCS Concepts

• **Applied computing** → Personal computers and PC applications; • **Information systems** → Multimedia information systems; Multimedia databases.

Keywords

Petroglyphs of Bangudae Terrace, Deep Learning, Displacement Detection, DexiNed, PiDiNet, DeepCrack, Cultural Heritage

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1 Introduction

The Petroglyphs of Bangudae Terrace in Daegok-ri, Ulju, are the earliest known Neolithic rock carvings, depicting detailed whale hunting scenes [1]. Due to their immense cultural and historical value, these remarkable petroglyphs have been designated as a National Treasure of South Korea [2]. Given their global significance, they have been selected as a candidate for UNESCO World Heritage listing under the name 'Daegokcheon Petroglyph Group,' with a final decision expected in 2025.

Despite their recognized importance, the Petroglyphs of Bangudae Terrace face significant threats. Located upstream of the Sayeon Dam, they are submerged for approximately 40 days annually when water levels exceed 53 meters during the summer [3]. This submersion, coupled with seasonal freeze-thaw cycles, accelerates natural weathering. Water infiltrates the rock, freezes, and expands, exacerbating existing cracks and forming new ones. These environmental factors are causing irreversible damage. Due to the fragile nature of stone cultural heritage, restoration efforts after damage are extremely challenging and often incomplete. Therefore, early detection of damage and prompt response are crucial to preserving these invaluable artifacts.

To address these challenges, we need new technologies to efficiently monitor and manage cultural heritage sites [4]. Recently, there has been a surge of research focusing on digital content for cultural heritage using advanced technologies like virtual and augmented reality [5], digital scanning and 3D modeling [6], artificial intelligence, and machine learning [7]. However, there are relatively few applications of these technologies for preservation and management [8, 9]. Based on previous researches on slope prediction and displacement determination of cultural heritage [10-14], this research proposes a new methodology using three Deep Learning models [15-17] using edge detection [18, 19] and crack segmentation [20] to process and analyze data in real time. This research employs a displacement detection system that integrates three Deep Learning architectures—DexiNed [15], PiDiNet [16], and DeepCrack [17]—based on edge detection and crack segmentation technologies.

We will extract displacement characteristics of the Petroglyphs of Bangudae Terrace joint and derives detection results. This approach analyzes weathering, cracks, and exfoliation using Deep Learning, offering a meticulous alternative to traditional methods like precision measurement and 3D photography. Ultimately, this research provides practical solutions for the preservation and management of the Petroglyphs of Bangudae Terrace and other cultural heritage sites, based on experimental results obtained in this research, ensuring their protection for future generations.

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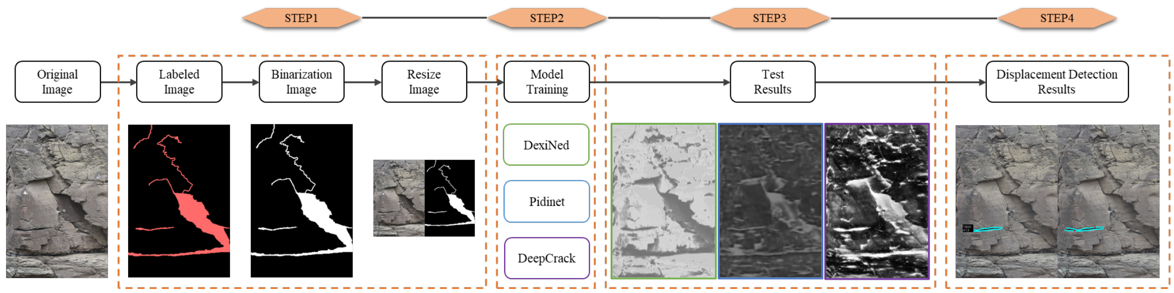


Figure 1: Process of the Displacement Detection Experiment for Petroglyphs of Bangudae Terrace in Daegok-ri, Ulju

2 METHODOLOGY FOR DISPLACEMENT DETECTION OF PETROGLYPHS OF BANGUDAE TERRACE

2.1 Deep Learning Architecture

In this research, we performed displacement detection of the joint in Petroglyphs of Bangudae Terrace in Daegok-ri, Ulju using Convolutional Neural Network (CNN), open-source based Deep Learning models: DexiNed, PiDiNet, and DeepCrack [17]. DexiNed [15] and PiDiNet [14] are models specialized in edge detection, while DeepCrack is tailored for crack segmentation. All three models excel in extracting high-level features in image and video processing, enabling the effective detection of specific patterns within images. For the three models, we applied the latest technology that showed good results in Edge Detection and Crack Segmentation to see if it was also possible to detect displacement of cultural heritages.

Figure 1 illustrates the overall process of the displacement detection experiment for Petroglyphs of Bangudae Terrace, conducted by integrating the three Deep Learning architectures. In the preprocessing stage, labeled images are created from the original monitoring images of the Petroglyphs of Bangudae Terrace using a labeling tool called Labelme [21]. Labelme, one of the Annotation Tools, is a tool that can find and label fractions, rectangles, lines, points, etc.

Additionally, binarized images with pixel values of 0 and 255, as well as resized images reduced to 10% of their original size to match the training data specifications, are sequentially generated using the original images. These datasets are used as training data to train three Deep Learning models and extract edges [14]. Subsequently, the test results are evaluated to confirm that each model has been trained stably without overfitting or underfitting. Finally, the displacement detection results are analyzed through quantitative measurements of the changes in area and perimeter of each joint. Based on this analysis, the performance of each model is evaluated, allowing for an understanding of the characteristics and strengths of each model.

2.2 Datasets

The training data for this research comprises original images of Petroglyphs of Bangudae Terrace, captured daily over 100 days from 2016 to 2022 under various environmental conditions. The images, taken at the same time each day, divide the petroglyphs into 12 horizontal sections. The dataset includes polygon-labeled joint areas and binarized images, resized to 491 x 736 pixels for compatibility with Deep Learning algorithms. A total of 93 days of data were used for model training, excluding 7 days due to issues like submersion or strong winds. This dataset extends a previous experiment [14], which previously utilized 10 days of data.

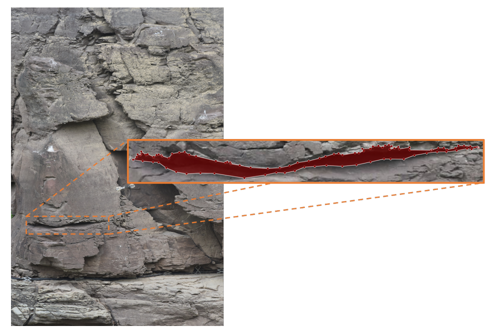


Figure 2: Setting the Displacement Detection Area

The test data were prepared to compare displacement between 2016 and 2022, using a total of 24 images taken at monthly intervals from January 15 December 15 in both 2016 and 2022 to verify the displacement detection results. (see Table 1).

2.3 Setting the Joint's Area for Displacement Detection

To analyze the displacement trends of the Petroglyphs of Bangudae Terrace, the joint depicted in Figure 2 was selected as the focusing joint. A rectangular area encompassing this joint was established for displacement detection. Unlike most of the joints that are oriented upward, the focusing joint is tilted sideways and intersects with other joints, which could lead to wedge failure. Additionally, the joint is prone to submersion when the water level of the Daegokcheon stream rises, which flows in front of the Petroglyphs of Bangudae Terrace. These structural and locational characteristics suggest that significant displacement can occur in this area.

3 Experiment Results and Analysis

3.1 Experimental Preparation

In this research, Petroglyphs of Bangudae Terrace datasets were divided into training, validation, and test datasets. The analysis model for displacement detection utilized three Deep Learning architectures. The experiments were conducted on an Ubuntu 22.04

Table 1: Training/Validation/Test datasets

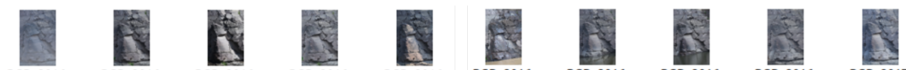
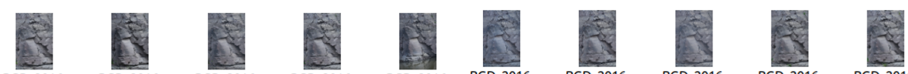
Datasets	Method	Image Files
Train-nig	Original	 BGD_2016-03-04_seq03.jpg, BGD_2016-03-06_seq03.jpg, BGD_2016-03-07_seq03.jpg, BGD_2016-03-08_seq03.jpg, BGD_2016-03-10_seq03.jpg, BGD_2016-04-21_seq03.jpg, BGD_2016-04-22_seq03.jpg, BGD_2016-04-29_seq03.jpg, BGD_2016-05-02_seq03.jpg, BGD_2016-05-12_seq03.jpg
Train-ing	Labeled	 BGD_2016-04-21_seq03.png, BGD_2016-04-22_seq03.png, BGD_2016-04-29_seq03.png, BGD_2016-05-02_seq03.png, BGD_2016-05-12_seq03.png, BGD_2016-03-04_seq03.png, BGD_2016-03-06_seq03.png, BGD_2016-03-07_seq03.png, BGD_2016-03-08_seq03.png, BGD_2016-03-10_seq03.png
Valida-tion	Original	 BGD_2016-02-25_seq03.jpg, BGD_2016-04-26_seq03.jpg, BGD_2016-05-03_seq03.jpg, BGD_2016-05-13_seq03.jpg, BGD_2016-09-01_seq03.jpg, BGD_2016-10-05_seq03.jpg, BGD_2016-10-15_seq03.jpg, BGD_2016-10-17_seq03.jpg, BGD_2016-12-26_seq03.jpg, BGD_2017-02-19_seq03.jpg
Valida-tion	Labeled	 BGD_2016-10-05_seq03.png, BGD_2016-10-15_seq03.png, BGD_2016-10-17_seq03.png, BGD_2016-12-26_seq03.png, BGD_2017-02-19_seq03.png, BGD_2016-02-25_seq03.png, BGD_2016-04-26_seq03.png, BGD_2016-05-03_seq03.png, BGD_2016-05-13_seq03.png, BGD_2016-09-01_seq03.png
Test	Original	 BGD_2016-06-15_seq03.jpg, BGD_2016-07-15_seq03.jpg, BGD_2016-08-15_seq03.jpg, BGD_2016-09-15_seq03.jpg, BGD_2016-10-15_seq03.jpg, BGD_2016-01-15_seq03.jpg, BGD_2016-02-15_seq03.jpg, BGD_2016-03-15_seq03.jpg, BGD_2016-04-15_seq03.jpg, BGD_2016-05-15_seq03.jpg

Table 2: Hyperparameter configuration

Hyperparameter	DexiNed	PiDiNet	DeepCrack
Epoch(Training)	80	100	50
Epoch(Test)	20	20	20
Workers	16	16	16
Batch Size	8	8	16
Learning Rate	0.005	0.005	0.005
Learning Rate Type	Linear	Multistep	Linear
Weight Decay	0.00000001	0.0001	0.0002
Optimizer	Adam	Adam	SGD
Eta	0.5	0.3	-
Lamda	-	1.1	1

Table 3: Training/Validation/Test time

Model	Training Time(s)	Validation Time(s)	Test Time(s)
DexiNed	462.51	6.79	21.61
PiDiNet	937.50	6.43	20.87
Deep-Crack	114.19	13.22	24.89

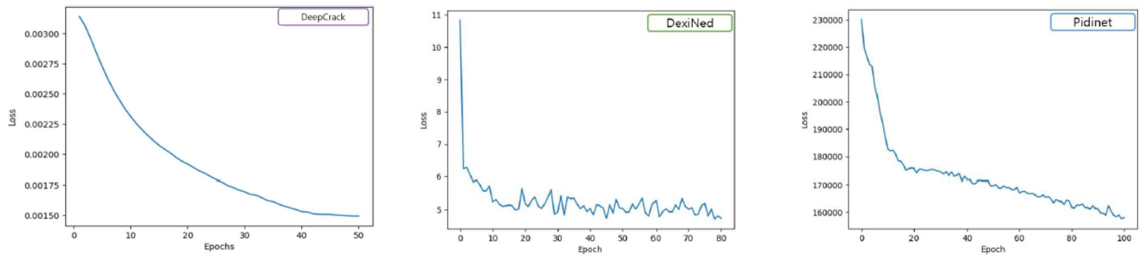
LTS (x86_64) operating system with an NVIDIA Quadro RTX 8000 graphics card. Table 2 shows the hyperparameter settings applied to the three Deep Learning models, optimized to improve model performance and minimize loss.

3.2 Training Three Deep Learning Models

To detect displacements in Petroglyphs of Bangudae Terrace, DexiNed, PiDiNet, and DeepCrack models were trained using optimized hyperparameters configured during the experimental preparation. Figure 3 represents the loss convergence of each model over epochs. Analysis of the loss curves showed that DeepCrack model quickly reduced its loss values within a few epochs, indicating its potential for stable and reliable results. In contrast, DexiNed model exhibited irregular convergence with variability, leading to inconsistent outcomes. PiDiNet model demonstrated slower convergence, requiring extended training periods and experiencing delays in reaching full convergence.

3.3 Displacement Detection of the Joint

In this research, we compared and analyzed displacement detection results using the predicted maps generated by each Deep Learning model, with a focus on measuring the area and perimeter of the joint. The analysis of training times revealed that the DeepCrack model processed the data the fastest, with an average time of 114.1 seconds, significantly outperforming the DexiNed model with 462.5 seconds and the PiDiNet model with 937.5 seconds. But, in terms of validation and testing times, the PiDiNet model was slightly faster than both the DexiNed and DeepCrack models, with times of 6.4 seconds and 20.8 seconds, respectively (see Table 3).



(a) DeepCrack (b) DexiNed (c) PidiNet

Figure 3: Loss vs. Epoch Learning Graph for the Three Models

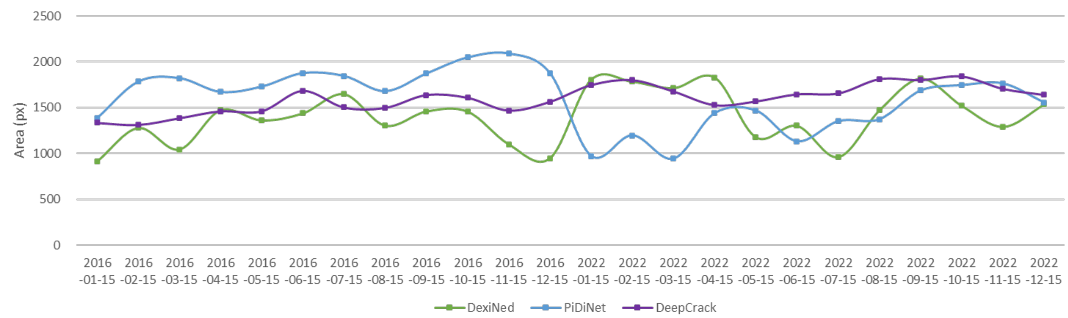


Figure 4: Displacement Detection Results of Joint Area by Date for the Three Models

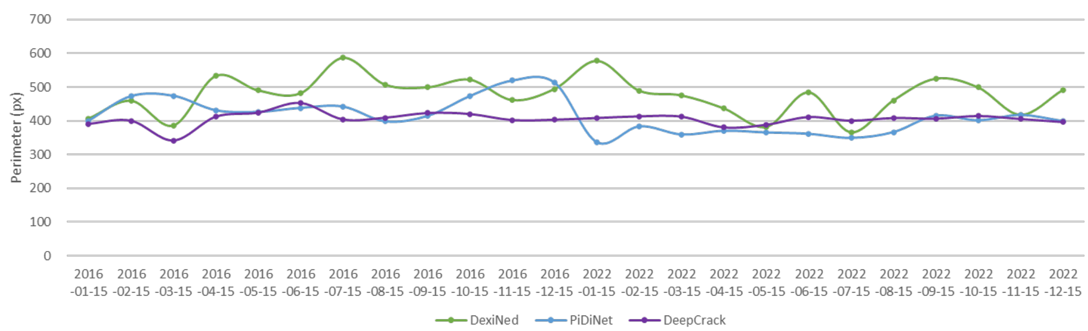


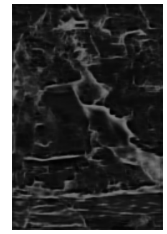
Figure 5: Displacement Detection Results of Joint Perimeter by Date for the Three Models

Figure 4 illustrates the displacement detection results based on changes in joint contours over time. The displacement measurements for the area were calculated by summing the pixel values within the contours extracted from each image. Among the various models, the DeepCrack model effectively detected the increase in area associated with seasonal variations, demonstrating overall stability and consistency in its results.

Figure 5 presents the displacement detection results for the joint perimeter, based on contours calculated at different time points. The analysis indicated that the deviations in perimeter measurements were smaller compared to those for the area. The DexiNed model showed an average perimeter value of 476, which significantly deviated from the actual measurements. While, the DeepCrack model provided the most accurate and reliable displacement measurements, with an average perimeter value of 405.1, closely aligning with the actual measurements, making it the most reliable among the three models for displacement detection.

Table 4 compares the test results and displacement detection outcomes for the three models for October 15, 2022. The DexiNed and PiDiNet models are excellent in generating quicker results, as they are fast in producing sharp prediction maps and effectively extract fine edge details, making them particularly suitable for smaller datasets or scenarios with limited training cycles. On the other

Table 4: Test and displacement detection results

Results	DexiNed	PiDiNet	DeepCrack
Test			
Displacement Detection			

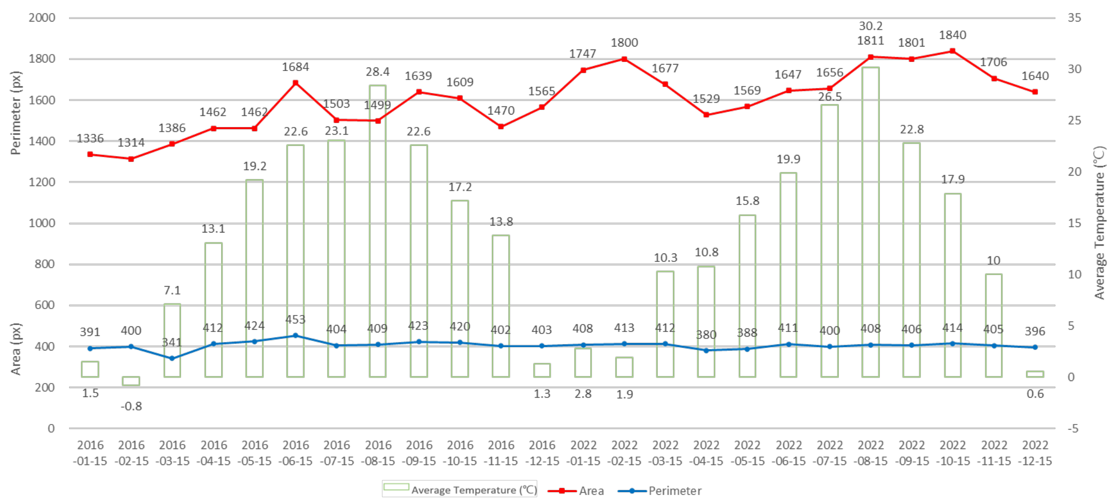


Figure 6: Displacement Detection Results of Joint Area and Perimeter by Average Temperature with DeepCrack

hand, the DeepCrack model demonstrated exceptional performance in processing large volumes of image data, making it well-suited for tasks requiring extensive datasets. Specifically, it is highly effective in accurately predicting joint boundaries, making it the preferred model for scenarios demanding high pixel-level accuracy.

Among the three models, the DeepCrack model produced the most reliable displacement detection results, which were further analyzed in relation to environmental factors. The analysis revealed a significant correlation between the data and the average temperature data from the Korea Meteorological Administration [22] (see Figure 6).

When we analyzed data from 2016 and 2022, we found that the joint area showed considerable changes during periods of rapid temperature fluctuations. For instance, the joint area and perimeter consistently expanded during the period of rising average temperatures between May and June 2016 and between July and August 2022, as well as during the period of falling average temperatures between November and December 2016.

Notably, the results indicate that the average joint area measured in 2022 increased to 1791.92 compared to 1510.75 in 2016, suggesting that ongoing damage to the Petroglyphs of Bangudae Terrace due to natural disasters and other environmental factors is contributing to the expansion of the joint area.

Additionally, during the 40-day maintenance period from early April to mid-May 2022, we observed that the joint area and perimeter decreased by 248 and 32, respectively. These findings emphasize the importance of preserving and managing cultural heritage. They demonstrate that systematic management and precise maintenance job can significantly contribute to the conservation of cultural heritage with Deep Learning technology help.

4 Conclusion

We explored the application of Deep Learning models—DexiNed, PiDiNet, and DeepCrack—to the detection of displacements in the Petroglyphs of Bangudae Terrace, a significant cultural heritage site. The analysis revealed that each model exhibited distinct strengths and weaknesses. The DeepCrack model demonstrated its capability to rapidly reduce loss values within a few epochs, suggesting its potential for delivering stable and reliable displacement detection results. This model's robust performance in processing large volumes of image data makes it particularly well-suited for tasks requiring extensive datasets and high precision, such as monitoring and managing the structural integrity of cultural heritage sites.

On the other hand, the DexiNed model showed irregular convergence patterns with significant variability due to environmental factors while it was effective in producing sharp prediction maps. This inconsistency indicates that the DexiNed model can be beneficial for quick assessments, but it cannot be reliable for long-term monitoring where consistency is crucial.

The PiDiNet model excels in extracting fine edge details although it is slower in converging and requiring extended training periods. This characteristic makes PiDiNet particularly valuable in scenarios where detailed analysis of small features is necessary. However, its delayed convergence suggests that it may be less efficient for real-time applications or situations requiring fast analysis.

Overall, this research highlights the importance of selecting the appropriate Deep Learning model based on the specific requirements of the task at hand. These findings mean that DeepCrack is the most suitable model for comprehensive and precise displacement detection in large-scale heritage conservation projects. while, DexiNed and PiDiNet can provide valuable capabilities for more focused or explored analyses.

In future research, we will research on identifying a Deep Learning model that is practically suitable for displacement detection and apply it to the dataset by generating abnormal image data containing artificial displacements to simulate various displacement scenarios. This will enhance the ability of each model to detect and analyze displacements under a wider range of conditions, ultimately contributing to the effective conservation and management of cultural heritage sites worldwide and exploring ways to provide comprehensive solutions. We will conduct experiments to confirm whether it can produce reasonable displacement detection results by applying it to various types of cultural heritage sites such as pagodas and buildings as well as rock-based stone cultural heritage sites. Through this, we aim to test the limits of the model and understand its boundaries.

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