AUTOMATIC SURFACE DAMAGE CLASSIFICATION DEVELOPED BASED ON DEEP LEARNING FOR WOODEN ARCHITECTURAL HERITAGE

Jungmin Lee[1], Jeong Min Yu[1]*

Dept. of Cultural Heritage Industry, Korea National University of Cultural Heritage, Buyeo, Republic of Korea
- (20212071, jmyu)@nuch.ac.kr

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ABSTRACT:

In this paper, we propose a system that automatically classifies the surface damages of wooden architectural cultural heritage based on deep learning algorithms. Commonly, on-site surface damage inspections of cultural heritage are carried out manually by field experts. However, it is difficult to manage cultural heritage because experts are not always onsite to check for damage. To overcome this problem, a deep-learning-based classification method is designed to detect surface damage automatically so that cultural heritage monitoring can be done in real time. The dataset required for the development of the deep learning model utilized 4,000 images taken directly from cultural heritage sites. As a result of a comparative analysis of the performance of four deep learning models for several examples of wooden architectural heritage, the damage detection rate of the deep learning model built in this study showed excellent performance between 94.00 and 96.50%. When gradient-weighted class activation mapping is applied to visualize the damage detection results, the performance of the model with the best performance stood out. The results of this paper are significant as a basic study of the development of a real-time remote damage detection system applicable to cultural heritage sites.

1. INTRODUCTION

Cultural heritage can be damaged for various reasons over time. Existing studies thus far have been conducted to protect Korean cultural heritage, especially those consisting of paper and wood, as these materials are relatively vulnerable over time (Oh et al., 2022). When 5,000 state-designated and registered cultural heritage articles in Korea are divided according to their materials paper is the most common at 18.9%, followed by wood at 16.4% and stone at 14.1% (Cultural Heritage Administration of S. Korea, 2022). Among them, wooden cultural heritage articles are relatively more vulnerable to degradation factors and external shocks than those made of stone due to the physical characteristics of wood. In addition, they are directly affected by various damage factors existing in the outdoor environment as they are mainly in the form of buildings, such as palaces and temples. Currently, these artifacts are under the threat of rapidly changing environmental factors such as frequent earthquakes and abnormal weather on the Korean Peninsula, necessitating changes in the management techniques for existing outdoor cultural heritage sites.

With the recent emergence of advanced digital technology, there is a movement to digitalize the existing cultural heritage preservation management method based on various hardware and software. In the field of outdoor building safety management, the status of cultural heritage is regularly monitored using three-dimensional scanning technology (Kim et al., 2019). Displacement and damage studies based on digital shape data constructed through terrestrial laser scanning and unmanned aerial photogrammetry are being actively conducted domestically and internationally (Jaafar et al., 2017). However, current methods used to document and compare objects using three-dimensional scanning technology are limited in that real-time measurements are impossible as the measurements are conducted at regular time intervals.

Several local governments have also attempted to incorporate ICT technology into their cultural heritage disaster prevention strategies over the years in an effort to establish a new cultural heritage safety management system. Intrusions and fires are detected mainly through motion detection sensors, and cracks and tilting are detected by attaching measurement sensors to the target surface (Choi et al., 2017). Beyond simply detecting intrusions and fires, it is necessary continuously to explore the trends in the amounts of damage and displacement so as to consider the proper types of risk situations at cultural heritage sites and the forms that will appear in the long term. However, in order to determine the current degree of damage, it is inevitable that some form of surface contact must be utilized on the target articles.

To address this issue, we propose a system for detecting surface damage on cultural heritage artifacts based on a deep learning algorithm. Since the development of the convolutional neural network (CNN) (LeCun et al., 1989) and AlexNet (Krizhevsky et al., 2012), research in this area has been actively conducted. Recently, the CNN was utilized in works related to cultural heritage, with several studies attempting to detect damage to cultural heritage articles using CNN-based technology (Pathak et al., 2021). However, there is a lack of research on monitoring systems feasible for use at actual cultural heritage sites, and there has been no research on wooden cultural heritage artifacts. In this paper, using a CNN-architecture-based model, we develop a system that enables real-time on-site monitoring and automatically detects damage to wooden cultural heritage.

* Corresponding author

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Several pre-trained models are used for system development to verify their performance and to examine the possibility of applying them in the field for use with wooden heritage artifacts. In particular, the main contributions of paper are as follows:

- We construct an image database of South Korea's wooden architectural heritage. Many wooden architectural heritage artifacts located in South Korea have been photographed under various illumination and angle change conditions, and these images are partially segmented to build deep learning models.
- We automatically detect surface damage to wooden heritage artifacts in real time. The proposed non-destructive damage detection system enables remote management and the continuous monitoring of these items.
- We apply recent deep learning models to the image dataset. Using the pre-trained models, surface damage types on test images are classified and the performance capabilities of the models are presented.
- We develop a gradient-weighted class activation map (Grad-CAM) (Selvaraju et al., 2017) that indicates the importance of each pixel in the image based on the slope value. It is applied to the classification result to confirm the strength of the state-of-the-art model. Applying Grad-CAM, it is possible to visualize damage locations within these images.

2. METHODOLOGY

2.1. Target Wooden Heritage

The Yeongnamnu Pavilion in Miryang is a representative wooden structure in South Korea and is considered one of the three largest pavilions in Korea both in terms of historical value and scale. A pavilion is a tall building of two or three stories without doors or walls so that visitors can see all directions for events or games in palaces, government offices, and castles. Among outdoor cultural heritage artifacts, pavilions are directly affected by environmental factors due to their considerable exposure to the atmosphere given their morphological and geographical characteristics (National Research Institute of Cultural Heritage of South Korea, 2020). Due to the structural characteristics of wooden buildings, if proper measures are not taken when the components deteriorate, structural problems can arise. Accordingly, detailed, daily management practices are required. In addition, given that most of these structures are made of wood, they are highly vulnerable to fires and fire prevention measures. Considering this, care must be taken not to damage them in an emergency or disaster situation.

Figure 1. Yeongnamnu Pavilion

Yeongnamnu Pavilion currently has a number of damaged members, and although the damage does not have a significant effect on the overall stability of the structure, it is a stage that requires careful attention for a deformed area. The main types of damage are cracks, exfoliation and deterioration of the columns, details of which are shown in Figure 2 (National Research Institute of Cultural Heritage of South Korea, 2018). A crack is a discontinuity in an architectural surface or its painting, resulting in a visible separation of one part from another that extends through one or more layers (Weyer et al., 2015). Exfoliation is a type of detachment totally independent of the wooden structure. It refers to the peeling of the wood skin parallel to the surface, and the thickness of the skin generally varies from the millimeter to the centimeter scale. Deterioration refers to decay of the wood when the fibers are decomposed by fungi; it is a phenomenon by which the wood is discolored and its strength is reduced.

Crack Exfoliation Deterioration

Figure 2. Major types of damage at Yeongnamnu Pavilion

The lower part of the pillar on the first floor of the pavilion lacks foundation stones and grounding surfaces and is in a state of corrosion. As a result of electro-optical wave measurements of the deformation behavior of the top and bottom columns, progressive deformation in a certain direction was not confirmed (National Research Institute of Cultural Heritage of South Korea, 2018). Because most of the deformation behavior measured for one year converges to the initial value with a change of around 1 to 2 mm in the final value, thus far it is difficult to find abnormal deformation of the column. The current level of crack occurrence is not to the extent that it affects the overall amount of displacement of the building, but continuous monitoring is required because the possibility that the deformation behavior will proceed more rapidly in the future cannot be ruled out.

2.2. Image Dataset

To train a CNN model, first we construct an image dataset. Because wooden cultural heritage artifacts have different characteristics depending on the culture and region, it is necessary to establish training image data that pertains to Korean wooden cultural heritage artifacts. In that there is no existing image dataset of cultural heritage with which to train a CNN model, a wooden cultural heritage database in Korea is constructed. Based on the constructed image dataset, we design and train a model specialized for Korean cultural heritage.

A training dataset is built with actual still images of architectural cultural heritage taken with a digital camera. The training dataset targets Korean cultural heritage, but it excludes special cases such as those in which traditional pigments are not utilized during the painting of the artifact or where columns are rectangular. The testing dataset is extracted from CCTV images of the pillars of Yeongnamnu Pavilion, the target of the experiment. All of the individual image data instances were taken under various weather conditions, but dark images acquired at night are not used in the experiment.

The constructed image data are classified as either normal or abnormal. It is difficult to distinguish whether one image corresponds to one type of damage because several types of damage appear together on the pillar surfaces of the furniture part, which is the center of the architectural cultural heritage.

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Therefore, a binary classifier for determining damage is used in place of a multi-class classifier. Parts with good preservation status of the columns are sorted into the normal class, while parts with damaged columns are categorized as abnormal to delineate the dataset.

In addition, damage to columns does not cover the entire surface. Considering the characteristics of these types of damage, preprocessed images are used for learning. The pre-processing sequence of the training images is shown in Figure 3. By segmenting the actual image into patches, a more precise analysis becomes possible. Furthermore, the image segmentation method overcomes the quantitative limitation of the dataset without augmenting the data. Cultural heritage images, for which distortion of the original appearance should be guarded against, have the advantage of not having to be artificially converted by means such as simple rotation, enlargement, reductions, or symmetry and/or brightness changes. Segmenting an image naturally separates shadowed and non-shadowed portions, thereby increasing the training data as one aspect of different types of image transformation that also mitigates the overfitting problem caused by data quantitative limitations.

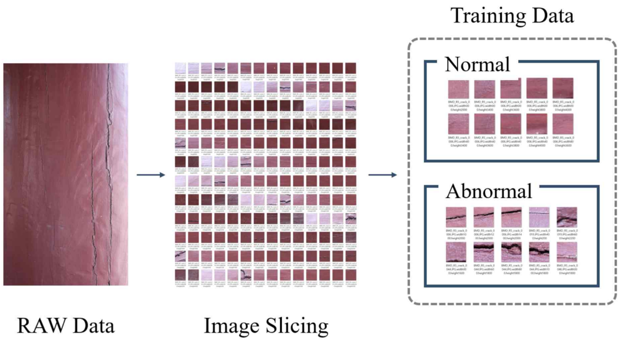

Figure 3. Pre-processing of training images

2.3. Process of Proposed Method

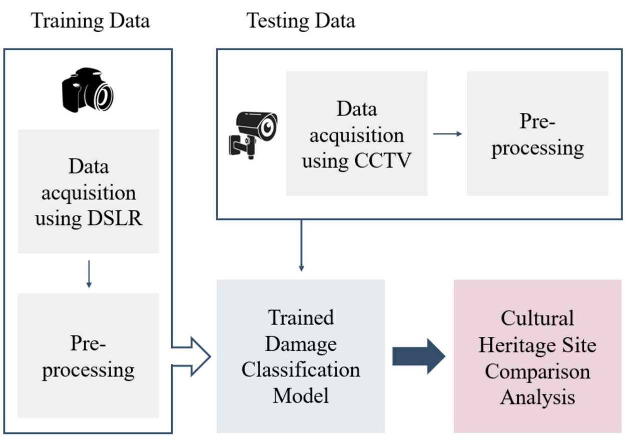

Figure 4. Workflow of the proposed method

In order to enable the real-time monitoring of Yeongnamnu Pavilion, a CNN specialized in image analysis among deep learning methods is used. A CNN can be used to create a deep network by repeatedly arranging convolution and pooling layers to suit the user's purpose, ultimately positioning a fully connected layer to determine whether or not the column is damaged (Krizhevsky et al., 2012). In this paper, among representative CNN models, models that have recently performed well in the field of image analysis are used in experiments to compare their image classification performance capabilities. Four models, VGG16 (Simonyan and Zisserman, 2014), InceptionNetV3 (Szegedy et al., 2016), ResNet50 (He et al., 2016), and EfficientNetB0 (Tan and Le, 2019), are used in this paper to extract the deep features of images. The overall workflow of the proposed method is shown in Figure 4.

2.3.1. VGGNet

A CNN with a deep structure and a method that involves the use of ReLU were proposed for VGGNet (Simonyan and Zisserman, 2014). The basic idea of VGG is to increase the non-linearity by stacking many 3x3 convolutional layers and adding ReLUs. VGGNet has a simple structure, but it is easy to learn and has excellent performance, and the 16-layer VGG16 structure is mainly used. Because VGG16 uses a small 3×3 filter in all convolutional layers, it can form a deep neural network and has high accuracy. However, there is a disadvantage in that there are many parameters with high memory usage.

2.3.2. InceptionNet

Inception is a network published by Google that is known as GoogLeNet (Szegedy et al., 2016). The core idea of Inception is a reduction in the number of parameters by decomposing convolution and reducing the amount of computation, thus enabling rapid learning. The network was constructed via concatenation of the resulting values by configuring several small convolution layers 3×3 or 1×1 in size as a single module. Inception-V3 applies batch normalization and Inception module and changes the optimizer to the RMSProp method. Its main feature is that it learns by distributing very small values rather than using one-hot encoded values when learning correct answers.

2.3.3. ResNet

ResNet refers to a deep structured network realized by constructing an ensemble by stacking as many as 152 layers (He et al., 2016). ResNet50 is a model with 50 layers among ResNets, with the advantage of reducing the complexity and improving the recognition accuracy through a shortcut structure as the convolutional layers are repeated. ResNet makes it possible to construct deep neural networks using skip connections to pass inputs from previous layers to the next layer. In order to learn the features of a large amount of input data well, it solves problems such as vanishing and exploding gradients that appear as the layers of the CNN model deepens.

2.3.4. EfficientNet

EfficientNet uses more layers along with more receptive fields and channels relative to existing networks, allowing the model to learn the features of the images more efficiently (Tan and Le, 2019). In the scaling-up process, a compound scaling method is proposed as a method of balancing the deepening and widening the network in three dimensions while maintaining the accuracy and efficiency and increasing the resolution of the input data. EfficientNet is a deep learning model that applies compound model scaling using a neural architecture search process, which serves to find a baseline network based on reinforcement learning.

2.4. Experiments

Using the constructed dataset, four pre-learning models are trained. In total, 4,000 data instances are used in the experiment, created by dividing the train, test, and validation datasets at a ratio of 6:2:2. The numbers of specific images are summarized in Figure 5. All images are converted to a size of 224 x 224 in order to proceed with training from weights pre-learned with ImageNet; for the InceptionNetV3 model, they are converted to a size of 299 x 299. Then, preprocessing is carried out by normalizing the pixel values. The Adam (Kingma and Ba, 2014) optimizer is used as the optimizer for learning, and cross-entropy is used as the loss function. The batch size is 32, and 30 epochs at most are used for training. A deep learning framework based on the Python language is used, and a related diagram is shown in Figure 5. Training is conducted using an NVIDIA GeForce RTX 3080 graphics card in the Windows 10 environment.

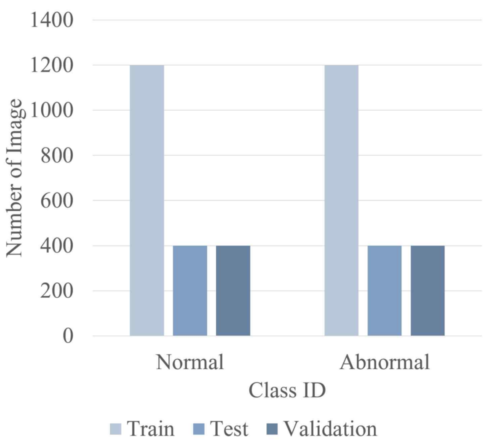

Figure 5. Overall image dataset configurations

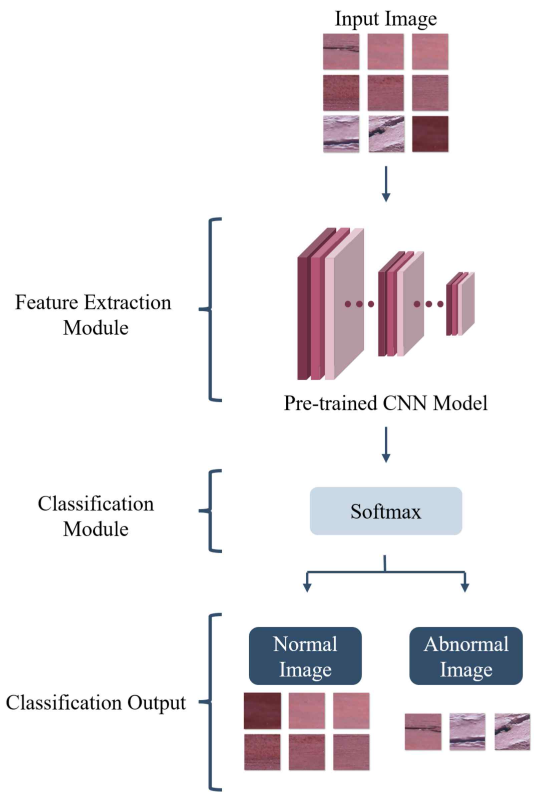

Figure 6. Architecture of the CNN model

3. RESULTS

3.1. Performance Measures

To validate the classification accuracy, we use data from a randomly split test set to evaluate how well the model performed on new data. Data from the test set are separate from the training data used for training and are used only for performance validation. To verify the classification performance of the model, commonly used quantitative indicators, in this case accuracy, precision, recall, and the F1 score, are used (Chicco and Jurman, 2020). Additionally, a normalized confusion matrix is presented to ensure the clear identification of misclassified categories.

Accuracy is the probability of how many classes have the correct label in the entire set, and precision is an indicator of the predictive ability in the set that is positively discriminated. Recall represents the probability of a certain number of positive classes in the set of total positives having the correct label. The F1 score is the harmonic average of precision and recall, and the performance when the label of the data has an unbalanced structure can be expressed as a single number and thus evaluated. The calculation formula for the performance index is expressed by equations (1) to (4) below.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \tag{1}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3}$$

$$\text{F1}_{\text{Score}} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

True Positive (TP) and True Negative (TN) represent the number of correctly predicted normal and abnormal images, respectively. False Positive (FP) and False Negative (FN) correspondingly represent the number of normal and abnormal images that are predicted incorrectly. The statistical metrics of accuracy, precision, recall, and the F1 Score can be correspondingly calculated via TP, TN, FP, and FN. A confusion matrix is a matrix that visually shows the results of the TP, TN, FP, and FN classifications. It shows the predictions made by the model for each category. Through the confusion matrix, it is possible to determine the classification accuracy according to whether or not the column is damaged, and it is possible to analyze which classification item the model incorrectly predicted for each item.

3.2. Evaluation of Deep Learning Models

The accuracy of the classification of the column surface damage is evaluated for Yeongnamnu Pavilion in Miryang, a representative wooden structure in South Korea. The final damage image classification performance is identified through the derived probability value for each class. The performances of each of the models compared to the 800 test data instances are summarized in Table 1. EfficientNetB0, VGG16, ResNet50, and InceptionNetV3 are the top performers, in that order. The EfficientNetB0 model shows the highest accuracy at 96.50%, and the InceptionNetV3 model shows the lowest at 94.00%. Hence, these results indicate that the performance comparison of CNN models for general images such as those from ImageNet does not apply precisely when assessing images in a specific field, such as cultural heritage.

Model	VGG 16	InceptionNet V3	ResNet 50	EfficientNet B0
Accuracy	0.9475	0.9400	0.9462	0.9650
Precision	0.9613	0.9210	0.9660	0.9673
Recall	0.9325	0.9625	0.9250	0.9625
F1 score	0.9466	0.9412	0.9450	0.9649

Table 1. Experimental results of CNN models

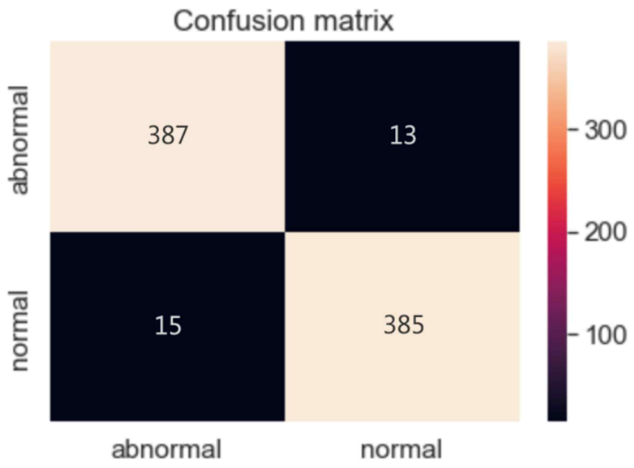

Figure 7. Confusion matrix of the EfficientNetB0 model

According to Figure 7, EfficientNetB0, as a model for determining surface damage during the remote monitoring of wooden cultural heritage sites, is confirmed to have suitable classification performance. In order to interpret the classification performance and analyze the features that affect the classification results, the convolution layer of the classification model is visualized as a heat map using Grad-CAM. In this paper, the strength of EfficientNetB0 can be confirmed when Grad-CAM is applied to the damage detection results. As shown in Figure 8, when Grad-CAM is applied to the same image, damage is not detected in the classification result image of the ResNet50 model, whereas damage is clearly detected in the classification result image of the EfficientNetB0 model.

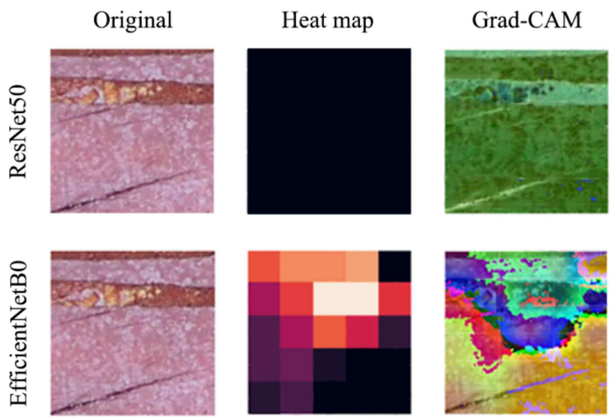

Figure 8. Visualization results of ResNet50 and EfficientNetB0

The four models misclassify the presence or absence of damage in images at an average rate of approximately 5%. As shown in Figure 9, the misclassified images have certain characteristics in common. Where the crack width is relatively narrow and short, where the boundary of the damaged area is not clear, and where the image is blurry, the model classifies the image into the normal category despite it belonging in the abnormal category. In cases in which normal images are classified as abnormal, recognition of a crack occurs in cases where the preservation state of the column is good but the grain of the wood shown in the image is clear. In addition, a normal case may be determined as abnormal depending on whether or not a shadow is cast.

On the other hand, images with obvious damage are correctly classified as abnormal. The crack width is wide and the color of the spalling area is clearly visible in such cases. Images that are well classified as normal have clean surfaces at all illumination levels. Well-classified images are not ambiguous even during a human inspection. As a result, the model performs well in field applications as a surface damage classifier for wooden heritage sites.

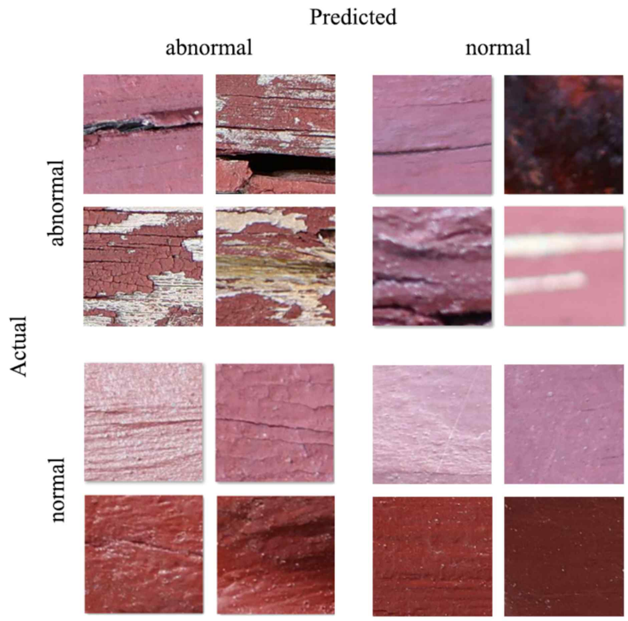

Figure 9. Classification results

4. CONCLUSION

A damage classification model based on a CNN that automatically detects surface damage on architectural heritage artifacts is proposed. In a performance verification that involved image data of the Yeongnamnu Pavilion in Miryang, the EfficientNetB0 model showed the best performance at 96.50%, indicating that it is possible to determine the damage of wooden cultural heritage sites using a CNN. This paper overcomes the limitation of professional personnel being unable to manage and supervise heritage sites continually, as the method introduced here detects damage in real time using images from CCTV devices installed at the sites. This is possible regardless of whether images are taken at day or night, and the method has the advantage of being applicable to cultural heritage sites that have blind spots or areas with low accessibility that may be difficult to discover with the naked eye.

In addition, it is possible intuitively to check the state of conservation of cultural heritage sites through a damage determination network and accumulate images at the time of the damage to compile a database. In emergency cases, it will be possible to enact an initial response and undertake appropriate preservation efforts based on the image database. In this way, by applying artificial intelligence services to actual sites, it becomes possible to break away from the existing cultural heritage preservation system that relies on the experience and subjective judgments of a small number of experts, and to bring better efficiency in terms of time use and cost in the long run. This study is meaningful as a basic study of the development of a remote damage detection system of the type required for various cultural heritage artifacts that will require protection in the future.

For application of the proposed model to numerous architectural heritage sites, convergence research is needed, not only involving wooden artifacts but also on other materials along with heritage at other locations. The results of this paper also demonstrate the possibility of expanding the research to studies of cultural heritage of different types and of different materials and locations. For application to a wide range of cultural heritage, follow-up studies are also needed to test whether the findings pertain to features commonly identified in cultural heritage images. Based on this paper, the characteristics of useful models should be studied to develop models that are most suitable for cultural heritage sites and artifacts in Korea.

A good quality dataset is essential to achieve high performance in extended study and to expect reliable results. In order to deal with about 5% of misclassification, a dataset built by thoroughly planning the camera shooting distance, angle, and illuminance in various ranges is required. Since the performance and accuracy of deep learning models depend on data characteristics, a large number of data with consistency and diversity must be secured. Since it takes a lot of time and expense to build dataset for cultural heritage, it is necessary to establish and open database nationally. These follow-up procedures have important implications for developing a remote monitoring system for cultural heritage.

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