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PAVEMENT CRACK SEVERITY MANAGEMENT BASED ON DEEP LEARNING

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Abstract. *This study presents a deep learning-based analysis and management method for Pavement Maintenance System (PMS). Existing systems collect and analyze a variety of data manually in order to assess the condition of the pavement and develop a maintenance plan. However, the manual crack analysis process takes a lot of time, and many human errors may occur due to the difficulty of objective and correct identification of fine or small cracks. In the proposed method, a CNN (Convolution Neural Network) is trained for the classification using pavement analysis information and surface images accumulated in the PMS. A memory efficient architecture SqueezeNet is used as the architecture of the training model. In addition, the effectiveness of training has been increased by using various Keras modules. The trained model classifies the images into three classes depending on the severity of the cracks in the image: no crack, preventive maintenance needed, and maintenance required. The innovative deep learning-based method proposed in this paper enables fast and objective road condition evaluation by automating the existing manual crack analysis process.*

Keywords: Pavement crack, Crack severity, Deep learning, CNN

1. Introduction.

In general, the life expectancy of the pavement in Korea is expected to be about 20 years at the time of initial construction. However, the actual repaving cycle of old roads is 5-10 years. In addition to environmental factors such as increased traffic and weather, paved roads have a significantly shorter life cycle than expected due to irregular temporary factors such as vehicle accidents and excavation recovery. In Korea, the Pavement Management System (PMS) for road management has been introduced since the 1990s. The PMS uses a mobile scanner (KRISS: Korea Roadway Infrastructure Survey System) to collect a variety of information, including road facilities, surface images, and distortions, to investigate, evaluate, and establish repair plans.

However, most crack analysis, including road condition assessment, is performed manually by human operators. The operator visually inspects the collected images to check the presence or absence of cracks, and subjectively inputs information on the size and type of cracks in accordance with established criteria. Then, the PMS analyzes the information entered by the operator and classifies the road images into three classes depending on the crack rate in the images: ‘less than 2% – no cracks’, ‘more than 2% and less than 30%

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– preventive maintenance', and 'more than 30% – maintenance required'. The operator analyzes only a few dozen photos per hour, and the accuracy is not that high. Detecting and classifying types of irregularly shaped cracks with very small size included in high resolution images is enormously difficult to apply objective criteria.

When training a deep learning model, the deeper the layer of hidden layers, the more memory is required. However, the road surface image used in this study has a very high resolution of the raw data. Therefore, in this study, the process of reducing the size of the image is necessary. However, since the area represented by the crack is very small compared to the image size, there is a high risk of loss of crack pixels in the process of reducing the size. We minimized the loss of the crack area by using an appropriate interpolation method; thus, we were able to train a deep learning model to classify small cracks.

With this background, this paper discusses how to train objective road crack severity classification model using CNN for image classification and historical data accumulated in the PMS. We trained the model to classify road images based on the data accumulated in the PMS, and propose a classification model that can replace the manual process of the existing PMS.

The PMS has been operating continuously since the 1990s, according to the network, project and research levels shown in [1]. Road information, which is the source of maintenance, uses the mobile dedicated equipment in [2] and is systematically managed according to the basic components of the PMS shown in [3]. However, the PMS currently contains manual processes that cause problems in many respects.

Various methodologies using image processing techniques have been proposed to detect cracks in pavement images. [4] applied a block-wise grid to the road images to classify the crack and non-crack regions by the pixel values contained in each block. [5] used the Gabor filter to detect the edge of an object and recognized the crack based on the filter's response and the gradient variation of the contrast. [6] identified crack regions by preprocessing the surrounding area with respect to the center point and characterizing the connectivity of the threshold pixels. Most studies assume that the noise contained in the image is not severe and the difference between crack and non-crack is obvious. Unlike previous studies, there are various difficulties in learning the classification model of road surface images used in this study. [7] described such difficulties and conducted a study on image processing methodology to increase the effectiveness of machine learning model learning.

The remainder of this paper is organized as follows. Section 2 presents the framework for training pavement crack classification model. Section 3 proposes a preprocessing method for the preparation of data to be used for training the classification model, and Section 4 describes the model training process. Finally, Section 5 offers conclusions of this study.

2. **Framework.** The proposed framework is shown in Figure 1. First, we assigned labels for each crack severity level based on the images and road information stored in the past PMS. However, data accumulated in the PMS contains unnecessary information such as survey time, investigator, road name, area, road distortion, and road parallelism, as well as crack information. For model training, only information related to cracks should be extracted, evaluated, and labeled accordingly in order to classify the cracks in the images. In addition, each road image needs to be scaled down for training the CNN model because of its high resolution of $10000 * 3739$. Appropriate resizing methods are needed to avoid losing small crack information in the image. The resized images and the corresponding label data are split into training and validation set. The training set is used for training the CNN classification model, and the classification performance is evaluated with validation accuracy using the validation set.

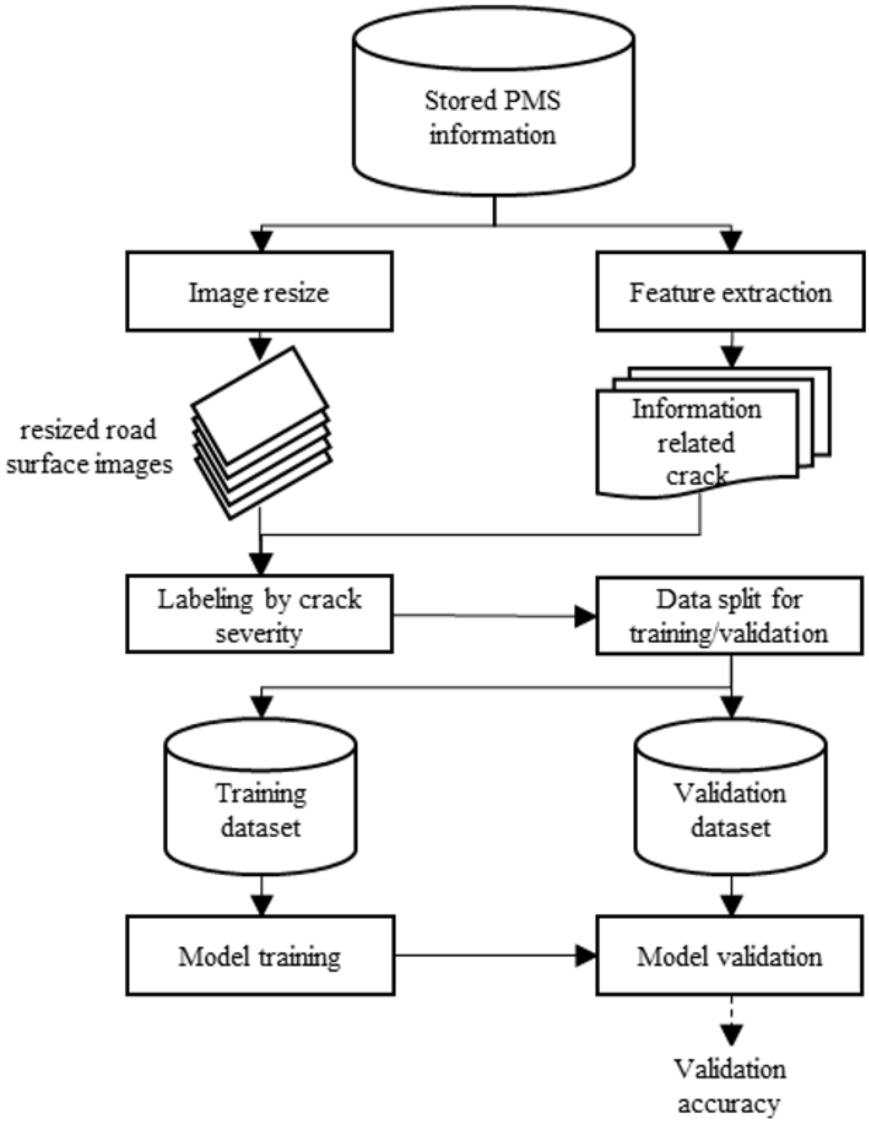

Figure 1. Framework for training pavement crack classification model

Table 1. Crack severity classification criteria

The value ranges of crack rate	Maintenance required classes
0∼2	No cracks
2∼30	Preventive maintenance needed
30∼	Maintenance required

3. **Data Preparation.** Past road information is stored in the form of a two-dimensional table. There are 8 variables related to crack, which are the comprehensive indicators: amount of crack, rate of crack, and amount of crack of each crack type (6 types). Using the extracted crack-related information, the labels of 'no cracks', 'preventive maintenance needed' and 'maintenance required' are assigned by applying the actual PMS severity criteria.

The rate of crack and the amount of crack are comprehensive metrics for six types of cracks. It is weighted and summed with different weights depending on the type, and finally, maintenance needs are classified according to the rate of crack. Table 1 shows the level of maintenance required according to the crack rate, and the image is labeled to learn the 3 classes in the table as output classes of the deep learning model.

A high-resolution image with approximately 38 million pixels of size 10000∗3739 must be scaled down for the deep neural network training. Depending on the input image and the structure of the neural network, the memory required for training increases exponentially. We scaled down an image of 38 million pixels with a resolution of $10000 * 3739$ to 100000 pixels' image with a resolution of $500 * 200$. That is, the raw image was reduced to a ratio of 1 in 374. However, it is necessary to adopt an appropriate interpolation method to preserve crack pixels appearing in small areas. Figure 2 shows the result of applying different interpolation methods to a crack image. Of the six interpolation methods applied, the Area interpolation method, unlike other linear interpolation methods, handles noise on asphalt surfaces while preserving fine cracks.

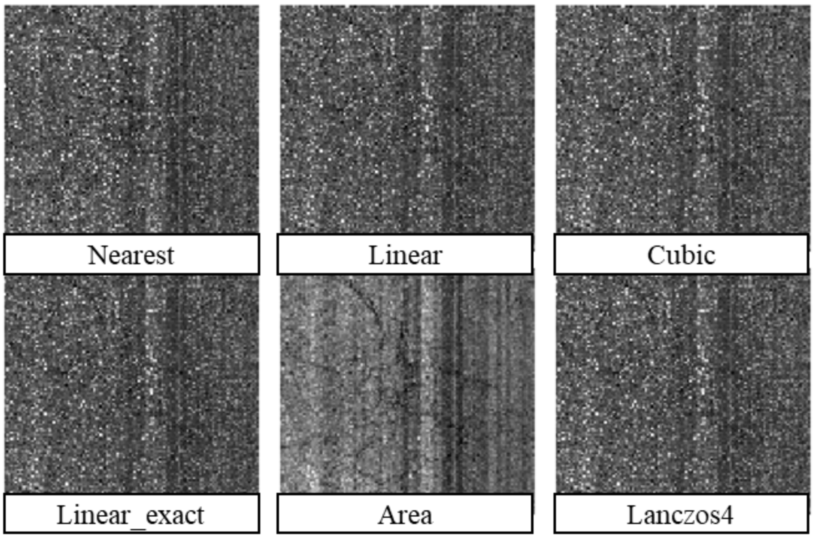

Figure 2. Crack region of reduced image with interpolation methods

4. **Training and Learning Results.** This section presents the model training for the classification by crack severity and analyzes the learning results. We used SqueezeNet, a low-memory CNN architecture developed in July 2016, and tuned for the purpose of this research. SqueezeNet delivers classifying performance similar to AlexNet and can save 50 times the memory required [8]. Considering the possibility of using small devices such as mobile devices in the future, we performed model training using low memory architecture. Table 2 details the CNN architecture tuned for this study.

In addition, we used Keras' callback classes, EarlyStopping and ReduceLROnPlateau, for the effectiveness of the model training. They operate on a loss function, each of which enables pre-termination and adjusts the learning rate for the epoch of learning that tends to overfit.

Table 2 shows a SqueezeNet-based modified model used in the study. The input layer and output layer were modified according to the image size and classes used in this study. The Conv layer extracts the features of a region by convolutional operation, and the Maxpool layer pools the regions in which prominent features appear by considering the response value of the convolution operation. The Fire layer, the most characteristic layer of the architecture, allows to maintain accuracy while using fewer parameters of the deep learning model. The Dropout layer prevents overfitting of the model, and the final class is classified with Softmax layer.

Table 3 shows the array size of the dataset, which separates 20% for validation from a total of 6000 images, and the images are grayscale images of channel 1 with a resolution of $500 * 200$. Each image is a one-hot encoded label with one of three labels: 'no cracks', 'preventive maintenance needed', and 'maintenance required'.

Table 2. Details of CNN architecture

Layer	Output shape	# of parameters
Input_1	(None, 500, 200, 1)	–
Conv1	(None, 250, 100, 64)	640
Maxpool1	(None, 124, 49, 64)	–
Fire2	(None, 124, 49, 128)	10,368
Fire3	(None, 124, 49, 128)	10,368
Maxpool3	(None, 61, 24, 128)	–
Fire4	(None, 61, 24, 256)	41,216
Fire5	(None, 61, 24, 256)	41,216
maxpool5	(None, 30, 11, 256)	–
Fire6	(None, 30, 11, 384)	92,544
Fire7	(None, 30, 11, 384)	92,544
Fire8	(None, 30, 11, 512)	164,352
Fire9	(None, 30, 11, 512)	164,352
Fire9_dropout	(None, 30, 11, 512)	
Conv10	(None, 30, 11, 2)	1,026
Global_average_pooling2d	(None, 3)	–
Softmax	(None, 3)	–
		722,370

Table 3. Array shape of training dataset

	Training dataset	Validation dataset
Image array shape	$(4800, 500, 200, 1)$	$(1200, 500, 200, 1)$
Label array shape	$(4800, 3)$	$(1200, 3)$

Table 4. Hyper-parameters of training model

Loss function	Categorical cross-entropy
Optimizer	Adam
Metrics	Accuracy
Epochs	300
Batch size	32

As shown in Table 4, categorical cross-entropy loss function and Adam optimization algorithm are used for training. The epochs values in Table 3 are only maximum values and the values can be pre-terminated less than 300 times depending on the operation of Keras EarlyStopping.

Figure 3 shows the learning curve for the classification model. Along with learning rate variation curve, the loss function values and accuracy are shown for each training and verification data set. Accuracy is not converged up to about 130 epochs, but the effect of ReduceLROnPlateau reduces the learning rate and prevents overfitting, converging to 77% of accuracy.

5. **Conclusions.** This paper showed how to transform the manual process of pavement maintenance management system into a deep learning-based automated classification model. In the current process, the operator directly examines the image and identify crack. This causes problems such as time and cost, subjective intervention of workers, and a high rate of human errors. In order to classify the image by the crack severity level, the dataset was prepared and the CNN was trained using the stored data of the PMS

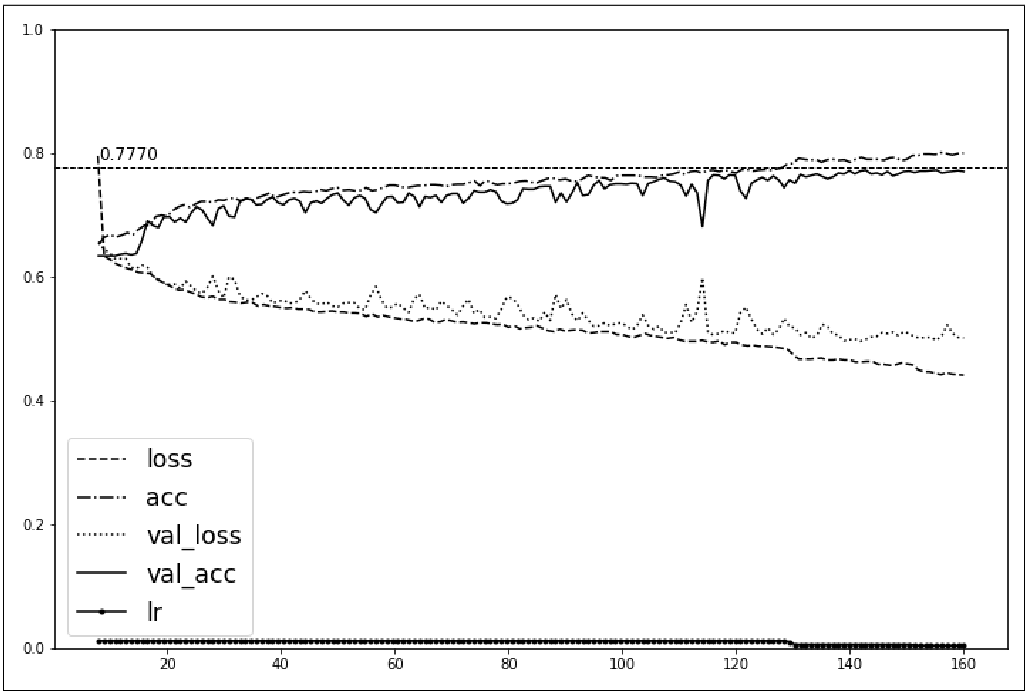

Figure 3. Learning curve of training model

analyzed in the past. As the CNN architecture for training, SqueezeNet was tuned for the purpose of this study and Keras callback was used for model learning effects. As a result, the accuracy of the classification model converges to 77.7%.

In the future, the following study will be conducted. Advanced image processing techniques are needed to preserve fine crack pixels lost during image resizing and to enhance the effectiveness of model training. In addition, an extended research is needed to determine the exact location and type of cracks. The proposed method in this study classifies the crack severity of each image, but does not know the location and type of cracks. If a precise detection of the location and type of cracks included in the image would be possible, then a more complete management system could be implemented to determine the crack repair plan.

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