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Pavement Crack Severity Management Based on Deep Learning

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Introduction

In Korea, a lot of labor is required in the process of evaluating the condition of paved roads for road management. It is a situation in which workers directly inspect and evaluate the road surface image. Detecting and classifying small cracks included in high resolution images is difficult to apply objective criteria. With this background, this paper discusses how to train objective road crack severity classification model using CNN. We trained the model by using past accumulated system's data, and proposed the model that can replace existing manual process.

Data Preparation

When we resized the images, risk of losing the crack pixels was the most concerned issue. Because tiny pixel values easily can be smoothed in scaling down the high-resolution images. Several interpolation methods were applied and appropriate methods (area interpolation) were adopted. Below is showing crack information was preserved in the 400 times scaled down image.

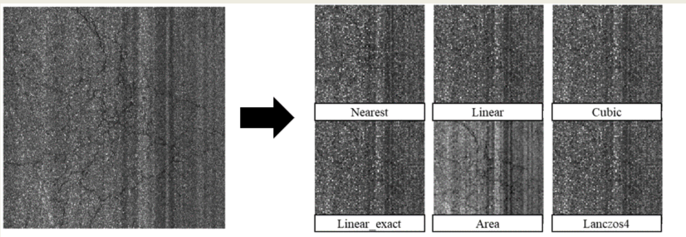

FIGURE 2. Crack region of reduced image with each interpolation applied

Research Framework

Our study was researched according to the following framework. first, we labeled for crack severity levels based on the images and pre-survey data in PMS (Pavement Management System). Next preprocess the images (like resizing), and split the labeled dataset to two parts of training and validation set. Lastly, we trained the CNN model and evaluated the classification accuracy with each dataset.

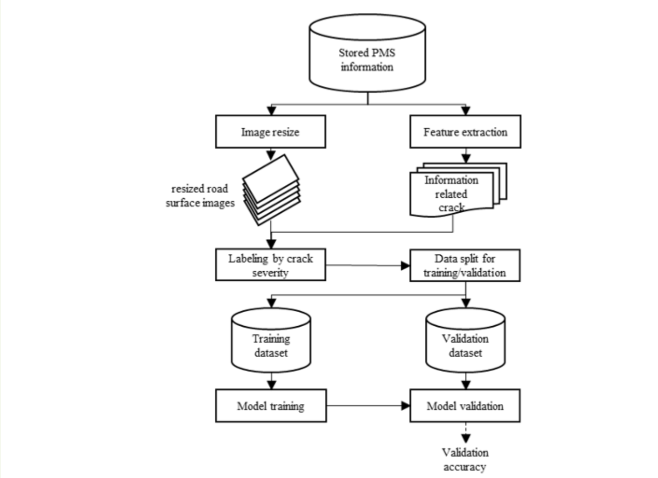

FIGURE 1. Framework for training pavement crack classification model

Model Training

Labeled dataset is used for training the classification model that predicts severity levels of cracks. Each image in dataset was labeled into one of the three classes 'no crack', 'preventive maintenance needed', 'maintenance required'.

We used SqueezeNet, a low-memory CNN architecture developed in July 2016, and tuned the one for the purpose of research. When model was trained, several Keras` modules were used for performance which are EarlyStopping and ReduceLROnPlateau.

TABLE 1. 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

For effective model training, we modified the original SqueezeNet architecture. The table above shows the layer specifications of the classification model architecture trained in the study.

TABLE 2. Array shape of training dataset

	Training dataset	*Validation dataset*
Iamge array shape	(4800, 500, 200, 1)	(1200, 500, 200, 1)
Label array shape	(4800, 3)	(1200, 3)

Table 2 shows the array shape of dataset, which is split for training and validation into 80:20.

TABLE 3. Hyper-parameters of training model

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

Table 3 is the hyper-parameters set of CNN model training. However, the epoch is variable due to EarlyStopping Keras model which can prevent overfitting.

Result

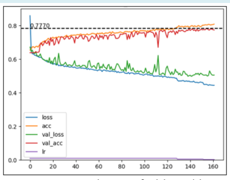

FIGURE 3. Learning curve of training model

This figure is the learning curve of model training, showing learning rate variation, with loss function value and accuracy of each training and validation. With the effect of ReduceLROnPlateau, we can see decreasing of the learning rate and the curve that converges after 130 epochs. The model has a performance of about 77% accuracy.

Conclusion

In this paper, we 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 identifies crack. This causes problems such as time and cost, subjective intervention of workers, and a high rate of human errors.

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 where the cracks are located and what type of the crack is. If a precise detection of the location and type of cracks included in the image would be possible, then a complete management system could be implemented to determine the crack repair plan.