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APPLYING MACHINE LEARNING TECHNIQUES FOR PAVEMENT ROAD CRACK DETECTION

Le Minh Nguyen[1] **Ngoc Dung Bui**[2]

[1]Division of Information Technology, Campus in Ho Chi Minh City, University of Transport and Communications, Ho Chi Minh City, Viet Nam minhnl_ph@utc.edu.vn

[2]Faculty of Information Technology, University of Transport and Communications, Ha Noi, Viet Nam *dnbui@utc.edu.vn*

***Abstract*. In a pavement management system, evaluating the pavement condition is an essential step in determining the appropriate rehabilitation strategy to use for pavement. Pavement condition evaluation includes crack identification, which plays a vital role in assessing the pavement's in-situ condition based on the existing surface distresses. However, it remains challenging due to the intensity inhomogeneity of cracks and complexity of the background, e.g., the low contrast with surrounding pavement and possible shadows with similar intensity. These conditions are a limiting factor when working with computer vision systems based on conventional digital image processing methods. In this study, the developed crack detection model relies on a deep learning convolutional neural network (CNN) image classification algorithm. For this work, a dataset with 40.000 images of concrete surfaces balanced between images with and without cracks was used. This dataset was divided into training, validating, and testing data at a 75/15/10 ratio. In each experiment, the model's accuracy was recorded to identify the best result. For the dataset used in this work, the best experiment yielded a model with an accuracy of 95.99%, showcasing the potential of using deep learning for concrete crack detection.**

Keywords; deep learning, convolutional neural networks, road crack detection, image classification

I. INTRODUCTION

Cracks are the most common road pavement surface defects. Capturing imagery of pavement surface during road surveys for crack detection and characterization is considered an adequate procedure for collecting data about the condition of the pavement surface. Keeping roads in good condition is vital to safe driving and is an important task of transportation maintenance departments. One crucial component of this task is to monitor the degradation of road conditions, which is labor-intensive and requires domain expertise.

Fig. 1. Example of road crack

Automatic crack detection and characterization systems are being developed for fast and reliable pavement surface defect analysis, instead of relying solely on the slower and subjective traditional human inspection procedures, contributing to the development of a safer survey methodology, particularly when monitoring high-speed roads like highways. Recently, computer vision and machine learning techniques have been successfully applied to automate road surface surveys. In the past decades, image-based algorithms of crack detection have been investigated widely; thresholding [1], edge detection [2] and mathematical morphology [3] are the most popular approaches among the algorithms. A recent publication [4] proposes a methodology to detect cracks using a multiscale approach based on Markov random fields to segment fine structures (cracks) in road pavement surface images. Cracks are enhanced using a 1-D Gaussian smoothing filter and then processed by a 2-D matched filter to detect them. A total of 64 road pavement surface images representing several crack types are considered for experimentation, producing a qualitative evaluation.

In [5], crack detection starts with a al. linear filter to enhance the contrast between distresses and the image background. Then, segmentation by

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thresholding and finally a pixel-based connectivity analysis is performed to identify cracks. A fractional differential and wavelet transform is presented in [6], being qualitatively compared with other edge detection operators like Sobel, Prewitt, and Logarithm of Gaussian (LoG), to show its superior performance. Afterimage smoothing with a bidimensional empirical mode decomposition, a Sobel edge detector is proposed in [7] to detect cracks. The traditional framework for crack detection designs a variety of gradient features for each image pixel, which are followed by a binary classifier to determine whether an image pixel contains a crack or not. A local binary pattern (LBP) based algorithm for crack detection is developed in [8], whereas a crack detection method using the Gabor filter is proposed in [9]. Other approaches, based on segmentation by thresholding to automatically detect cracks, where results using the Otsu threshold selection method [10] and the entropic method of Kapur [11] are compared with the neighboring difference histogram method proposed in [12]. Although hand-crafted features are widely used and support top-ranking algorithms on the well-acquired dataset, it is essential to note that they are not discriminative enough to differentiate the crack and complex background in low-level image cues. On the other hand, the impressive performances for many medical imaging and computer vision tasks have showcased the effectiveness of deep features learned by deep neural networks, which are likely to replace the conventional hand-crafted features [13]. Recently, deep learning has been proven as a powerful technique for image classification and object detection and therefore has been applied to detect cracks on the pavement.

For instance, Mandal et al. [14] used deep convolutional neural networks (DCNN) to detect road crack automatically. The author utilized images acquired from mobile cameras to make a dataset for training and testing a deep learning model. Yusof et al. [15] used DCNN for crack detection on asphalt pavement. The authors classified images into four classes, including non-crack, longitudinal, transverse, and fatigue crack. These images were used for training and testing the DCNN model. However, DCNN can only be used for image classification, which is impossible to differentiate various crack types within one image. Hence, it is necessary to propose another approach to improve the accuracy of crack detection and classification of crack type. The earlier a crack is detected, the better the chance to counter the side effects that derive from them. When performing damage assessment of infrastructures, a visual inspection provides an easy means to detect damages, especially concrete cracks, since they are apparent. However, for large infrastructures, visual inspections are time-consuming and challenging, let alone the safety aspects when dealing with areas that are hard to reach, e.g., on the highway. To facilitate that, we proposed using unmanned aerial vehicles (UAV) for visual inspection of structures, mainly because the UAV industry is providing reliable, easy-to-use, and affordable UAVs that can help inspectors improve their efficiency. In this paper, we propose a new method for pavement road crack detection with high precision. From there, build an automatic identification model by UAV.

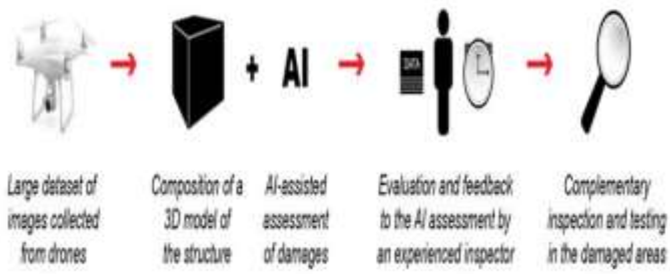

Fig. 2. Road crack detection using UAV

II. PROPOSED METHOD

With the given image of the pavement, the objective of a crack detection problem is to determine whether a specific pixel is a part of a crack. To deal with this problem, the proposed solution, based on a CNN network, is trained on square image patches with ground truth information to classify patches with and without cracks.

III. EXPERIMENT AND EVALUATION

A. Dataset

Medealy data is a secure cloud-base repository with 28.4 million datasets. The images were collected from the web and labeled by METU Campus Buildings. To train the CNN network, a total of 40,000 images with a size of 227x227 pixels were used in this study. The main idea was to collect images of concrete services at different surface appearances to increase the diversity of the dataset and, consequently, of the AI system that learns from this dataset. The classified dataset is composed of 20,000 and 20,000 images with

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and without cracks, respectively. Examples are shown in Figure 3. The dataset is divided into a training, validation, and testing dataset at a 75/15/10 ratio.

```
_________________________________________________________________
Layer (type)                 Output Shape
=================================================================
conv2d (Conv2D)              (None, 227, 227, 32)
_________________________________________________________________
activation (Activation)      (None, 227, 227, 32)
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 113, 113, 32)
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 111, 111, 32)
_________________________________________________________________
activation_1 (Activation)    (None, 111, 111, 32)
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 55, 55, 32)
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 53, 53, 64)
_________________________________________________________________
activation_2 (Activation)    (None, 53, 53, 64)
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 26, 26, 64)
_________________________________________________________________
flatten (Flatten)            (None, 43264)
_________________________________________________________________
dense (Dense)                (None, 64)
_________________________________________________________________
activation_3 (Activation)    (None, 64)
_________________________________________________________________
dropout (Dropout)            (None, 64)
_________________________________________________________________
dense_1 (Dense)              (None, 1)
_________________________________________________________________
activation_4 (Activation)    (None, 1)
-----------------------------------------------------------------
```

Fig. 3. Our proposed new method

B. Experiment setup

Our experiments have been conducted using Python programming language with Keras, Tensorflow on Google Colab with Tesla K80 GPU.

C. Processing

The model is trained according to the algorithms described in the previous section. We set the batch size equal to 250. We initialize all of the weights using a Gaussian distribution with the zero mean and standard deviation of 0.02. Each layer has some same parameters: the bias is initialized by 1, the momentum is set as 0.9, and the weight decay for L2-regularization is set as 0.02. The dropout rate for two fully connected layers before the last one is set to 0.5. The model is trained in 30 epochs.

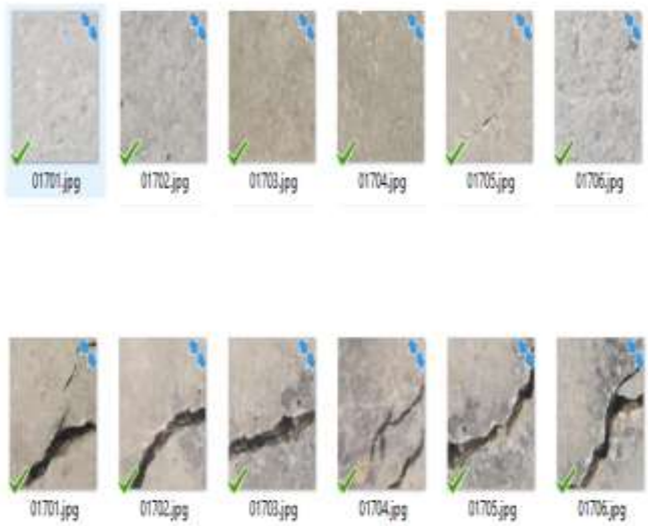

Fig. 4. Examples of the images that compose the reference concrete image dataset

D. Result

Figure 5 shows the plot of model accuracy and loss during the training phase. And table 1 shows the comparison of our proposed method with the other methods.

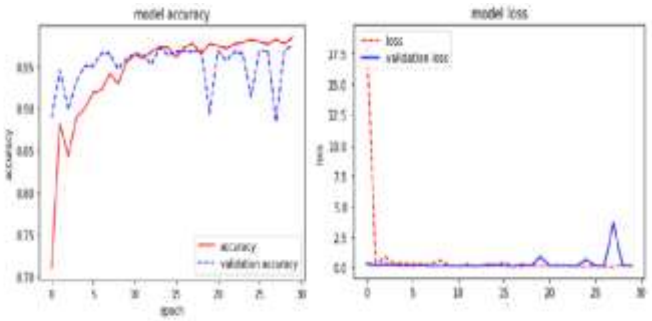

Fig. 5. Accuracy and loss during the training phase

TABLE 1. CRACK DETECTION PRECISION

Method	Precision
SVM	0.8112
Boosting	0.7360
ConvNets	0.8696
Our proposed	0.9599

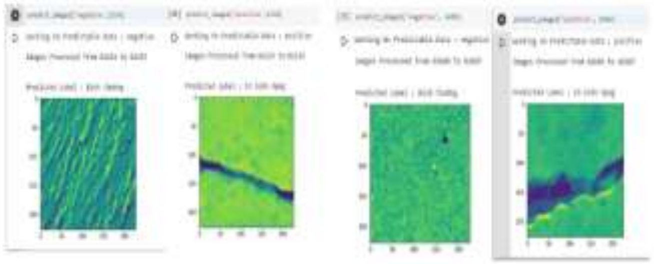

Fig. 6. Sample detection results of our method

The results after training were tested on 2km of highways, using the UAV Phantom 4 flying device with a 4K camera, 2m above the road surface, with an accuracy rate of 60%. The UAV collects images data through the camera and sends it to the device controlled by a smartphone. Smartphone software uses the trained data from the above model to identify and detect cracks, thereby providing warnings and GPS location to transportation departments. Data is processed according to two methods: real-time and post-processing

IV. CONCLUSION AND PERSPECTIVES

We proposed an automatic detection method based on deep convolutional neural networks. The features are automatically learned from manually annotated image patches acquired by a low-cost sensor, i.e., smartphone and automatic devices like UAV. To the best of our knowledge, this study applies a deep learning-based method to road crack detection problems with high precision. In the future, we will optimize the proposed detection method and build a low-cost integrated system for real-time road crack detection.

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