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Deep convolution neural network for crack detection on asphalt pavement

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Abstract. Asphalt cracks are one of the major road damage problems in civil field as it may potentially threaten the road and highway safety. Crack detection and classification is a challenging task because complicated pavement conditions due to the presence of shadows, oil stains and water spot will result in poor visual and low contrast between cracks and the surrounding pavement. In this paper, the network proposed a fully automated crack detection and classification using deep convolution neural network (DCNN) architecture. First, the image of pavement cracks manually prepared in RGB format with dimension of 1024x768 pixels, captured using NIKON digital camera. Next, the image will segmented into patches (32x32 pixels) as a training dataset from the original pavement cracks and trained DCNN with two different filter sizes: 3x3 and 5x5. The proposed method has successfully detected the presence of crack in the images with 98%, 99% and 99% of recall, precision and accuracy respectively. The network was also able to automatically classify the pavement cracks into no cracks, transverse, longitudinal and alligator with acceptable classification accuracy for both filter sizes. There was no significant different in classification accuracy between the two different filters. However, smaller filter size need more processing training time compared to the larger filter size. Overall, the proposed method has successfully achieved accuracy of 94.5% in classifying different types of crack.

1. Introduction
Road has constructed and carefully designed as a the most primary element for connecting urban and rural areas [1] that gives benefit to economic and social development [2]. The road network usually consists of thousands of miles of pavement [3] which exposed to different environmental conditions such as repeated traffic loading, temperature fluctuation and moisture variation which roadway defects may arise due to these problem [4][5].

Cracks are one of the most serious defects in the asphalt road surface [6]. Common types of cracks are mainly categorized into three groups: transverse cracks, longitudinal cracks, and alligator cracks [5] [7][8] as shown in Figure 1. Potholes are formed making the road becomes more dangerous if these early deteriorations are left untreated [9]. Therefore, an early detection and maintenance programs have been developed with the aim to monitoring the pavement crack information [10], thus, increase the performance and lifespan of the pavement.

Figure 1. (a) Transverse crack   (b) Longitudinal crack   (c) Alligator crack

In developing countries, crack detection analyse by human inspection, so called non-computer vision as the main method for conducting pavement inspection [11][12]. The non-computer vision methods involved the traditional inspection of pavements by surveyors, going over the road which is uneconomical, labour intensive, human subjectivity and dependency of expert knowledge [13]. In contrast, rapid development of computer vision and image processing has become dominant approach [14][15], and successfully applied since automated crack detection systems are faster, low cost and more robust to detect cracks [16].

Image processing become the cost-effective and efficient method [17][18] for pavement crack detection. Image processing techniques such as the intensity thresholding, edge detection and sub-window based hand-crafted feature extraction methods are widely used in practice [19]. These systems have proven their effectively of detected pavement surface, but there remains a need for further improvement, especially in classification for types of pavement cracks [20]. However, non-computer vision and computer vision method suffer from several issues such as struggling in extracting cracks features from the pavement consists of shadows and complex background of pavement [19] and extract cracks using low-level image cues [20]. Presently, road condition monitoring in Malaysia has been struggling to produce production-worthy, low cost and fully automated systems. Furthermore, no previous method that can be distinguish between crack and non-crack and further classify to recognised cracks into specific cracks such as transverse, longitudinal, and alligator cracks [20]. Therefore, it is an advantage for surveyors to apply these research results directly in practical scenarios.

Deep Convolutional Neural Network (DCNN), introduced in 1980 [20] and in the early 2000s increasingly continuing as the most powerful technology and remarkable performance for image classification [21][22][23], image segmentation and recognition of object [24][25] compared to other computer vision method. DCNN also have shown highly effective in processing visual data, such as images and videos.

Cha et al. [26] and Zhang et al. [27] demonstrated CNN in recognizing cracks on surface of concrete structures without designing hand-crafted feature extractor. The proposed DCNN was compared their performance with traditional Canny and Sobel edge detection methods. Their study achieved high performance on pavement crack classification regardless of the intensity inhomogeneity and complexity of background. Furthermore, the application of DCNN for road surface damage identification has been proposed by few studies, for example, studies by Zhang et al. [27] demonstrated an automatic detection method based on deep convolutional neural using a 99×99 patch obtained from a 3264×2448 pixel image with comparison existing hand-craft methods.

Considering this, the study proposed the end-to-end pavement crack detection and classification method based on deep convolution neural network to the asphalt pavement cracks and verify network with the newly created pavement cracks dataset and respect to processing time as well. The rest of the

paper is organized as follows. In Section 2, we discuss the related works. Details of network new dataset are presented in Section 3. The experimental results are explained in Section 4. Finally, Section 5 concludes the paper.

2. Methodology

This section will discuss in detail on the proposed methodology. The method consists of three (3) steps which are developing of pavement crack image acquisition system, pavement crack dataset for training DCNN and crack detection and classification using DCNN.
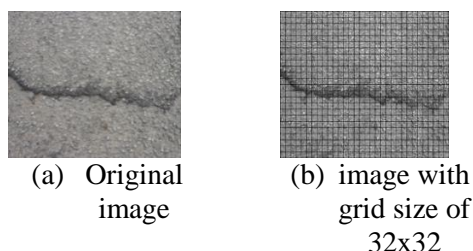
2.1 Pavement Crack Image Acquisition Method

Image acquisition plays a crucial role in preparing the raw images to the network which apply on static image with all the images are taken by Nikon digital camera with a resolution of 16 Megapixels with its optical axis perpendicular to the ground surface. The image capturing will serve during daylight with the distance of crack images to the ground level is approximately 70 cm to 100 cm contains noises such as shadows, oil spots and water stains, and different variations of background. Image data was collected at various sections of roads in Kedah and Penang district. A total of 4000 RGB images which consist of 1000 images each for no crack, transverse, longitudinal and alligator are randomly selected from the collected dataset. The original images produced a resolution of approximately 3500 x 4500 pixels and then resized to 1024x768 pixels to reduce the memory usage and processing time while ensuring the input dimension fit with the DCNN.

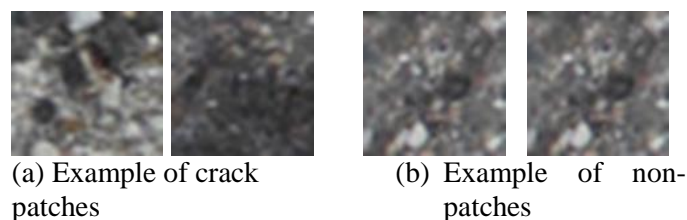### 2.2 Pavement Crack Dataset for Training DCNN

The network prepares two sets of training and testing dataset: crack and non-crack dataset, and binary dataset consists of no crack, transverse, longitudinal and alligator.

2.2.1 Training dataset for crack and non-crack

The development of crack and non-crack training dataset does not need the whole captured images to train as crack and non-crack dataset. In this work, we set the patch grid size of 32x32 pixels to segmented the image with a dimension of 1024x768 pixels (refer Figure 2(a) to create 768 patches (refer Figure 2(b)) for each image. Therefore, 400 RGB images (10% from the total capture image) to generate crack (refer Figure 3(a)) and non-crack (refer Figure 3(b)) patches. Out of the grid scale generated, the total patches obtained 307,200 patches consists of 24,576 crack patches and 282,624 non-crack patches. As the input image segmented, both training and testing dataset are made of these patches. The 9000 patches are chosen which divided into 4500 patches of crack and 4500 patches of non-crack as a training dataset. Table 1 shows the the number of training and testing dataset for crack and non-crack. Table 2 tabulates the number of training and testing dataset for crack and non-crack patches.

(a) Original image	(b) image with grid size of 32x32

Figure 2. RGB input image

(a) Example of crack patches	(b) Example of non-patches

Figure 3. Crack and non-crack patches

Table 1. Number of patches for crack and non-crack

No of image	No of patch	Crack	Non-crack
1	768	66	702
400	307,200	24,576	282,624

Table 2. Number of training and testing dataset

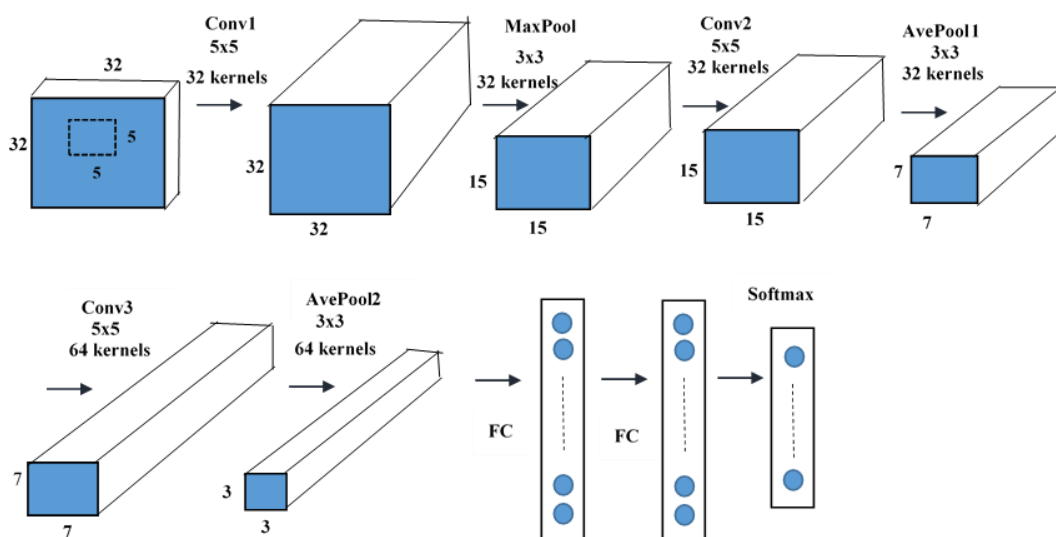|	Crack	Non-crack
Training set	4500	4500
Testing set	500	500

2.2.2 Training dataset for no crack, transverse, longitudinal and alligator
The RGB images were collected by manual to train the DCNN per category for no crack, transverse, longitudinal and alligator images, preparing for classification. Thus, the training data included 5700 binary images, and the testing data had 460 images. This network adopted as the optimizer with default setting with the initial learning rate is 0.001. The batch size is set to 10 for every 50 iterations.
The binary images as the input of the DCNN aims to evaluate the classification performance on 360 testing images for further classify cracks into three types: transverse, longitudinal and alligator using filter size of 3x3 and 5x5 as well.

2.3 Crack Detection and Classification using DCNN
The proposed DCNN architecture for crack detection and classification is illustrated in Figure 4.

Figure 4. Proposed DCNN architecture

This study proposed a DCNN with three convolution layers, three pooling layers and two fully connected layers. The patches of crack and non-crack are used as input of the network with 3 channels in

DCNN. Convolution layers: Conv 1, Conv2 and Conv3 are equipped with filter size of 3x3 or 5×5 and stride of 1 respectively. According to previous study in DCNN [28][29][30], all filters are suggested to have size not greater than 7x7 to avoid difficulty during the training process. In addition, convolutional layers are parameterized by the number of channels, filter size, number of stride, and number of padding [31].

Convolutional networks may include pooling layer, hence the proposed network consists of max pooling (MaxPool) and average pooling (AvePool) which performed with stride 2 over a 3×3 window. The stride defines how many of columns and rows in the receptive field slide to produce new input width and height [26]. Computational process may reduce if using a larger stride size which leads to produce fewer receptive field applications and a smaller output size. In contrast, larger stride size may also lose features of the input data. Another key aspect of the DCNN is a pooling layer. Max pooling takes the max values from an input array's sub-arrays, whereas average pooling takes the average values [26]. Finally, the flattened output fed into multiple fully connected (FC) as the last layer to predict the pavement detection [31] into two classes: crack and non-crack and pavement cracks classification into no crack, transverse, longitudinal and alligator. The rectifier linear unit (ReLU) was introduced by Nair and Hinton [32] as a nonlinear activation function, adopted after convolution layer for dealing with nonlinearity for multi classification [32].

The study employed quantitative analyses to evaluate the performance of DCNN in classifying the pavement patches. The performance of crack detection was computed using three (3) performance indicators; recall, precision, and accuracy. Recall refers to the percentage of actual crack grid that were correctly classified by the DCNN. Precision may refer to the percentage crack pixels classified correctly with corresponding to a total number of cracks in the dataset. Meanwhile, the accuracy refers to the percentage of total crack and non-crack classified correctly with corresponding to the total of crack and non-crack in the dataset [33]. The recall, precision and accuracy can be calculated as follows:

$$\mathrm{Re}\,call = \frac{TP}{TP + FN}$$

(1)

$$\mathrm{Pr}\,ecision = \frac{TP}{(TP + FP)}$$

(2)

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)}$$

(3)

3. Experimental Results

In the first step, the trained DCNN was applied to 1000 testing dataset to explain how the input image has been classified for crack and non-crack of its patches of 32x32. The DCNN was applied to the testing images for analysis on network performance for crack and non-crack detection using the filter size of 3x3 and 5x5. Recall, precision and accuracy are calculated and used in validating the network performance. The results are shown in Table 3.

Table 3. Recall, precision and accuracy with different filter size

Filter size	Recall	Precision	Accuracy
3x3	98.1%	99.1%	99.0%
5x5	98.0%	99.0%	99.0%

Table 3 shows the experimental result achieved network performance in terms of recall, precision and accuracy of 98.1%, 99.1% and 99.0% respectively with the objective to determine the crack detection for filter size of 3x3. Whereas, by using filter size of 5x5, it seems no different in network performance which provides 98.0%, 99.0% and 99.0% for recall, precision and accuracy respectively. However, smaller filter size (3x3) need a higher processing time to train the network compared to larger filter size (5x5). Therefore, the filter size of 5x5 finish to train faster compared to the smaller size

After crack and non-crack detection was analyse, another testing dataset was fed to the same architecture of DCNN. The second stage demonstrated the binary image as the input of the DCNN aims to evaluate the classification performance on 360 testing images for further classify cracks into three types: transverse, longitudinal and alligator. Table 4 summarises the performance of the network with overall transverse, longitudinal and alligator performance which demonstrates that all of them can perform a high accuracy classification using filter size of 3x3 and 5x5. Meanwhile, Table 5 lists the comparison on performance of the network using DCNN. In general, these methods show the high performance in terms of precision (Pr), accuracy (Acc) for pavement detection and transverse (T), longitudinal (L) and alligator (A) for pavement classification as well. By referring to Table 4, Paul et al. [33] used 500 RGB pavement images as testing dataset, achieved 91.9% and 90.2% for precision and accuracy respectively to detect crack and non-crack.

Table 4. Three type cracks classification with different filter size

Filter size	Transverse	Longitudinal	Alligator
3x3	97.1%	97.4%	99.0%
5x5	97.0%	97.1%	99.0%

Table 5. Comparison result using DCNN architecture

Method	Crack detection		Crack classification		
	Pr	Acc	T	L	A
Pauly et al., 2017	91.9%	90.2%	-	-	-
Cha, Choi, & Büyüköztürk, 2017	-	97.9%	-	-	-
X. Wang & Hu, 2017	-	-	97.6%	97.2%	90.1%
Our method	99.1%	99.0%	97.0%	97.1%	99.0%

According to Cha et al. [34], used 332 images and create 40K images as a training dataset and 55 images for testing. They trained CNN to detect crack and non-crack that achieved the result of accuracy is 97.9%. Compare to our proposed method, the network managed to achieve 99.1% and 99.0% for precision and accuracy respectively with only 9K for training dataset purposes with 1000 testing images.

Refer to X.Wang et al. [35] result, they managed to get 97.6%, 97.2% and 90.1% for correct classification of transverse, longitudinal and alligator by using 310 testing images. The proposed of the study, obtained the experimental result to classify into three classifiers with promising performance of 97.0%, 97.1% and 99.0% for transverse, longitudinal and alligator respectively using 360 testing images with only used 4.5K training dataset with filter size of 5x5 as the optimal performance.

To be useful for the surveyors, it is essential to compose additional classification to reflect the real situation. Hence, the pavement with no crack also demonstrated for crack classification. By using 5.7K

training dataset and 460 testing images, the network explore the performance for four types of pavement classification using the same DCNN architecture.

Table 6. Four type pavement classification with different filter size

Filter size	Transverse	Longitudinal	Alligator	No crack
3x3	91.2%	90.0%	99.0%	98.0%
5x5	91.0%	90.0%	99.0%	98.0%

Based on experimental result in Table 6, the classifications of transverse crack and longitudinal crack have a lower accuracy than others. It happened when the DCNN confused to distinguish cracks pattern between transverse and longitudinal cracks with no cracks pavement. This may be caused image consist of complexity background such as noise, oil stain and water spot indicates the similarity darker background that the pixel is more likely to be a crack pixel.

Table 7. Comparison result using DCNN with different filter size

Experiment 3					
Method	NC	T	L	A	Overall
Li et al., 2018	93.0%	97.7%	97.3%	89.3%	94.3%
Our method	98.0%	91.0%	90.0%	99.0%	94.5%

From Table 7, shows summarising the recent research works on pavement crack classification. In general, Li et al. [20] achieved high performance using the same filter size of 5x5 for no crack (NC), transverse (T), longitudinal (L) and alligator (A) classification with overall performance of 94.3%. Our proposed method can obtained 94.5% accuracy, slightly higher than Li et al. [20]. The proposed method has a reliable performance to classify pavement cracks into four categories with the minimal training dataset (refer Table 8).

Table 8. Composition training and testing dataset

Method	Dataset	NC	T	L	A
Li et al., 2018	Training	5552	5184	5419	5445
	Testing	300	300	300	300
Our method	Training	1200	1500	1500	1500
	Testing	100	130	130	100

4. Conclusion

In this study, an automatic pavement crack detection and classification has been proposed. The system uses DCNN for both to detect and classify the asphalt pavement crack. In total, four types of cracks are successfully trained using DCNN with 9K training dataset to classify two classes (crack and non-crack) and 5.7K training dataset for four classes (no crack, transverse, longitudinal and alligator). The experimental results reveal that the size of filter has an important influence on processing training times where smaller filter size require far more iterations to converge compared to the larger filter size. On the other hand, the filter size (3x3 and 5x5) has almost no effect on the classification performance of the proposed DCNN. The research shows that the proposed DCNN with filter size of 5x5 is the optimal one. Although the results of the analysis showed a great potential for using the system as an automatic road

pavement detection, but still facing problems in image consists of noisy background. The existence of noisy patterns such as shadows, oil stains, and water spot on pavement surfaces makes detecting cracks very challenging task since most of the noisy patterns have similarity of crack intensity and stronger contrast compared to the tiny cracks [36]. Further research should be conducted on how to contribute the pavement cracks to classify into four categories especially for transverse and longitudinal cracks by improving pixels algorithm in order to manage pavement consist of noise pattern.

Acknowledgement

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