Automated Recognition of Asphalt Pavement Crack using Deep Convolution Neural Network

Nor Aizam Muhamed Yusof[1], Muhammad Khusairi Osman[1], Mohd Halim Mohd Noor[2], Nooritawati Md Tahir[3], Anas Ibrahim[4], Norbazlan Mohd Yusof[5]

***Abstract*— Pavement distress results in huge predicament such as environmental pollution, traffic congestion, accident and mental health. It can be classified into cracking, potholes rutting and ravelling, however cracking is the most prevalent damage on asphalt pavement. Effective and efficient pavement maintenance is crucial to identify the underlying problem, analysis of the information and selection of the most suitable rehabilitation measure. In road maintenance work, surface cracks provide insight and important information to the surveyors regarding unfavourable pavement condition in order to take effective action for maintenance and rehabilitation plan. Recently, crack identification and evaluation system using image processing technique has been proposed by several researchers to automate the manual survey process in road maintenance. However, the proposed methods often yield poor and unsatisfactory performance due the complexity of pavement texture, uneven illumination, and non-uniform background. This study proposed a deep convolution neural network (DCNN) as an alternative to image processing method to detect the existence of pavement crack in corresponding size of input image. Firstly, the study segmented the input image of the pavement into three different sizes: 28x28, 32×32 and 64×64 to produce training dataset for the network. Each training dataset is used to train the DCNN which consists of 6000 crack and non-crack patch images. Experimental results show that the highest crack detection rate was achieved by using image size of 32x32. The DCNN using this image size obtained recall, precision, accuracy and F-score of 98.7%, 99.4%, 99.2% and 99.0% respectively.**

***Keywords*—asphalt pavement, deep convolution neural network, pavement crack detection, pavement distress**

This manuscript is submitted on 13th May 2019 and accepted on 31th July 2019. N.A.M Yusof[1] and M.K. Osman[1] are from Faculty of Electrical Engineering, Universiti Teknologi MARA, Pulau Pinang, Malaysia.

M.H.M. Noor[2] is with the School of Computer Science, University Sains Malaysia, Malaysia.

N.M. Tahir[3], is from Faculty of Electrical Engineering, Universiti Teknologi MARA, Shah Alam, 40450 Selangor, Malaysia.

A. Ibrahim[4], is from Faculty of Civil Engineering, Universiti Teknologi MARA, Pulau Pinang, Malaysia

N.M. Yusof[5] is from PLUS Berhad (e-mail:bazlan@plus.uemnet.com).

I. INTRODUCTION

Scheduled road assessments and a well-planned program of maintenance are essential to maintain the road in a safe and satisfactory serviceable condition Scheduled road assessments and a well-planned program of maintenance are essential to maintain the road in a safe and satisfactory serviceable condition [1].

Surveyors routinely measure pavement cracking as a part of road management activities with an effort to maintain pavements in a cost-effective manner [2]. Mainly, in civil engineering field, several different types of pavement distress can develop in asphalt pavements such as cracking, rutting, fretting, and loss of texture [1].

Cracks are the most common pavement distress and typically divided into transverse crack, longitudinal crack and alligator crack [3][4]. Transverse cracks occur roughly perpendicular to the centerline of the pavement while longitudinal cracks occur parallel to the centerline of the pavement. Alligator cracking is an interconnection of rectangular cracks on an asphalt pavement surface [5]. Moreover, cracks tend to deteriorate with time under the influence of repeated traffic loading and environmental variations, therefore, the use of fast and accurate monitoring techniques becomes critical for pavement detection and classification [6].

Pavement crack detection can be analysed by using two ways inspection which is manual inspection and automated inspection [7]. Manual inspection involved direct human intervention [8][9]. The road surveyors need to travel along the road to detect the defects of pavement using visual inspection which dependancy on knowledge and experience of surveyors. However, this method has certain drawbacks as they are not capable on a large area of crack inspection in a timely manner which costly and very time consuming techniques.

In order to overcome this problem, several researchers have applied image processing techniques and artificial intelligence to automate the pavement crack detection process [10][11]. Image processing is one of the tools of computer algorithm and become the most commonly computer tool technique to employ in a wide range of efficient algorithms in many applications [12][13].

Talab et al. [14] have converted the original concrete image to gray scale image and applied Sobel filter to eliminate noise in order to get the region area. They successfully extract background and foreground image using a suitable threshold in a binary image for detecting cracks in concrete image structures.The study show the ability of image processing technique to provide a fast, accurate and non-subjectivity crack detection rate, as well as the alternative to manual inspection. However, image processing is facing challenges to analyse the pavement images that consist of shadows and complex background caused by scattered lighting condition, oil spot on the pavement surface, shadows and unwanted objects may further decrease the performance of pavement detection and classification [15][16].

Qingbo et al. [4] implemented grey level transformation, median filter and image intensification using image processing method. The main function of grey level is to extract the background image whereas the median filter method can eliminate isolated noise points in the image. Additionally, image intensification applicable to concentrate over contrast and brightness of the image. The results show that the proposed method has effectively removed the isolated noise point, smoothen the edge and improved the segmentation accuracy.

Tsai et al. [17] developed a fully automated system for pavement crack detection. The system using emerging 3D laser technology evaluated the crack detection with images consist of poor intensity under different lighting condition. The results show the system can effectively detect cracks during night time, daytime with shadow and no shadow, and cracks involved with low intensity contrast as well. Cheng and colleagues [18] determined the crack darker pixels for gray levels by calculating the brightness function based on the algorithm of fuzzy logic in the image. The result shows the system can effectively check the connectivity of the darker pixels and finally are able to classify cracks even from complex pavement images. Other than that, threshold method using Otsu method proposed by Wang et al. [19], has been widely used in detecting the pavement crack. Some other researchers proposed different prevalent work such as morphological operations [17], geometric features [16], wavelet features [20], or histogram of oriented gradient (HOG) [21]. However, all of these approaches still produced unreliable results when handling images with different illumination intensity, irregularities in crack surface, and variation of the crack texture [20][21].

To overcome these problems, a number of researcher have focused on improving crack detection algorithms by integrating the image processing techniques with artificial intelligence [22]. Saar et al. [23] proposed an automatic system that used image processing techniques to extract features from road images. They used a neural network approach to perform detection of the image region and further classify cracks into longitudinal, tramsverse and alligator. The proposed system showed effectively identify and classify defects with good results for longitudinal and transverse but alligator crack classification showed poorest results due to thin cracks which the system was unable to detect. They are expected to have a better result by increasing the training dataset to improve the alligator result.

Other researcher, Kaseko and colleagues [24] presented an integration of artificial neural network models with conventional image processing techniques to classify pavement surface cracking by the type and severity of cracks detected. They used an automatic thresholding for image segmentation and also used the same thresholding method to determine the crack type with the severities in each image as well. The proposed method successfully detect and distinguish the types of cracking asphalt concrete pavement surfaces with quite reasonable accuracy but still requires further research due to the loss of fine cracks during the process of image segmentation.

Recently, a branch of artificial neural network called deep neural network (DNN) with a specialised architecture has shown a high potential in solving different illumination intensity and the complexity of crack background. DNN consists of more layers compared to typical neural network where the models are able to extract and build better features than shallow network in order to achieve better result in detecting pavement crack [25].

The area of DNN started gaining popularity in 2012 when Alex Krizhevsky proposed a DNN called AlexNet to demonstrate the capability of deep network architecture.Based on Krizhevsky et al. [26], they trained a large, deep convolutional neural network to classify the 1.2 million high-resolution images in the ImageNet LSVRC-2010 contest to classify 1000 image classes. Their work achieved error rates of 37.5% and 17.0% which is considerably better than the previous state-of-the-art method.

Pauly et al. [27] has proved that as the number of layers are increased the accuracy and recall of the network will also increases. The proposed method provided high accuracy because as the networks get deeper it learns more and more discriminative features from the images that helps the networks to differentiate the pavement cracks from non-crack images.

Deep convolution neural network (DCNN) is one of the possible solutions to adapt in various research applications for image classification and recognition. The DCNN able to increase the detection rate using its three primary layers called convolutional layer, pooling layer and the fully connected layer is widely used for classification.

Zhang and colleagues [28] demonstrated a DCNN for pavement crack detection using six layers network consist of four layers of convolution and pooling and two fully connected layers. This study conducted on a data set of 500 images of size 3264 × 2448 collected by a low cost smart phone, segmented into 99x99 image size and finally generated 640,000 patches are used as the training set.. The proposed method was the first study applied DCNN and successfully provided superior performance in correctly classify crack and non-crack patches from the image. The results show 86.9%, 92.5% and 89.6% for precision, recall and F-score respectively.

Meanwhile, X.Wang & Hu [29] applied CNN using 64x64 scales of grid to detect pavement cracks.The images were captured using iphone with the pixel of camera was 3264×2448.prepared 30,000 images as a training dataset. The segmented image size of 64×64 showed better comprehensive performance for recall and F-score. The experimental result achieved 97.2%, 97.6% and 90.1% correct rate of classification for longitudinal crack, transverse crack and alligator crack, respectively.

The study by Y.Cha et al., [30] introduced DCNN to build a classifier for detecting concrete cracks from images. The 277 images were cropped into 40 K images with 256 × 256 pixel resolutions for training and validation. The result showed better performance and can indeed find concrete cracks in realistic situations with accuracy of 98.22%.

Other researcher, A.Zhang et al., [31] developed CrackNet consists of five layers trained with 1,800 training images and successfully detected cracks under various condition. The image collected by the PaveVision3D system with size 4,096 × 2,048. The total of 200 testing images of size 1,024 × 512 as a whole input image, achieved 90.13%, 87.63% and 88.86% of precision, recall and F-score simultaneously.

In view of all that has been mentioned DCNN so far, it is clearly proved as a robust classifier and consistently shown successes in detecting pavement cracks into crack and non-crack that is less influenced by the noise caused by lighting, shadow, oil stain and water spot. However, most studies in the field of DCNN for pavement crack detection have only focused on selection a large size of input image that need a longer processing time due to the large image is more difficult to be trained instead of using the smaller image size. Furthermore, using large input image need a high computational cost such as a good performance of graphic processing unit (GPU) and computer hardware optimization to execute the computational efficiency in preparing a large scale of training dataset.

Therefore, this work try to fill this gap and study the effects using different input size of image are employed in DCNN. The main purpose of this study is to develop pavement crack detection using a smaller input size of image considering to reduce the processing time of network with acceptable performance. The novelty of the study is a design of a new architecture for crack detection where the network composed of five layers to explore how well the performance affects the recall, precision, accuracy and F-score. The other content is described as follows. Section 2 explains in detail the image sample and methodology used in this study. The results and discussion are presented in Section 3. Finally, Section 4 concludes the finding of this study.

II. Methodology

This section discusses in detail the entire process of the proposed methodolgy. In general, the method comprises four (4) parts which are image acquisition, image pre-processing and labelling, detection and classification using DCNN and performance evaluation. The following sub-sections will discuss each part of the methodology in detail:

A. Image acquisition

Image acquisition is the first part of preparing raw images to be processed for any computer vision system. Images were captured using a digital camera, Nikon Coolpix S6150 under natural lighting conditions. The image acquisition system was placed on a flat road surface and camera was positioned perpendicular to the road surface with the height range is from 0.8 m to 1.0 meters from the ground level (Refer to Fig. 1). In order to prevent the presence of shadows, the images were taken on a sunny day and tried to avoid direct bright sunlight while the images were captured.

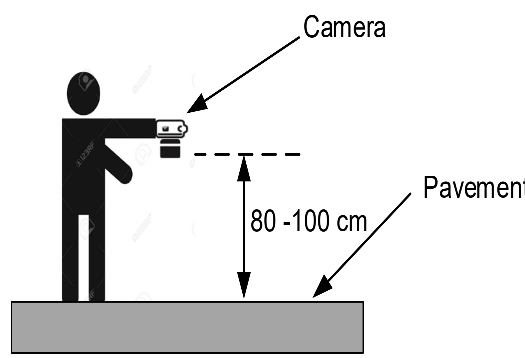


Fig. 1. Set up of image acquisition

The original pavement image captured by camera is a high resolution colour (RGB) image with resolution of 3456x4608 pixels. These images were saved as a file in jpg format. A total of 120 RGB images consist of 40 images each for transverse, longitudinal and crocodile cracks were captured throughout the road in Kedah and Penang district. Example of images are shown in Fig 2. The original images were then resized to the dimension of 1024x768 pixels to reduce computational cost, memory usage, tailor to the proposed DCNN architecture and without losing its quality.

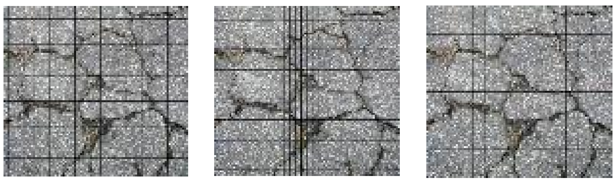
(a) (b) (c)

Fig. 2. Example images captured using the digital camera;
(a) longitudinal crack (b) transverse crack and (c) crocodile crack

B. Image pre-processing and labelling

The network prepares three sets of training and testing dataset. For the first training set, a total of 100 RGB segmented for grid scale of 28x28, 32x32 and 64x64.

Selection of proper input image size is important in training a DCNN. After image resizing process, the image is partitioned into sub-images or patches, as shown in Fig. 3a. In this study, patches of three (3) different sizes (28x28, 32x32 and 64x64) as shown in Fig. 3b are extracted from the sub-images and used to analyse them for training the DCNN. Each extracted patch is then labelled with the value of 1 for crack patch, or 0 otherwise. Table I tabulates the number of extracted patches according to their patch size. The patches are then presented as input image to the DCNN.



(a) 28x28 (b) 32x32 (c) 64x64

Fig. 3a. Example image of partition

(a) 28x28 (b) 32x32 (c) 64x64

Fig. 3b. Example of crack images with different patches size

Table I
Number of patches for crack and non-crack

Input size	Crack patch	Non-crack patch
28x28	13,255	106,745
32x32	8,763	83,397
64x64	3,188	19,852

The input images are divided into two (2) categories which are training and testing dataset. For the sake of fair comparison, a total of 6000 and 1000 patches were chosen as training and testing dataset, respectively for each patch size. To further improve the DCNN training performance, the dataset was ensure to has equal balance between the crack and non-crack patches. Table II tabulates the number of training and testing dataset for crack and non-crack patches.

Table II
Number of training and testing dataset

	Crack	Non-crack	Total
Training dataset	3000	3000	6000
Testing dataset	500	500	1000

C. Classification using DCNN

A DCNN consists of many and different types of neural network layers such as convolutional, pooling and fully connected layers [26] [29]. Figure 4 shows the proposed procedure for pavement crack detection using DCNN. The procedure starts by capture the RGB crack image. Then, it will be segmented into three different grid scale consists of 28x28, 32x32 and 64x64 and fed to DCNN. Next, the network creates a binary image, all pixels in a grid scale is assigned to 1 if the DCNN's output belongs to crack, and 0 for non-crack. Finally, performance of crack detection was computed using three (3) performance metrices; recall, precision, accuracy and F-score.

In this study, DCNN with five (5) layers are proposed, as illustrated in Fig. 5. The network consists of three (3) convolution and pooling layers, and two (2) fully connected layers. By referring to Fig. 5, the first layer is the input layer of 32x32x3 pixel which the dimension indicate the height, width and channel respectively.

Next layer is the convolution layer (Conv). The role of the convolution layer is feature representation that learns to differentiate between crack and non-crack. Each convolution layer consists of several feature maps, so called filters or kernels. The feature map is obtained by sliding a filter or kernel to the input layer with predefined stride as shown in Fig. 5.

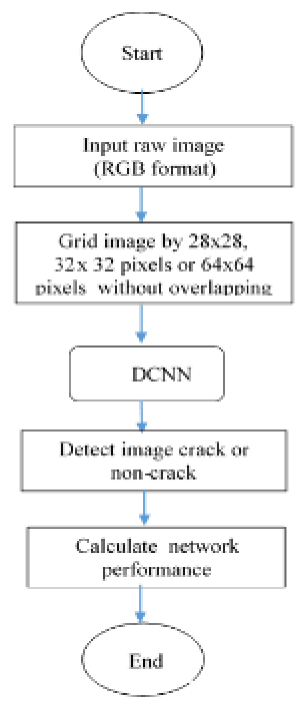


Fig. 4: Proposed pavement crack using DCNN

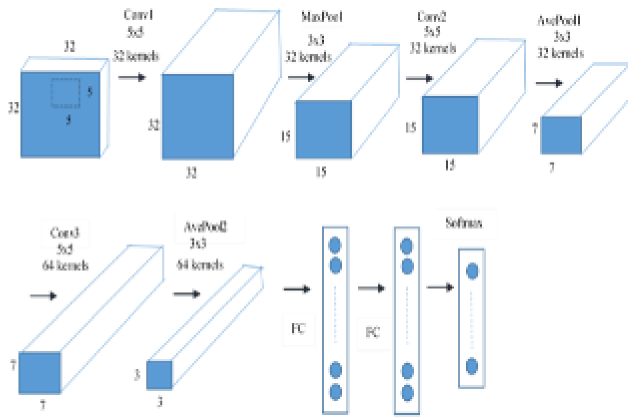


Fig. 5. Proposed deep CNN architecture for input image size of 32x32

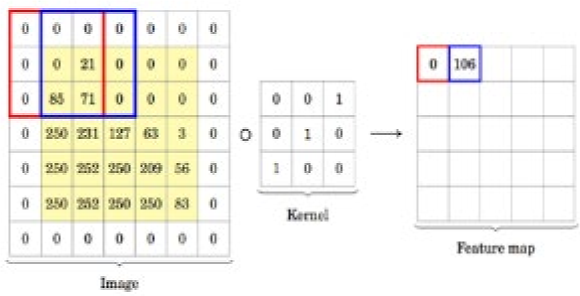


Fig. 5. Illustration of feature map in convolution layer

The rectifier linear unit (ReLU) is adopted after convolution layer to perform nonlinear transforms. In these convolution, the weights used in the kernels are learned during training of the network. Pooling layer is usually comes after the convolution layer. In this study, maximum pooling (*MaxPool*) and average pooling (*AvePool*) are used to reduce features parameter and prevent over-fitting. Maximum pooling, as illustrated in Fig. 6, takes the maximum values from the output feature maps whereby average pooling takes the average values. In pooling layer, the dimension of feature map reduced by condensing the output of small region of neurons into a single output [21]. This help to simplify the following layer and reduce the number of parameters that the model needs to learn and lead faster convergence and better generalisation [32]. Meanwhile, the fully connected (FC) layer which located on the last layer is used to classify the pavement patches into crack (1) or non-crack (0).

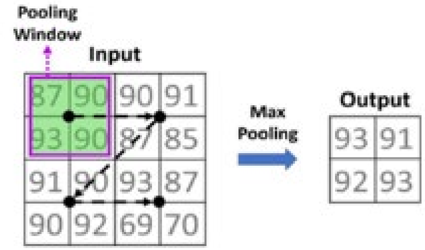


Fig. 6. Max pooling operation

D. Performance Evaluation

The study employed quantitative analyses to evaluate the performance of DCNN in classifying the pavement patches. Four (4) performance indicators are selected which are precision, recall, f-score and accuracy. These indicators are commonly used metrics in evaluating many crack detecting algorithms [28][29][33]. Precision refers to the percentage of crack pixels classified correctly with respect to all detected pixels, while recall represents the percentage of crack pixels classified correctly with respect to all true crack pixels [34]. The F-score is the harmonic mean of precision and recall and can be achieved only when the precision and recall are both high. Meanwhile, the accuracy refers to the number of true classification among the total number of dataset. The precision, recall, f-score and accuracy be calculated as follows:

$$\mathrm{Re}\,call = \frac{TP}{TP + FN} \tag{1}$$

$$\mathrm{Pr}\,ecision = \frac{TP}{(TP + FP)} \tag{2}$$

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \tag{3}$$

$$Fscore = \frac{2(\mathrm{Pr}\,ecision \times \mathrm{Re}\,call)}{(\mathrm{Pr}\,ecision + \mathrm{Re}\,cal)} \tag{4}$$

where *TP* and *TN* represent total number of the crack and non-crack patches that the correctly classified by the DCNN, respectively. *FN* and *FP* are the total number of crack and non-crack patches that are incorrectly classified by the network, reespectively.

III. RESULTs AND DISCUSSION

This section will discuss in detail the result in DCNN for crack detection. The size of segment grid has an impact on pavement crack detection.This study took 6000 grid images as training set images and 1000 of images were testing set images.

The original crack image (see Fig. 8a) will segmented into 28x28, 32x32 and 64x64 and result will presented according to the different size of input image. Too large size will lead detection not detail enough and tends more difficult to be trained. Otherwise, too small size will effect the network divergence and over-fitting.

The ground truth image obtained through labelling by manual identify patch was able to detect crack and non-crack with good result. The value 1 (skeleton block) means the existence of crack while the value 0 (black block) means the existence of non-crack as shown in Fig.8b. Next, the network of DCNN transformed into a binary image as shown in Fig.8c to evaluate the network performance.

Fig. 8a. Examples of original crack

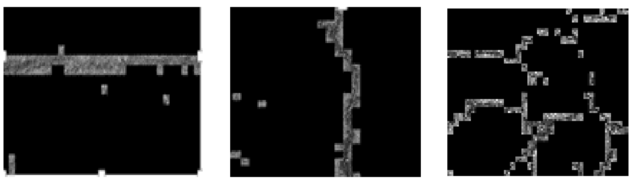


Fig. 8b. Examples of ground truth image

Fig. 8c. Examples of binary image

The network measure the quantitative analysis that shows an impact using the different size of input image on DCNN. Fig. 9 shows a result for crack and non-crack detection, presented in confusion matrix of crack classification using input image of 28x28, 32x32 and 64x64.

	crack	non-crack
crack	97.7%	2.3%
non-crack	1.40%	98.60%

(a) Input image of 28x28

From the experimental result, crack and non-crack patches image of 28x28 that correctly classified is 97.7% and 98.6% respectively. These results evidently demonstrate that the features extraction learned from the DCNN outperform the hand-crafted features in describing complex patch image.

	crack	non-crack
crack	99.4%	0.6%
non-crack	1.00%	99.00%

(b) Input image of 32x32

Compared to the result with input image of 32x32, it have better comprehensive performance than the segment grids of 28x28. The patch that correctly classified for crack is 99.4% while non-crack patch is 99.0%. This is due to the network was able to produce more detailed distributions of pavement containing cracked compared to 28x28. The detail about distribution of crack pattern would raised the correct crack and non-crack classified rate. Otherwise, smaller input image result seems not so good because the network incapable of sensing image with cracks on edges due to the hardly to recognize crack features.

	crack	non-crack
crack	94.6%	5.4%
non-crack	19.00%	81.00%

(c) Input image of 64x64

Fig. 9. Confusion matrix of crack classification using different size of input image

In contrast, increasing the input image to 64x64 has worsen classification performance which only achieved 94.6% and 81% that correctly classified for crack and non-crack patch respectively. One of the reason might be that the network using large image is more difficult to be trained. The network facing challenges to classify the non-crack precisely due to the existence of different texture on pavement background with low contrast which extremely similar to pavement cracks if they are viewed via large input size of image.

To evaluate the affections of crack detection using the different size of image, the network evaluated the pavement crack by the recall, precision, accuracy and F-score as shown in Table III.

Table III
Network performance with different size of input image

Input image	Recall	Precision	Accuracy	F-score
28x28	98.60%	97.70%	98.10%	98.15%
32x32	**98.70%**	**99.40%**	**99.20%**	**99.00%**
64x64	83.30%	94.60%	87.80%	88.60%

By referring to the result in Table III, it clearly shows that input size of 32x32 performs generally better than the 28x28 and 64x64 in terms of recall, precision, accuracy and F-score. A great improvement for accuracy of the network has been achieved with grid scale of 32x32 which from 87.8% to 99.2%. The network also obtained high recall and precision of crack detection compared to 28x28 and 64x64 grid scale.

Larger input size of image 64x64 faces difficulties to train the network in typical noise pattern which highly misclassified non-crack to crack due to failed identify continuous cracks. This could be the feature extractor does not grasp hairline and fine cracks sufficiently. Therefore, regarding a computational speed, it showed insuffient due to highly processing time taken.

Meanwhile, the smaller size of input 28x28, resulted the fastest convergence for the network due to fewer parameters are needed to train but produced slightly lower performance for the network.

Table IV
Comparison result using DCNN with 32x32 input size

Method	Recall	Precision	Accuracy	F-score
X.Wang et al., 2017	88.30%	97.30%	-	92.50%
Pauly et al., 2017	-	91.90%	90.20%	-
Cha, Choi, & Büyüköztürk, 2017	-	-	97.90%	-
Proposed Method	98.70%	99.40%	99.20%	99.00%

The study also benchmarked the proposed DCNN with the similar work on pavement crack detection, as given in Table IV. In general, Wang et al. [29] using 4 layers of DCNN consist of two convolution and pooling layers and two fully connected layers achieved 88.3%, 97.3% and 92.5% for recall, precision and F-score respectively. They built 30K images as training set images and used 510 testing images using the input size of 32x32.

Refer to Pauly and collegues [27], adopted DCNN to classify the patches image into crack and non-crack. They 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. According to Cha et al. [35], 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%.

Our proposed DCNN obtained better performance with 98.7%, 99.4% and 99.0% for recall, precision and F-score respectively. Although, this work used the smaller input size, the proposed method managed to achieve more than 98.0% for overall network performance. Besides that, the proposed method used only 6K images as a minimal training dataset that effectively produced an automated pavement crack detection systems with a good performance and low processing time as well.

CONCLUSION

In this work, a novel end-to-end trainable deep convolutional network was proposed for crack detection. The study, a DCNN with five (5) layers was proposed to enhance network capability for pavement crack detection. The network utilized different size of input image: 28x28, 32x32 and 64x64 has a novel method which achieved an acceptable performance in terms of recall, precision, accuracy and F-score with the minimal training of dataset.

According to the experiment on 1000 testing images, the input size of 32x32 image behaves generally better than the 28x28 and 64x64. The overall recall, precision, accuracy and F-score of 32x32 were above 98% which successfully resulted image has less noise than the other approaches.

Through the comparison study, input size of 32x32 produced yields the highest overall F-score on testing data compared with those input images, indicating that increasing the sizes of input image does not necessarily promise better performances. Besides that, input size of image 32x32 was found to be more robust in detecting fine or hairline cracks on pavement cracks at the pixel level. Experimental results also showed that the DCNN was not sensitive to noisy crack labeling and could well handle bright cracks.

Future plan of the study are anticipated to develop on classification pavement cracks into transverse, longitudinal and alligator.

ACKNOWLEDGMENT

The author would like to thank to Advanced Rehabilitation Engineering in Diagnostic and Monitoring Research Group (AREDiM) for providing facilities in the area of study. Also, appreciation goes to the Ministry of Higher Education (MOHE) for giving great privilege in providing scholarship as inspiring encouragement for the success of this research.

REFERENCES

[1] S. Mathavan, M. Rahman, and K. Kamal, “Use of a Self-Organizing Map for Crack Detection in Highly Textured Pavement Images,” *J. Infrastruct. Syst.*, vol. 21, no. 3, p. 04014052, 2015.

[2] K. Gopalakrishnan, S. K. Khaitan, A. Choudhary, and A. Agrawal, “Deep Convolutional Neural Networks with transfer learning for computer vision-based data-driven pavement distress detection,” *Constr. Build. Mater.*, vol. 157, pp. 322–330, 2017.

[3] Y. Sun, “Automated Pavement Distress Detection Using Advanced Image Processing Techniques The University of Toledo College of Engineering,” no. December, pp. 29–47, 2009.

[4] Z. Qingbo, “Pavement Crack Detection Algorithm Based on Image Processing Analysis,” *2016 8th Int. Conf. Intell. Human-Machine Syst. Cybern.*, pp. 15–18, 2016.

[5] A. Cubero-Fernandez, F. J. Rodriguez-Lozano, R. Villatoro, J. Olivares, and J. M. Palomares, “Efficient pavement crack detection and classification,” *Eurasip J. Image Video Process.*, vol. 2017, no. 1, p. 39, 2017.

[6] Q. Zou *et al.*, “DeepCrack : Learning Hierarchical Convolutional Features for Crack Detection,” *IEEE Trans. Image Process.*, vol. 28, no. 3, pp. 1498–1512, 2019.

[7] P. P. S. Yadav, “Crack Detection Using Image Processing : Review,” vol. 7, no. 03, pp. 121–124, 2018.

[8] M. Salman, S. Mathavan, K. Kamal, and M. Rahman, “Pavement crack detection using the Gabor filter,” in *16th International IEEE Conference on Intelligent Transportation Systems (ITSC 2013)*, 2013, pp. 2039–2044.

[9] S. Chambon and J. M. Moliard, “Automatic road pavement assessment with image processing: Review and comparison,” *Int. J. Geophys.*, vol. 2011, 2011.

[10] R. G. Lins and S. N. Givigi, “Automatic Crack Detection and Measurement Based on Image Analysis,” *IEEE Trans. Instrum. Meas.*, vol. 65, no. 3, pp. 583–590, 2016.

[11] R. Madli, S. Hebbar, P. Pattar, and V. Golla, “Automatic detection and notification of potholes and humps on roads to aid drivers,” *IEEE Sens. J.*, vol. 15, no. 8, pp. 4313–4318, 2015.

[12] T. B. J. Coenen and A. Golroo, “A review on automated pavement distress detection methods,” *Cogent Eng.*, vol. 4, no. 1, pp. 1–23, 2017.

[13] G. K. Choudhary and S. Dey, “Crack Detection in Concrete Surfaces using Image Processing, Fuzzy Logic, and Neural Networks,” *IEEE fifth Int. Conf. Adv. Comput. Intell.*, pp. 404–411, 2012.

[14] A. M. A. Talab, Z. Huang, F. Xi, and L. Haiming, "Detection crack in image using Otsu method and multiple filtering in image processing techniques," *Optik (Stuttg).*, vol. 127, no. 3, pp. 1030–1033, 2016.

[15] Q. Zou, Y. Cao, Q. Li, Q. Mao, and S. Wang, "CrackTree: Automatic crack detection from pavement images," *Pattern Recognit. Lett.*, vol. 33, no. 3, pp. 227–238, 2012.

[16] Y.-J. Cha, W. Choi, and O. Buyukozturk, "Deep Learning-Based Crack Damage Detection Using Convolutional Neural Networks," *Comput. Civ. Infrastruct. Eng.*, vol. 32, no. 5, pp. 361–378, 2017.

[17] Y.-C. Tsai, V. Kaul, and R. M. Mersereau, "Critical Assessment of Pavement Distress Segmentation Methods," *J. Transp. Eng.*, vol. 136, no. 1, pp. 11–19, 2010.

[18] H. D. Cheng, J. R. Chen, C. Glazier, and Y. G. Hu, "Novel approach to pavement cracking detection based on fuzzy set theory," *J. Comput. Civ. Eng.*, vol. 13, no. 4, pp. 270–280, 1999.

[19] L. Wang and J. Bai, "Threshold selection by clustering gray levels of boundary," *Pattern Recognit. Lett.*, vol. 24, no. 12, pp. 1983–1999, 2003.

[20] K. Gopalakrishnan, S. K. Khaitan, A. Choudhary, and A. Agrawal, "Deep Convolutional Neural Networks with transfer learning for computer vision-based data-driven pavement distress detection," *Constr. Build. Mater.*, vol. 157, pp. 322–330, 2017.

[21] Y. Cha and W. Choi, "Deep Learning-Based Crack Damage Detection Using Convolutional Neural Networks," vol. 32, pp. 361–378, 2017.

[22] K. Gopalakrishnan, S. K. Khaitan, A. Choudhary, and A. Agrawal, "Deep Convolutional Neural Networks with transfer learning for computer vision-based data-driven pavement distress detection," *Constr. Build. Mater.*, vol. 157, no. September, pp. 322–330, 2017.

[23] T. Saar and O. Talvik, "Automatic Asphalt pavement crack detection and classification using Neural Networks," *2010 12th Bienn. Balt. Electron. Conf.*, pp. 345–348, 2010.

[24] M. S. Kaseko and S. G. Ritchie, "A neural network-based methodology for pavement crack detection and classification," *Transp. Res. Part C*, vol. 1, no. 4, pp. 275–291, 1993.

[25] C. Senthilkumar and M. Kamarasan, "a Survey on Leaf Disease Detection Using Image Processing Techniques," vol. 118, no. 8, pp. 2–4, 2018.

[26] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," *Adv. Neural Inf. Process. Syst.*, pp. 1–9, 2012.

[27] L. Pauly, H. Peel, S. Luo, D. Hogg, and R. Fuentes, "Deeper Networks for Pavement Crack Detection," no. Isarc, pp. 479–485, 2017.

[28] L. Zhang, F. Yang, Y. Daniel Zhang, and Y. J. Zhu, "Road crack detection using deep convolutional neural network," in *2016 IEEE International Conference on Image Processing (ICIP)*, 2016, pp. 3708–3712.

[29] X. Wang and Z. Hu, "Grid-based pavement crack analysis using deep learning," in *2017 4th International Conference on Transportation Information and Safety, ICTIS 2017 - Proceedings*, 2017, pp. 917–924.

[30] Y. Cha and W. Choi, "Deep Learning-Based Crack Damage Detection Using Convolutional Neural Networks," no. September, 2017.

[31] A. Zhang *et al.*, "Automated Pixel-Level Pavement Crack Detection on 3D Asphalt Surfaces Using a Deep-Learning Network," *Comput. Civ. Infrastruct. Eng.*, vol. 32, no. 10, pp. 805–819, 2017.

[32] K. Gopalakrishnan, S. K. Khaitan, A. Choudhary, and A. Agrawal, "Deep Convolutional Neural Networks with transfer learning for computer vision-based data-driven pavement distress detection," *Constr. Build. Mater.*, vol. 157, pp. 322–330, 2017.

[33] A. Zhang, K. C. P. Wang, Y. Fei, Y. Liu, J. Q. Li, and C. Chen, "Automated Pixel-Level Pavement Crack Detection on 3D Asphalt Surfaces Using a Deep-Learning Network," vol. 00, pp. 1–15, 2017.

[34] A. Zhang *et al.*, "Deep Learning–Based Fully Automated Pavement Crack Detection on 3D Asphalt Surfaces with an Improved CrackNet," *J. Comput. Civ. Eng.*, vol. 32, no. 5, p. 04018041, 2018.

[35] Y.-J. Cha, W. Choi, and O. Büyüköztürk, "Deep Learning-Based Crack Damage Detection Using Convolutional Neural Networks," *Comput. Civ. Infrastruct. Eng.*, vol. 32, no. 5, pp. 361–378, 2017.

Nor Aizam Muhamed Yusof completed her Bachelor of degree in Electrical Engineering at Faculty of Electrical Engineering Universiti Teknologi Malaysia, Skudai in the year of 1998. She received her Master of Engineering in Electronic Engineering (Telecommnication Systems) at Faculty of Electronic and Computer Engineering, Universiti Teknikal Malaysia Melaka in the year 2012. She is currently a lecturer at Politeknik Tuanku Sultanah Bahiyah, Kedah under Department of Electrical Engineering. Her main interest in research are image processing and artificial intelligence.

Muhammad Khusairi Osman obtained his B.Eng degree in Electrical and Electronic Engineering in 2000 and MSc in Electrical and Electronic Engineering in 2004 from Universiti Sains Malaysia. In 2014, he obtained his Ph.D. in medical electronic engineering from Universiti Malaysia Perlis (UniMAP), Malaysia. He is currently a senior lecturer at Faculty of Electrical Engineering, Universiti Teknologi MARA (UiTM), Malaysia.

Mohd Halim Mohd Noor received the B. Eng (Hons) in 2004 and the M.Sc in 2009. In 2017, he received hid Ph.D in Computer Systems Engineering from the University of Auckland, New Zealand. He is currently a Senior Lecturer with the School of Computer Sciences, Universiti Sains Malaysia. His main research interests include mobile and sensor computing, computational intelligence and machine learning in pervasive healthcare.

Anas Ibrahim obtained his Bachelor of Civil Engineering (Honours) in 2000 and MSc (Geotechnical Engineering) in 2004 from University Sains Malaysia. He is currently a senior lecturer at Faculty of Civil Engineering, Universti Teknologi MARA (UiTM) Pulau Pinang. His research interest is in small strain and dynamic behaviour of soil engineering and highway material engineering study.

Nooritawati Md Tahir received her PhD in Electrical, Electronic & System Engineering from Universiti Kebangsaan Malaysia. She is currently a Professor at the Faculty of Electrical Engineering, Universiti Teknologi MARA, Malaysia. Her research interests include pattern recognition, computational intelligence and artificial intelligence

Norbazlan Yusof received his Bachelor Degree Honours in Surveying and Mapping Sciences from the University of East London in the United Kingdom in 1996. In 2009 he received his Master degree in Remote Sensing and GIS from University Putra Malaysia and in 2017 he received his Doctor of Engineering (D.Eng.) in the field of GIS and Geomatics Engineering from Faculty of Engineering, University Putra Malaysia. His research focuses on landslides analysis including landslide detection, susceptibility, hazard, vulnerability, assessment and risk using bivariate and multi bivariate statistical base analysis. He currently holds the post as Head at Centre of Excellence where he is responsible for Green Sustainability, PLUS Innovation Master Plan, GIS & Remote Sensing, Records & Management System, Quality Management System for IS0 9001, EMS 14001 and OHSAS 18001 as well as Green 5S and collaboration research with other agencies/universities.