CRACK DETECTION IN CONCRETE USING TRANSFER LEARNING

Article *in* Advances in Mathematics Scientific Journal · July 2020

DOI: 10.37418/amsj.9.6.69

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Advances in Mathematics: Scientific Journal **9** (2020), no.6, 3895–3906
ISSN: 1857-8365 (printed); 1857-8438 (electronic)
https://doi.org/10.37418/amsj.9.6.69 Spec Issiue on ICAML-2020

CRACK DETECTION IN CONCRETE USING TRANSFER LEARNING

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ABSTRACT. This work demonstrates the use of pretrained network for the detection of crack in the concrete. The SDNET2018 dataset is used for the training of the network which consists of more than 56,000 images. The dataset includes the images of Bridge Deck, Walls and Pavements. The images are captured under different surface and environmental condition. The dataset is divided into 90% training and 10% testing data for each of the category. This work provides the comparison of the AlexNet network with GoogLeNet and ResNet18 in transfer learning mode. It is observed that GoogLeNet and ResNet18 has introduced significant improvement in case of Bridge Deck and Walls but achieved only little improvement in case of Pavement images.

1. INTRODUCTION

Almost all the structures like Buildings, Bridges, and Pavements are comprised of concrete. An enormous number of deaths and injuries have been reported every year due to breakdown of these solid structures. Splits in concrete happen be-cause of numerous reasons like thermal movement, creep movement, poor construction, design, and maintenance. Detection of cracks in the concrete surface is necessary to ensure the reliability and durability of concrete structures. Timely detection of the cracks in the concrete is required to prevent the complete break-down of the concrete structure. Detection of crack can be done either manually or autonomously. Manual inspection

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2010 *Mathematics Subject Classification.* 68T99.
Key words and phrases. AlexNet, concrete, convolutions, deep, detection, GoogLeNet, ResNet18.

requires a supervisor to visit the location for crack detection which is both time consuming and prone to error. Autonomous crack detection overcomes the shortcomings of manual detection. Autonomous detection of crack involves taking the picture of the surface and then applying some image processing or machine learning algorithm to detect the crack in the surface. Various autonomous crack detection strategies have been proposed so far by the researchers. Image processing methods like morphological operations, wavelet transformation [1] image binarization [2, 3], LBP (Local Binary Pattern) [4], had been used for the detection of the crack in the concrete surfaces. Machine learning algorithms [1, 5, 6] are also used by researchers. Some researchers combine the advantage of both the image processing and neural network for the detection of cracks. Pre-trained networks like AlexNet [7, 8] is also used by the researcher for the detection of the crack in the concrete. This paper provides the comparison of pretrained network like GoogLeNet and ResNet18 with AlexNet for detection of crack in the concrete surfaces. The comparison result shows that GoogLeNet and ResNet18 provided better accuracy than the AlexNet network. The remaining of the paper includes Literature survey in Section 2. DataSet and Methodology used in this paper are included in Section 3. Result and Discussions are included in Section 4. Section 5 contains Conclusion and Future Work of this paper.

2. LITERATURE REVIEW

This section provides a brief idea about the various approaches used previously for autonomous detection of crack. Genetic Algorithm is employed by [9] to detect the crack in concrete surfaces. The authors employed genetic algorithm along with neural networks to avoid multiple local minima. The algorithm is applied on 100 crack images and achieved a success rate of $92.3 \pm 1.4\%$. The method employed in [10] includes two pre-processing methods to remove the noise from the images. It involves subtraction pre-processing and line filter based on Hessian matrix for image pre-processing. Then, thresholding based segmentation is used to highlight the crack on the surface. Multi Fractal analysis method is used in the [11] detection of crack. This method shows that as crack pattern grows, the value of multi fractal parameter also increases.

The method of Image binarization is used [2, 3] for detection of crack. Image binarization method use thresholding where a pixel value above certain threshold is defined as 1(white) and below is defined as 0 (black). Every binarization approach has its own thresholding scheme but generally statistical methods like standard deviation and mean are used. Digital Image Correlation (DIC) method was used in [12, 13] for Localization and flexural behavior of crack in concrete. This method has additional benefits over the other method that it provides high precision during initial stages of crack and measure the crack progress as the concrete continue to degrade due to strain or other factors. The paper [4] employed Local Binary Pattern (LBP) for detection of cracks in Pavements. In this paper authors modified the original LBP to classify the neighbor as only rough and smooth to make its robust against the noise. The segmentation is then applied on the rough area. A lookup table is also created for faster implementation. In [14] the authors developed a method to predict the probability of each pixel as belonging to either crack or non-crack in context of patch that surrounds that pixel. This prediction model is created using Convolution Neural Network (CNN).

The machine learning algorithms are also employed for the detection of crack in concrete surfaces. The Canny operator and modified k-means clustering method are used in [5] along with machine learning algorithm for detection of crack in concrete. In [1] Support Vector Machine (SVM) is used for classification of images of bridges as crack or non-crack based on the wavelet features. Conditional Random Field (CRF) and spatial-temporal non-filtering methods are used together in [6]. In [15] region based and canny method are employed for crack segmentation while the SVM is used for the removal of noise.

F. C. Chen et al. [16] employed a method for detection of cracked surfaces in individual video frame using Naive-Bayes and convolution neural network. The performance of the model is enhanced by a unique data fusion scheme which aggregates the information extracted from previous frame. The deep learning methods have been deployed by [17–21] for the detection of crack in roads, bridges and other concrete structures.

S. Dorafshan et al. [7] provides a comparison between edge detection algorithm and deep neural network for the detection of crack. In this paper authors provide the edge detection method both in spatial and frequency domain. Edge detection method like sobel, perwitt, LoG, Gaussian etc. is used for crack detection. The result showed that the AlexNet network performed better than the edge detector for cracks detection. In [22] multiple filtering, thresholding and morphological operations are applied for the detection of crack. The paper includes the operation like median filtering, sobel edge detector and Otsu thresholding for cracks detection. S. Dorafshan et al. [8] provide a benchmark for the detection of crack using pre trained AlexNet network in both full training and transfer learning mode. They showed that transfer learning provide better results than full training in less time. Edge detectors methods are used in [22–26] for crack detection.

3. DataSet and methodology

3.1. **DataSet.** The SDNET2018 dataset is used for the training and testing of the network. The dataset consist of 56,092 images of Bridge Deck, Walls and Pavements. The images are both cracked and non-cracked. The images are collected by capturing the image using 16 MP Nikon digital cameras [8]. Each image in the dataset is 256×256 pixel RGB image in JPEG format. The SDNET2018 image dataset is divided into three categories Bridge Deck, Walls and Pavements. Each of these categories consists of both cracked and non-cracked images which can be used for the training and testing of the algorithms. The Bridge Deck consists of 2,025 cracked and 11,595 non-cracked images. The Wall category consists of the 3,851 cracked and 14,287 non-cracked images while the Pavement consists of 2,608 cracked and 21,726 non-cracked images. The images are captured under different surface, environmental conditions. Any model trained on the SDNET2018 image dataset can identify the crack within the width range of 0.06mm to 25mm. The dataset includes the images with shadows, stains, edges, voids and other obstruction to make training of the algorithm robust. The images in the dataset are collected from Logan, USA and Utah. This dataset is freely available for academic research.

SDNET2018 dataset had already been trained on AlexNet in both the full training and transfer learning mode and provided bench-marking results for each of the categories.

FIGURE 1. SDNET2018 image dataset

Image Description		Number of cracked	Number of non-cracked	Total
Reinforced	Bridge Deck	2025	11,595	13,620
	Wall	3851	14,287	18,138
Unreinforced	Pavement	2608	21,726	24,334
Total		8484	47,608	56,092

FIGURE 2. SDNET2018 dataset description

3.2. **Methodology.** Transfer learning is a part of machine learning where a model proposed for one task can be used to solve the problem of another task. Deep learning models learn the weights and features that are necessary for the classification of images. These deep learning models can be reused for the problem of a similar type. The layers at the beginning of the network which are used for feature extraction are reused but the lower layers which are too task-specific are changed. One of the main uses of transfer learning is in the field of computer vision. Various algorithms had been proposed in computer vision that can be used for classification of image on which network is not trained by modifying the lower layers. In this paper, pre-trained model GoogLeNet and ResNet18 are used for task of crack detection.

3.2.1. *GoogLeNet*. GoogLeNet is the champion of the ILSVRC 2014 ImageNet competition and is also known as Inception V1 module. It achieves an error rate of 6.67%. The architecture of GoogLeNet differs from previous networks like AlexNet, VGGNet. The architecture of GoogLeNet uses the 1×1 convolution layer in the network and it also uses global average pooling instead of fully connected layer at the end of the network. It also contains inception module, which uses different size of convolution and pooling for same input and stack them on the output.

1×1 Convolutions. In GoogLeNet 1×1 convolutions are used as dimension reduction to reduce the number of computation so that depth and width of the network can be increased. The use of 1×1 convolutions reduces the number of operation to great extent.

Inception Module. In the inception model different types and sizes of convolutions are applied to same input and then output is stacked on one another. Various kinds of features are extracted as the image passes through different type of convolutions as well as max pooling is applied. The inception module with (FIGURE 4) and without (FIGURE 3) 1×1 convolution layer differ only in the number of operation. The 1×1 convolutions are included in the inception module for dimensionality reduction.

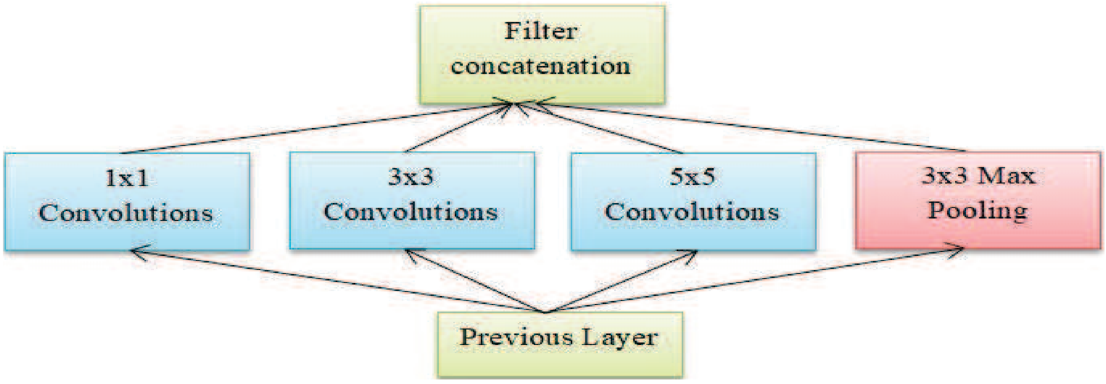

FIGURE 3. Inception module, naive version (without 1×1 Convolutions)

Global Average Pooling Layer. In GoogLeNet, global average pooling layer is used at the end instead of fully connected layer which improved the accuracy by 0.6%. Number of connections (weights) in FC = $5 \times 5 \times 1024 \times 1024$ = 26.2M (FIGURE 5). Number of connection in global average pooling = 0. This idea was taken from [27] to lessen the problem of overfitting.

Complete Architecture. The complete framework of GoogLeNet consists of 22 layers shown in FIGURE 6. These 22 layers include various inception modules in between input layer and output layer.

3.2.2. *ResNet Architecture.* ResNets, also known as Residual Neural Networks, are winner of ILSRVC 2015. ResNet introduced the concept of residual blocks to overcome the problem of deeper networks. The problem with deeper

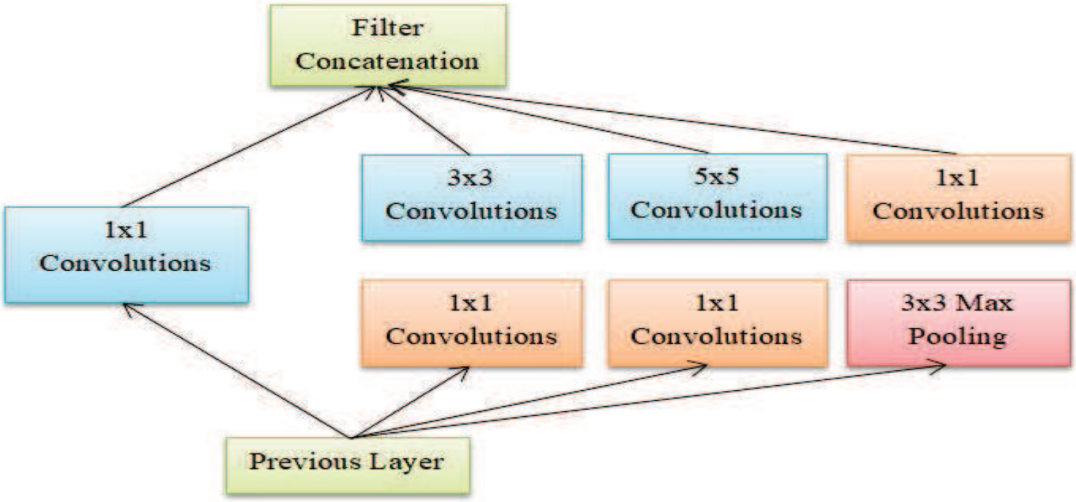

FIGURE 4. Inception module with dimension reductions (with 1×1 Convolutions)

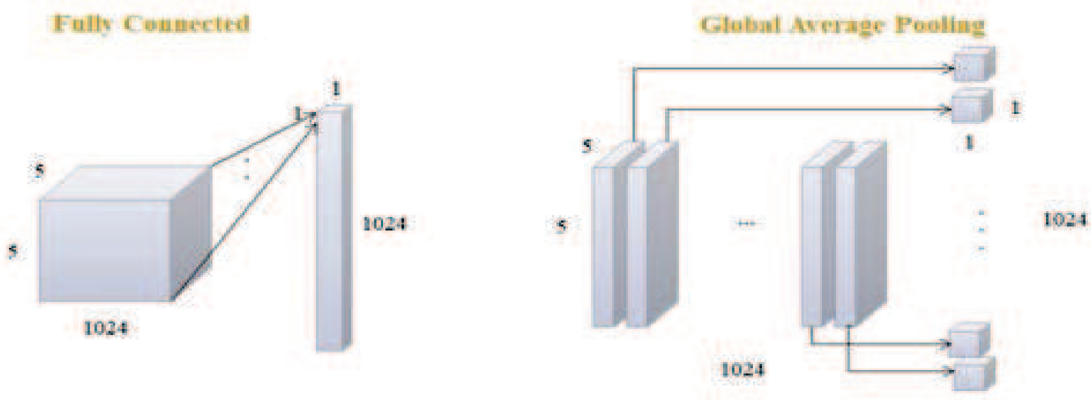

FIGURE 5. Fully Connected vs Global Average Pooling

network is that, as network starts to converge the accuracy of the network starts converging and then degrades. This problem is not associated with overfitting or by depth of neural network instead it shows that some systems are not easy to optimize. To overcome this problem of neural networks Microsoft introduces the concept of residual learning. Instead of anticipating that every few stacked layer fit to a desired mapping directly, they explicitly used the residual mapping. Residual mapping is introduced by the use of

Type	patch size/stride	output size	depth	#1x1	#3x3 reduce	#3x3	#5x5 reduce	#5x5	pool proj	param (K)	ops (M)
convolution	7x7/2	112x112x64	1							2.7	34
max pool	3x3/2	56x56x64	0								
convolution	3x3/1	56x56x192	2		64	192				112	360
max pool	3x3/1	28x28x192	0								
inception 3(a)		28x28x256	2	64	96	128	16	32	32	159	128
inception 3(b)		28x28x480	2	128	128	192	32	96	64	380	304
max pool	3x3/2	14x14x480	0								
inception 4(a)		14x14x512	2	192	96	208	16	48	64	364	73
inception 4(b)		14x14x512	2	160	112	224	24	64	64	437	88
inception 4(c)		14x14x512	2	128	128	256	24	64	64	463	100
inception 4(d)		14x14x528	2	112	144	288	32	64	64	580	119
inception 4(e)		14x14x832	2	256	160	320	32	128	128	840	170
max pool	3x3/2	7x7x832	0								
inception 5(a)		7x7x832	2	256	160	320	32	128	128	1072	54
inception 5(b)		7x7x1024	2	384	192	384	48	128	128	1388	71
avg pool	7x7/1	1x1x1024	0								
dropout (40%)		1x1x1024	0								
Linear		1x1x1000	1							1000	1
Softmax		1x1x1000	0								

FIGURE 6. Complete architectural detail of GoogLeNet from top to bottom

shortcut connection. Shortcut connection or identity function (FIGURE 7) skips one or more layer in the network, perform identity mapping and then their output are added to the output of the stacked layers. It is much the same as other simple plain network which uses combination of Convolutions layer, Relu (Activation Function), Max Pooling and other layers to classify the image. Additionally, the shortcut connection is added to overcome the problem associated with deep networks and converts this simple plain network into residual network as appeared in FIGURE 8. The identity function $F(x) + x$ can be straightly used when the dimension of the input and the output are same.

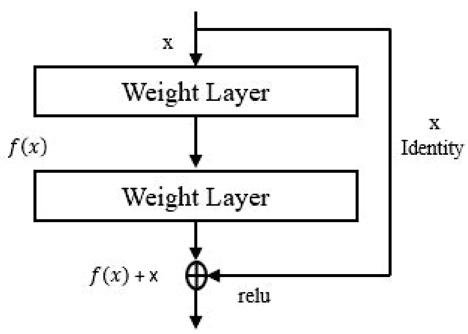

FIGURE 7. Identity Function or Skip Connection

When the dimension increases (case of dotted line) shown in FIGURE 8 then it uses either extra padding for increased dimension or projection shortcut using 1×1 convolutions are used to match the dimensions. In this paper, specifically pretrained ResNet18 architecture will be utilized for the crack detection in concrete.

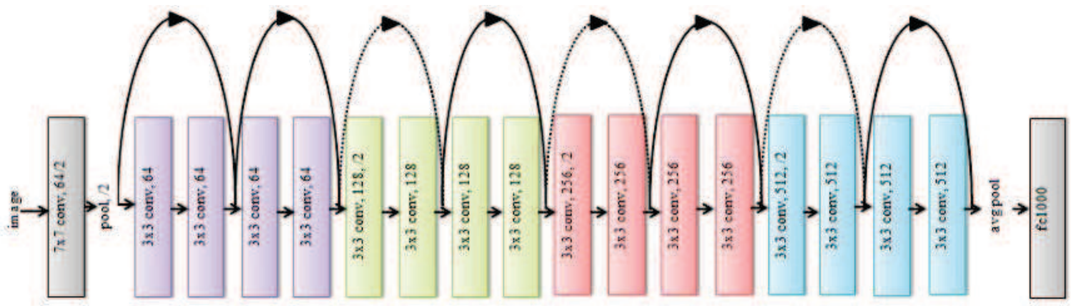

FIGURE 8. ResNet18 Architecture

4. RESULTS AND DISCUSSION

In this work all the training and testing is carried out on laptop with 8GB RAM, 1.80 GHz processor running GeForce MX110 GPU. The networks are programmed in Matlab2019. In this work pre-trained Deep Convolution Neural Networks (DCNN) are utilized for training the network instead of building the network from scratch. Transfer learning mode reduces the training time of network and significant results can be obtained in less amount of time. In this work the dataset is divided into 90% training and 10% testing for each of the category. The results of pre-trained GoogLeNet and ResNet18 are compared with the [8] which uses AlexNet for crack detection using the same number of training images, testing images and same number of epochs.

The result in FIGURE 9 shows that both the ResNet18 and GoogLeNet provide significant improvement in the case of Bridge Deck and Wall but provide a little improvement in case of Pavement.

Image Description	Number of epochs	Number of training images	Number of testing images	DCNN	Accuracy (%)
Bridge Deck	10	12259	1361	AlexNet	91.92
				GoogLeNet	92.95
				ResNet18	92.19
Wall	9	16324	1814	AlexNet	89.31
				GoogLeNet	91.95
				ResNet18	91.90
Pavement	10	21900	2434	AlexNet	95.52
				GoogLeNet	95.56
				ResNet18	95.56

FIGURE 9. Comparison of different pretrained network in transfer learning mode for crack detection

5. CONCLUSION AND FUTURE WORK

In this paper GoogLeNet and ResNet18 are trained in transfer learning mode. Transfer learning mode is used as it consumes less time instead if networks are trained from the scratch. The result shows that GoogLeNet and ResNet18 provide significant results even in the transfer learning mode. In future, other ResNet architectures like ResNet50 and ResNet101 can also be applied in transfer learning to provide more significant results. Due to hardware limitation, other architectures of ResNet cannot be trained but ResNet18 provides significant improvement in the results. So, it is assumed other ResNet architectures will perform better than these as they have more number of layers.

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