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Pavement cracks detection and classification using deep convolutional networks

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ABSTRACT: Pavement inspection is one of the most important steps in the implementation of the pavement management system and extend efforts have been conducted to increase the efficiency of this system by using new technologies. In recent years, transportation agencies focus on creating automatic and more efficient systems for pavement inspection and a large number of researches have been done for this aim. According to the progress of computer science, data mining and machine learning as computer-based methods are used more in various areas (such as engineering, medical and economy), and significant results have been achieved. In the pavement management area, several researches have been performed to apply the machine learning, especially in pavement distresses evaluation. In this paper, the theoretical concepts have been explained, and several models have been created based on deep convolutional networks using transfer learning to detect and classify pavement cracks as the most prevalent pavement distress, and the performance of these models has been evaluated considering learning and test speed, and accuracy as the most important performance parameters. The results of this research indicate that the speed of models almost depends on the characteristics of pre-trained models that applied in the transfer learning process. Also, the accuracy of models based on various metrics (Sensitivity, F-score, etc.) is in range of 0.94 to 0.99 and indicates that deep learning method can be used to create expert systems for detection, classification, and quantification of pavement distresses such as cracking.

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1. INTRODUCTION

Transportation infrastructures have a deep influence on economic development, urbanization, and globalization [1, 2]. Also, this part of the infrastructure improves the quality of people's life. Roads are one of the most important parts of transportation infrastructure that have an extensive and direct effect on the daily life of humans and provide the possibility to move peoples and goods [3]. The pavement management system plays a very important role in the management of roads and has a direct influence on the quality and safety of roads. An efficient pavement management system creates work planning for pavement maintenance in optimal time, by a correct maintenance technique, and with optimal cost [4]. These aims become possible when the pavement inspection information (such as pavement distresses) is collected correctly.

In recent years, data mining and machine learning approaches have been the most utilized methods for the reorganization of the pavement distresses [5, 6]. Pavement distresses can be divided into cracking and non-cracking distress. Cracking distress in the pavement are the most prevalent pavement distresses, and cracks have a great impact

on reducing the design-life [7, 8]. The pavement cracks can be divided into two general categories that are named surface cracks and linear cracks.

Deep learning is a kind of machine learning technique that is developed based on neural network concepts. The Convolutional Neural Network (CNN) is one of the most popular deep neural networks that have wide applications in processing and extraction of features from data such as pavement images [9-11].

In this research, a machine learning method based on convolutional neural networks has been applied with transfer learning for implementing the detection and classification task on pavement cracks. Also, the performance of the different models has been compared based on speed and accuracy.

2. METHODOLOGY

As can be seen in Fig. 1, the research process contains four main steps, including: data collection, pre-process, training and testing models, and evaluating the performance of the models.

Pavement images have been collected as inputs of the process in three classes, including surface cracking, linear cracking, and non-cracking. Then a pre-processing has been

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Fig. 1. Main steps of research

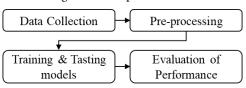


Table 1. Details of datasets

Dataset	Trainin	g dataset	Testing dataset	
	Training	Validation	Testing dataset	
Surface cracking	400	100	250	
Linear cracking	400	100	250	
Non-cracking	400	100	250	
Total	1500		750	

Table 2. Time spent in the various process (second)

Pre-trained CNN	Pre-processing for each image (on average)	Train for each image (on average)	Test for each image (on average)		
AlexNet	0.050	0.482	0.019		
SqueezNet		t 0.383		0.017	
GoogleNet		0.637		0.024	
ResNet-18		0.644	0.021		
ResNet-50	0.058	1.944	0.041		
ResNet-101		3.823	0.054		
DensaNet-201		12.908	0.089		
Inception-V3		2.951	0.053		

Fig. 2. Performance metrics

Models	Accuracy	Sensitivity	Specificity	Precision	Recall	Fscore
AlexNet	0.978	0.967	0.983	0.967	0.967	0.967
SqueezNet	0.991	0.986	0.993	0.986	0.986	0.986
GoogleNet	0.989	0.984	0.992	0.984	0.984	0.984
ResNet-18	0.979	0.968	0.984	0.969	0.968	0.968
ResNet-50	0.974	0.961	0.981	0.961	0.961	0.961
ResNet-101	0.972	0.957	0.979	0.958	0.957	0.957
DenseNet-202	0.984	0.976	0.988	0.976	0.976	0.976
Inception-V3	0.985	0.977	0.989	0.977	0.977	0.977

conducted on input images to creating more obvious and clear images. Table 1 presents more details on the prepared datasets for training and testing process.

In the training process, eight pre-trained models based on CNN have been applied by using transfer learning technique. AlexNet, GoogleNet, SqueezNet, ResNet-18, ResNet-50, ResNet-101, DenseNet-201, and Inception-v3 are pre-trained models that applied to retrained based on collected training datasets by using transfer learning. After the training process, the created models were applied to perform crack detection and classification on the testing dataset.

It should be noted that all computations were performed in MATLAB 2018b by using a personal computer with a 64-bit operating system, 8.0 GB memory, and Intel(R) Core i7-4710HQ @ 2.50 GHz processor running a GeForce GTX

850M graphics processing unit (GPU).

3. DISCUSSION AND RESULTS

After performing the experimental work (data preparing, training, and testing), the performance of the models has been evaluated based on two aspects including models speed in training and testing and models accuracy in the detection and classification of the pavement cracks.

The summarized information on time spent in data preprocessing, models training, and testing has been presented in Table 2. It should be noted that the speed of the models depends on the characteristic of pre-trained models applied in the training process.

As can be seen in Table 2, some of the models such as AlexNet, SqueezNet, GoogleNet, and ResNet-18 are significantly faster than others.

To evaluate the efficiency of the models in crack detection and classification, the confusion matrix was calculated to achieve performance metrics such as accuracy, sensitivity, specificity, precision, and F-score. The average of the performance metrics in three classes has been presented in Fig. 2.

As shown in Fig. 2, the performance metrics of all models are in the range of 0.94 to 0.99. Also, SqueezNet and GoogleNet have more effective performance than other models, and SqueezNet has the best performance according to all metrics.

4. CONCLUSIONS

This research tries to apply machine learning techniques for detection and classification of two general types of pavement cracks, including surface cracks and linear cracks. For this aim, eight pre-trained CNNs have been retrained based on pavement images using transfer learning method.

Results of the research indicate that SqueezNet has the best performance with regard to speed and performance metrics. Finally, according to the performed experiment and presented results, several important points can be concluded as follows:

- By using machine learning techniques, the data mining approaches provide efficient systems to perform pavement inspection tasks such as cracks detection and classification.
- Retraining the pre-trained CNN by utilizing transfer learning is an efficient method to create a classifier model for pavement crack detection and classification, especially when there is a constraint in processing power and available data.
- Prepared data for the training process and the characteristics of pre-trained models have a great influence on the model's performance.
- Determining the best model is a tradeoff between process power, available data and the level of performance required.

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