



Crackdet: An Improved Deep Learning Framework Base on Multi-Scale Convolutional Architecture for Detecting Road Cracks

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ABSTRACT

Highway is not only the carrier of transportation, but also the link of regional economy. However, with the longer service time of the pavement, various defects such as cracks, potholes, and deformation will appear on the road surface one after another. Traditionally, crack evaluation is conducted manually through human field surveys. Though, these manual survey methods have poor repeatability and reproducibility, need excessive time, consume great amounts of labor, and put surveyors in hazardous situations. In this research, we propose an improved deep learning framework base on multi-scale convolutional architecture for detecting road cracks. Firstly, deconvolution and fusion of CNN feature maps are proposed to add context and deeper features for better crack detection at low feature map scales. In addition, soft non-maximal suppression (NMS) is applied across cracks proposals at different feature scales to address the object occlusion challenge.

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INTRODUCTION

Highway is not only the carrier of transportation, but also the link of regional economy. As one of the most important parts of urban infrastructure, the road condition directly affects the people's life (Garber & Hoel, 2019). However, with the longer service time of the pavement, various defects such as cracks, potholes and deformation will appear on the road surface one after another. If the relevant departments do not pay attention to this problem, minor road diseases may develop into serious damage over time, which may not only lead to premature exit from the service life of roads, lead to traffic congestion, but also bring serious potential life safety hazards and death (Li, Zhao, & Li, 2019).

Cracking appears in different kinds of structures, such as pavements, buildings, and bridges. Since cracking can accelerate the deterioration process, occurrence and severity of cracking serve as important indicators that

maintenance is required (Mazzoli, Monosi, & Plescia, 2015).

Traditionally, crack evaluation is conducted manually through human field surveys (Hsieh & Tsai, 2020). However, these manual survey methods have poor repeatability and reproducibility, need excessive time, consume great amounts of labor, and put surveyors in hazardous situations. Also, the data collected may vary with different raters due to subjectivity. To overcome the shortcomings of manual surveys, there have been substantial research efforts to develop automated crack survey methods. Automatic crack evaluation consists of three components: data acquisition, crack detection, and crack diagnosis.

RELATED WORK

With the development of image analysis techniques, road crack detection and recognition have been widely investigated over the past few decades. In recent years, some novel algorithms have been proposed for

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automated road crack detection using deep learning algorithms. For example, (Mandal, Uong, & Adu-Gyamfi, 2018) proposed an automated road crack detection using deep convolutional neural networks. The F1 score for detection without predicting crack class was found out to be 0.8780 and for classification including crack class was 0.7394. However, google street-view images could be a good source for increasing the database with rich crack information for building much robust models.

Zhang et al., (2018) proposed deep learning-based fully automated pavement crack detection on 3d asphalt surfaces with an improved cracknet. The CrackNet II performs generally better than the original CrackNet in terms of both precision and recall. However, the research could not solve more complex problems, including detecting cracks on concrete pavement surfaces and suppressing crack like patterns (i.e., pavement joints, grooves, shoulder drop-offs, and pavement edges).

Fan et al., (2019) proposed road crack detection using deep convolutional neural network and adaptive thresholding. The experimental results illustrate that the network can classify images with an accuracy of 99:92%, and the cracks can be successfully extracted from the images using our proposed thresholding algorithm. However, the study fails to segment the positive images into a set of semantically meaningful regions, i.e., cracks and road surfaces using DNN.

Fei et al., (2019) proposed pixel-level cracking detection on 3D asphalt pavement images through deep-learning based cracknet. The CrackNet-V achieves a high performance with a Precision of 84.31%, Recall of 90.12%, and an F-1 score of 87.12%. However, it could suffer the limitations caused by the extremely small size of filters. Particularly, the detection accuracy on wide cracks is still not satisfying.

Hoang & Nguyen, (2019) proposed a novel method for asphalt pavement crack classification based on image processing and machine learning. The SVM has achieved the highest classification accuracy rate (87.50%),

followed by ANN (84.25%), and RF (70%). However, the study fails to utilize advanced image processing methods for detecting cracks in the presence of patches, potholes, and other irregular objects.

Li et al., (2019) proposed a method for detecting road pavement damage based on deep learning. After training with GPU using convolutional neural network, the average precision can reach 96.3%. However, Computation speed, as well as accuracy, is an important aspect to be considered. Similarly in 2019 (Naddaf-Sh, Hosseini, Zhang, Brake, & Zargarzadeh, 2019) proposed a real-time road crack mapping using an optimized convolutional neural network. The proposed CNN was able to classify the cracks with 97% accuracy. This study is limited to only one block size and 13 classification categories.

With the advancement of machine learning (ML) and deep learning (DL) witness in the papers that have been reviewed so far, we can noticed that there is a great opportunity to enhance the development of automatic crack detection algorithms. (Hsieh & Tsai, 2020) organize and provide up-to-date information on ML-based crack detection algorithms for researchers to more efficiently seek potential focus and direction. The authors first reviewed 68 ML-based crack detection methods to identify the current trend of development, pixel-level crack segmentation. The review and model performance comparison results showed that, solving the false-positive problem is an important step in further improving ML-based crack detection models. The research concluded that, the computation speed, as well as accuracy, is an important aspect to be considered.

Praticò, Fedele, Naumov, & Sauer, (2020) proposed detection and monitoring of bottom-up cracks in road pavement using a machine-learning approach. Results show the possibility of associating with great accuracy (i.e., MLP = 91.8%, CNN = 95.6%, RFC = 91.0%, and SVC = 99.1%) a specific vibro-acoustic signature to a differently cracked road pavement. However, the study fails to investigate the effect of different



types of distresses on the vibroacoustic signatures of the different road pavements in different environmental, boundary, and structural conditions (i.e., considering (a) daily, seasonal, and annual change

Similarly, (Feng et al., 2020) proposed pavement crack detection and segmentation method based on an improved deep learning fusion model the recognition accuracy of the pavement crack identification method for transverse, longitudinal, and alligator cracks is 86.8%, 87.6%, and 85.5%, respectively. However, the model could suffer the limitations caused by the extremely small size of the filters. Particularly, the detection accuracy on wide cracks is still not satisfying.

Recently in 2021, (Hu, Hu, Yang, Huang, & Li, 2021) proposed pavement crack detection method based on deep learning models. The detection accuracy of the YOLOv5l model is the highest, reaching 88.1%, and the detection time of the YOLOv5s model is the shortest, only 11.1 ms for each image. However, the research fails to study the detection based on anchor-free to improve the detection rate and reduce the resources is a problem.

Guan et al., (2021) proposed an automated pixel-level pavement distress detection based on stereo vision and deep learning. After obtaining the high-resolution pothole segmentation map, the automated pothole volume measurement is realized with high accuracy the severity of various pavement distresses may be considered to automatically evaluate by incorporating the 3D shape measurement algorithms.

Kanaeva & Ivanova, (2021) proposed road pavement crack detection using deep learning with synthetic data. The models, trained on synthetic crack data, give acceptable outcomes over 47% of IoU metrics on real images with surfaces' cracks. However, the proposed approach is weak and sensitive to shadows, road markings, and light condition.

In all of the above studies, object detection based on the deep learning method was used for road damage assessment studies. Various types of road damage were employed in

the previous studies. Therefore, as another contribution to these research field, parameters such as shooting conditions (weather conditions), illumination level, shooting distance and shooting height need to be examined to create a healthy dataset. In this way, the sensitivity results of the trained model can be revealed. Hence, (Haciefendioğlu & Başağa, 2022) proposed concrete road crack detection using deep learning based faster R-CNN method. The trained model was capable of detecting almost all of the cracks in the photographs on a sunny day. However, it was difficult for the model to detect cracks with the increase in darkness. As a result, it was understood that the effect of illumination on the detection of cracks was quite high. As the hours progressed, the detection rate of cracks decreased to 75%, when it was complete darkness, 15% of cracks could be detected.

Hoang, Huynh, Tran, & Tran, (2022) proposed a novel approach for the detection of pavement cracks and sealed cracks using image processing and salp swarm algorithm-optimized machine learning. The newly developed method has achieved the most desired predictive performance with an accuracy rate of 91.33% for crack detection and 92.83% for sealed crack detection. However, the study fails to investigate the CV-SSA-SVM performance with respect to different swarm sizes and the extension of the current image dataset to enhance the generalization of the computer vision model.

Du & Jiao, (2022) proposed an improvement of the lightweight convolutional neural network model based on the yolo algorithm and its research in pavement defect detection. Experimental results show that the proposed BV-YOLOv5S model in the mAP@.5 index improved by 4.1%, 3%, and 0.9%, respectively, compared with the deep network learning models YOLOv3-Tiny, YOLOv5S, and B-YOLOv5S. However, the major limitation of the study is that the study fails to apply to embedded devices in ordinary cars to further improve and realize the automatic detection of road surface defects

More recently in 2022 (Elghaish et al., 2022) developed a new deep-learning CNN

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model to detect and classify highway cracks. The accurate model here is the GoogleNet model as the accuracy is 89.08% and it is higher than AlexNet by 1.26%. While the computed accuracy for the newly created deep learning CNN model exceeded all pre-trained models by achieving 97.62% at a learning rate of 0.001 using Adam's optimization algorithm. However, the study fails to evaluate the severity degree of cracks. The summary of related work by proposed method, findings and limitation is presented in Table 1.

DISCUSSION

A large number of recent literatures in crack detection and characterization of pavement surface distresses clearly demonstrates an increasing interest in this research area (L. Zhang, Yang, Zhang, & Zhu, 2016). 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 patterns (LBP) based algorithm for crack detection is developed in (Makaremi, Razmjoo, & Ramezani, 2018), whereas a crack detection method using the Gabor filter is proposed in (Salman, Mathavan, Kamal, & Rahman, 2013). In (Zou, Cao, Li, Mao, & Wang, 2012), an automatic crack detection based on the tree structure, referred to as CrackTree, is introduced. A fully integrated system for crack detection and characterization is proposed in (Oliveira & Correia, 2012) and a comprehensive set of image processing algorithms for detection and characterization of road pavement surface crack distresses is

introduced in (Oliveira & Correia, 2014). Although hand-crafted features are widely used and support top-ranking algorithms on the well acquired data set, it is important to note that they are not discriminative enough to differentiate the crack and complex background in low level image cues.

Having the ability to perform various tasks with outstanding performance, machine learning (ML) has become a popular technique in almost every field. By providing a sufficient amount of data, ML algorithms can automatically digest intrinsic knowledge of the data, such as hidden structures or relationships (Alzubaidi et al., 2021). Traditional ML techniques require a predefined feature extraction stage to reduce the complexity of the data and make patterns more visible to learning algorithms. However, this also limits the performance of the models, even if more data are provided. In recent years, deep learning (DL), a subset of ML techniques that use multilayer neural networks, is rapidly developing. Compared with traditional ML, DL techniques are more intelligent as the features of the data are automatically learned through the training process. That is, DL does not require a predefined feature extraction stage, and a more general and robust model can be trained by providing more data (Sarker, 2021). With the success of the ML techniques, a large number of research efforts on ML-based crack detection have been conducted. ML, especially DL, has become a mainstream technology for developing enhanced crack detection algorithms (Hsieh & Tsai, 2020).

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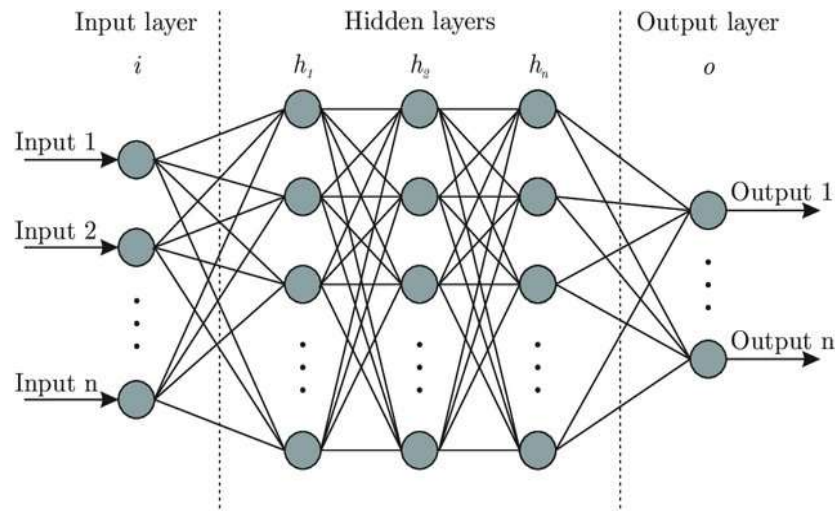


Figure 1: Structure of Artificial Neural Network
Source: [\(Bre, Gimenez, & Fachinotti, 2018\)](#)

Deep learning, as an extension of and supplement to machine learning, has become a new research front in the field of crack detection due to its superior performance in object detection and semantic segmentation (Elghaish et al., 2022). Generally, deep learning-based crack detection methods can be categorized into two main groups, namely region based and pixel-based methods. The emergence of deep learning has changed this situation to a certain extent. Convolutional neural network is the core technology of deep learning. It has better sensitivity to RGB images and can quickly identify and locate targets. Compared with the previous methods of image-based detection of pavement cracks, it has higher precision and stability.

In recent years, object detection technology based on deep learning has been gradually developed in the field of road traffic, including recognition of vehicle and license plate number, road traffic congestion identification and pavement damage detection (Li et al., 2019). Among them, on pavement damage detection, deep learning was firstly applied in (Liu, Zhang, Zhang, & Chen, 2020). A review of literature reveals that there has been intensive research over the last few years to utilize deep learning and CNN to detect cracks for highways and

tunnels. Therefore, there is a need to measure the capabilities of different CNN models to maximize the accuracy of detecting various types of cracks (Zheng, Lei, & Zhang, 2020).

Due to the challenging environment (e.g., large crack scale variation, object occlusion and bad light conditions), popular CNN detectors do not achieve very good object detection accuracy over the road pavement crack benchmark dataset. In this research, we propose three enhancements for CNN based visual object detection for road crack detection. To address the large crack scale variation challenge, deconvolution and fusion of CNN feature maps are proposed to add context and deeper features for better object detection at low feature map scales. In addition, soft non-maximal suppression (NMS) is applied across object proposals at different feature scales to address the object occlusion challenge. As road have distinct aspect ratio features, we measure their aspect ratio statistics and exploit them to set anchor boxes properly for better crack matching and localization. The proposed CNN enhancements are evaluated with various image input sizes by experiments over road pavement dataset. The proposed CNN enhancements are evaluated with various image input sizes by experiments over road crack dataset. It is believed that these

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techniques should aid the development of more discriminative frameworks that yield superior

performance. Figure 2: depicts the architecture of the proposed system.

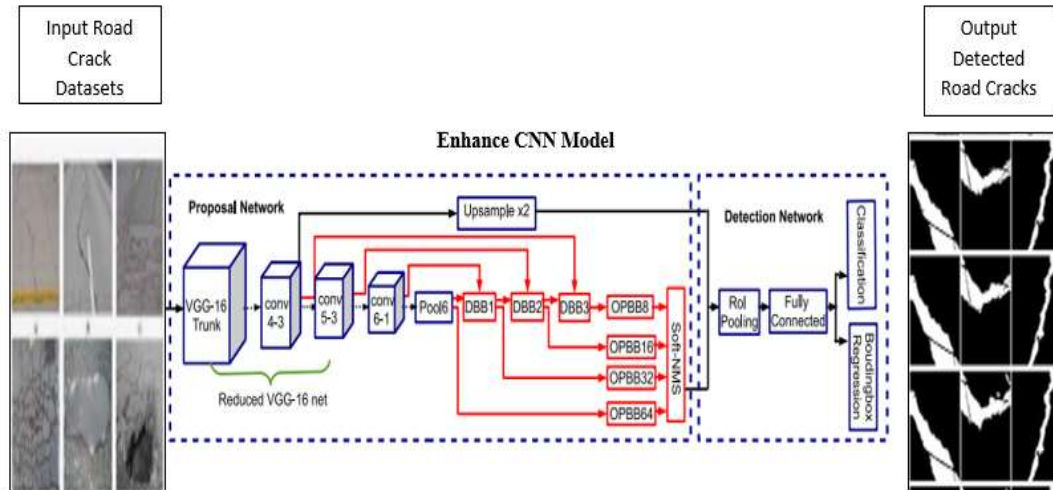


Figure 2: Architecture of the proposed system
Source: (Bre, Gimenez, & Fachinotti, 2018)

CONCLUSION

The proposed CNN-based road cracks detection will be tested using different optimization algorithms at different learning rates. Therefore, its accuracy will correspondingly increase with adding more images. This means that road maintenance agencies can use it for their work and the model will be robotically adjusted to their types of cracks, feature of images and other criterion. As such, the proposed CNN-based road cracks detector is scalable model compared to the pre-trained CNN model that were used to detect road cracks in similar researches.

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