

**DISTANCE INSENSITIVE CONCRETE CRACK DETECTION USING  
CONVOLUTIONAL NEURAL NETWORK WITH CONTROLLED  
BLURRINESS**

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## **ABSTRACT**

Structural health monitoring system has been implemented to assess structural damage with minimal manpower. Most of research and development interests in structural damage detection have moved towards the use of artificial intelligence to aid in such process. Recent research has highlighted the use of convolutional neural network (CNN) as one of the powerful tools for accurate and effective image recognition. Nonetheless, the application of CNN on crack damage detection is limited by the inability of the method to detect crack autonomously without a given distance. In view of this, the present study developed a CNN based artificial intelligence for detecting concrete crack autonomously at various distance. The innovation of this study is the use of blurred and sharp images to train CNN. This idea is inspired from the fact that images taken from further distance are blurrier. Eight databases with different combination of datasets are then considered and trained on designed CNN. It is found that all networks recorded with at least 95 % accuracy. The robustness and adaptability of the network with the use of sharp images only are tested on twenty-three images taken from Universiti Teknologi Malaysia under various conditions. Additionally, these eight networks are evaluated by classifying four different images taken in the distance of 0.5 m, 1.0 m, 1.5 m and 2.0 m, respectively. It is found that the most performing network across various image distances is the network solely made up of image with blurriness level 1. The results show that the presence of blurred images can potentially solve the image distance issue associated with CNN.

## ABSTRAK

Sistem pengawasan kesihatan struktur dilaksanakan untuk menilai kerosakan struktur dengan tenaga manusia yang minima. Kebanyakan penyelidikan dan pembangunan dalam pengesanan kerosakan struktur telah bergerak ke arah penggunaan kecerdikan buatan untuk membantu dalam proses sedemikian. Penyelidikan baru-baru ini telah menonjolkan penggunaan rangkaian neural konvolusi (CNN) sebagai salah satu daripada alat yang berkesan dalam pengesanan imej. Namun begitu, penggunaan CNN dalam pengesanan retak amat terhad disebabkan ketidakupayaan untuk mengesan retakan secara automatik tanpa jarak tertentu. Oleh itu, kajian ini telah membangunkan kecerdikan buatan berasaskan CNN untuk mengesan retak konkrit secara automatik pada jarak yang berbeza. Inovasi kajian ini adalah penggunaan imej yang kabur dan tajam untuk melatih CNN. Idea ini diinspirasi daripada fakta bahawa imej yang diambil dari jarak jauh semakin kabur. Lapan pangkalan data dengan kombinasi dataset yang berbeza telah digunakan untuk melatih CNN yang direka. Penyelidikan ini mendapati bahawa semua rangkaian telah mencatatkan ketepatan sekurang-kurangnya 95%. Kekukuhan dan kebolehsuaian rangkaian dengan penggunaan imej tajam sahaja telah diuji pada dua puluh tiga imej yang diambil dari Universiti Teknologi Malaysia dengan pelbagai keadaan. Di samping itu, lapan rangkaian tersebut telah dikaji dengan mengklasifikasikan empat imej yang diambil pada jarak 0.5 m, 1.0 m, 1.5 m dan 2.0 m masing-masing. Secara rumusnya, penyelidikan ini mendapati bahawa rangkaian yang paling berprestasi adalah rangkaian yang terdiri daripada imej dengan tahap kabur 1. Hasil tersebut menunjukkan bahawa penggunaan imej kabur berpotensi untuk menyelesaikan isu jarak imej yang berkaitan dengan CNN.

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## **LIST OF ABBREVIATIONS**

<b>CNN</b>	-	<b>Convolutional Neural Network</b>
<b>TP</b>	-	<b>True Positive</b>
<b>FP</b>	-	<b>False Positive</b>
<b>TN</b>	-	<b>True Negative</b>
<b>FN</b>	-	<b>False Negative</b>
<b>P</b>	-	<b>Positive</b>
<b>N</b>	-	<b>Negative</b>

## LIST OF SYMBOLS

$\sigma$  - standard deviation

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# CHAPTER 1

## INTRODUCTION

### 1.1 General

Over the years, concrete has been commonplace in civil infrastructures such as bridges, reservoirs and skyscrapers. Nonetheless, related structural damage includes cracks, corrosion and spalling might be encountered by the concrete structures over the course of time. Lighter damage has an impact on aesthetic value of the structure itself while severe damage could affect the durability and stability of the whole structure. Early detection followed by appropriate repair strategy plays an important role in ensuring structural safety. Therefore, this has increased the need of inspection and maintenance approach for structural damage detection.

### 1.2 Problem Background

Human-based visual inspection is a conventional practice widely carried out to detect and evaluate structural damage quantitatively. Generally, it is performed manually by certified inspectors or structural engineer regularly. However, the accuracy of human-conducted damage diagnosis is greatly influenced by the skill level and experience of inspectors (Li *et al.*, 2019). Additionally, this approach would consume large amount of resources for a large-scale inspection. To address these limitations, vibration-based monitoring condition has been thoroughly investigated. Based on the measurement by sensors, structural damage detection and assessment can be done by utilizing data in the time, frequency and modal domains. Albeit a significant amount of algorithms and frameworks have been produced and validated through a series of numerical and experimental studies, the deployment of vibration-based monitoring system in realistic engineering structures are restricted by expensive installation and maintenance of sensors networks (Feng and Feng, 2018).

In view of this, recent advancement in structural damage detection has shifted focus on the use of artificial intelligence to aid in such process. Due to the ability of imitating human cognition capability to execute tasks (Salehi and Burgueno, 2018), it is believed that artificial intelligence is capable of detecting structural damage as well. Among various kind of artificial intelligence approaches, convolutional neural network (CNN) has been the major interest of many researchers in structural health monitoring due to good performance in object recognition and classification. CNN is a deep neural network which inspired by the visual cortex of animals (Ciresan *et al.*, 2011). It mimics the network structure in brain with layer of connected nodes to develop similar pattern recognition mechanism in computer vision. CNN is primarily capable of capturing the 2D matrix of pixels such as images, videos, and speeches yet requiring less computations. Thus, it is highlighted as one of the promising tools for accurate and effective image recognition. To date, most of CNN applications involved crack detection for road pavements (Gao *et al.*, 2018), masonry structures (Wang *et al.*, 2019), steel structures (Dung *et al.*, 2019) and concrete structures (Cha *et al.*, 2017; Dung, 2019; Xu *et al.*, 2019).

### **1.3 Problem Statement**

Crack occurrence and propagation are commonly observed phenomenon in concrete structures (Wiktor and Jonkers, 2011). It occurs due to presence of unconsidered external loads, fatigue, freeze-thaw cycles and alkali-silica reaction. Without properly detecting these cracks early on, they would eventually lead to structural failure. While CNN is understood to be used on crack detection, there are still some major flaws for practical application.

As evidenced from recent trend of research, database for training and validation of CNN are mostly composed of images from controlled distance, sharp image and uneven illumination. Additionally, detailed study of the effect of blur image on the performance of CNN is limited. In Cha *et al.* (2017), they considered the blur image condition in their database. They found that the performance of the proposed CNN was not susceptible to distance change although the image was taken under very near

distance. However, far distance images have not been tested in the literature. Therefore, a question arises whether CNN is applicable to detect crack at significantly different distance from camera.

It is hypothesized that the blurriness of an image is related to distance between camera lens and concrete surface. This conjecture is based on the fact that an image is blurrier when the image is taken from a further distance or a very near distance. Therefore, training CNN with combined blurry and sharp image is capable of producing CNN which can detect cracks from various distance autonomously.

#### **1.4 Research Objectives**

The main objectives of this research are as follows:

- (a) To establish a database of relevant images on concrete crack damage.
- (b) To develop a CNN for detecting concrete crack autonomously.
- (c) To determine the intercorrelation between level of blurriness and performance of CNN on the distance change.

#### **1.5 Scope of Research**

The primary concern of this study is to detect concrete crack from the input image at various distance autonomously. Level of blurriness for the image condition is the main consideration in this study. Each of the image is blurred by using 2-D Gaussian smoothing kernel with standard deviation specified by sigma,  $\sigma$ . The higher the value of standard deviation, the higher the level of blurriness. For the scope of this study, the level of blurriness tested is within the range of 1 (slightly blurred image) to 3 (very blurred image).



As for database, the collection of image focuses solely on concrete cracks. The images collected are sharp and can be seen without soft edges. Distance between camera lens and concrete surface is in between 0.2 m to 1.0 m. In addition, the collected images are under different illumination level. The images are in JPG format. Since the proposed CNN is a supervised learning models, category labels for each pattern in the training samples are provided.

MATLAB Deep Learning Toolbox in MATLAB version R2018b is employed to train the CNN for this study. To ensure the robustness of the proposed networks in this research, the minimum number of images used to train CNN is set to 10 000.

## **1.6 Significant of Research**

Leveraging a state-of-the-art artificial intelligence technique, this research serves as an attempt to investigate the applicability of CNN in detecting concrete crack at various distance autonomously by considering blurred image technique. It aims to increase the performance of CNN that is less influenced by image distances and quality of images.

Moreover, abundant data taken under extensively varying conditions from previous researchers are collected to train the proposed CNN. Thus, it can further secure a wider range of adaptability of proposed CNN. The process for collecting data can also be more cost effective and time efficient. Lastly, the outcome and the framework of developing CNN used in this research is useful for future research to tackle the obstacles reported in recent research.

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