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# Development of Crack Detection and Measurement Method Using Deep Learning and Image Processing Techniques

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## Abstract

The presence of cracks in reinforced concrete structures is an indication of structural degradation. However, some cracks are more concerning than others, the maximum crack width is usually a good indication of the severity of a crack. The measurement of crack widths is typically done manually using crack width gauges, a method which tends to be tedious and susceptible to human error. Image processing algorithms have also been employed to measure crack widths, but these tend to give the measured crack widths in terms of number of pixels and not millimetres. It is difficult to assess the severity of the cracks when their widths are measured in pixel units. This is because design guides typically state the allowable crack widths are in units of millimetres rather than pixels. This paper presents a crack detection and quantification method that uses a deep learning model, a two-dimensional convolutional neural network, to detect the presence of cracks in captured images of reinforced concrete surfaces. The camera capturing the images has a laser pointer attached to it to project a circular laser light onto the measured plane. A relationship between the diameter of the laser projected on the measured plane and the distance to the measured plane was established. This relationship was used to convert the maximum pixel width, measured by using image processing algorithms in MATLAB, to millimetre width. The results of the study showed that the two-dimensional convolutional network was able to successfully detect cracks, with very high accuracy of 98.58%. The proposed method of converting pixel width to millimetre width also yielded positive results with percentage errors of less than 2%. Going beyond crack detection and measuring the crack widths in millimetres and not pixels can give a good insight into the condition

of the structure in question, in accordance with international codes such as the Eurocodes. This simple, low-cost method was found to be very effective.

**Keywords:** crack detection, crack width measurement, deep learning, image processing, structural health monitoring, computer vision

# 1 Introduction

Damage detection in reinforced concrete structures is a common practice and various methods exist such as visual inspection, vibration-based methods, and infrared thermography. There are also many types of failures/damage such as delamination, spalling, thaw etc [1]. The focus of this paper is on one of the most common damage types for reinforced concrete buildings, cracking. Technological advances have led to improved methods of damage detection, such as the use of machines and deep learning [2-5]. Majority of the existing literature focuses on the detection of cracks and very few studies go beyond crack detection to the quantification of crack characteristics such as maximum crack width, crack length and crack angle [6-9]. Crack quantification can be done by taking physical measurements of cracks on-site or by computer vision (CV) methods. Crack detection using CV images is typically carried out in two ways; patch-based methods or pixel-based methods. Patch-based methods rely on a sliding window (the patch) sliding across an image and detecting the presence of a crack using pattern recognition, template matching or a classifier [10]. The limitations of the patch-based method include the size of the patch and having to put the patches together to form final crack distributions makes it challenging to get characteristics of the crack such as angles, detailed shape and connectivity [10,11]. The limitations of the patch-based method make the pixel-based method a more preferred approach in recent studies. Pixel-based methods typically produce detailed crack shapes and angles by carrying out pixel-level segmentation. The general trend at present is to use deep learning networks to detect the presence of cracks and then use image processing techniques to quantify desired crack characteristics [6,7]. However, most of the studies measure the crack characteristics in terms of pixel size rather than millimetres.

This paper introduces a crack detection and quantification technique that makes use of a 2-D deep learning network that initially detects images that have cracks and then uses image processing with a laser beam to build a relationship between pixel width and millimetre width. By measuring the crack widths in millimetres, the deep learning algorithm can classify cracks in accordance with the relevant design standards thus providing the user with meaningful and applicable results. The rest of the paper presents the methods employed, the results obtained and some conclusions and recommendations for future work.

# 2 Methods

## 2.1 Deep Learning Network for Crack Detection

A 2-dimensional convolutional neural network (2-D CNN) was built using MATLAB R2021b. The purpose of the DCNN was to detect the presence of cracks on concrete surfaces. The network was built from scratch and trained using an independent concrete crack dataset created by (Özgenel, 2019). The images were collected from different campus buildings across Middle East Technical University. The dataset consisted of two classes of 227x227 RGB images, cracked and uncracked, with variances in surface finishes and illumination conditions.

The images in the dataset were augmented to a size of 224 x 224 RGB images. The dataset was shuffled and split up into training images, testing images and validation images at a ratio of 80%, 10% and 10% respectively. The architecture of the network consisted of an input layer; three stacks of convolution, batch normalisation, ReLU and max-pooling layers; a fully connected layer; a SoftMax layer and a classification layer. The output consisted of two classes: cracked and uncracked. The training was stopped with a validation accuracy of 98.58% after 126 minutes at 1515 iterations out of a possible 2133 iterations. Figure 1 shows the accuracy and loss as the training progressed.

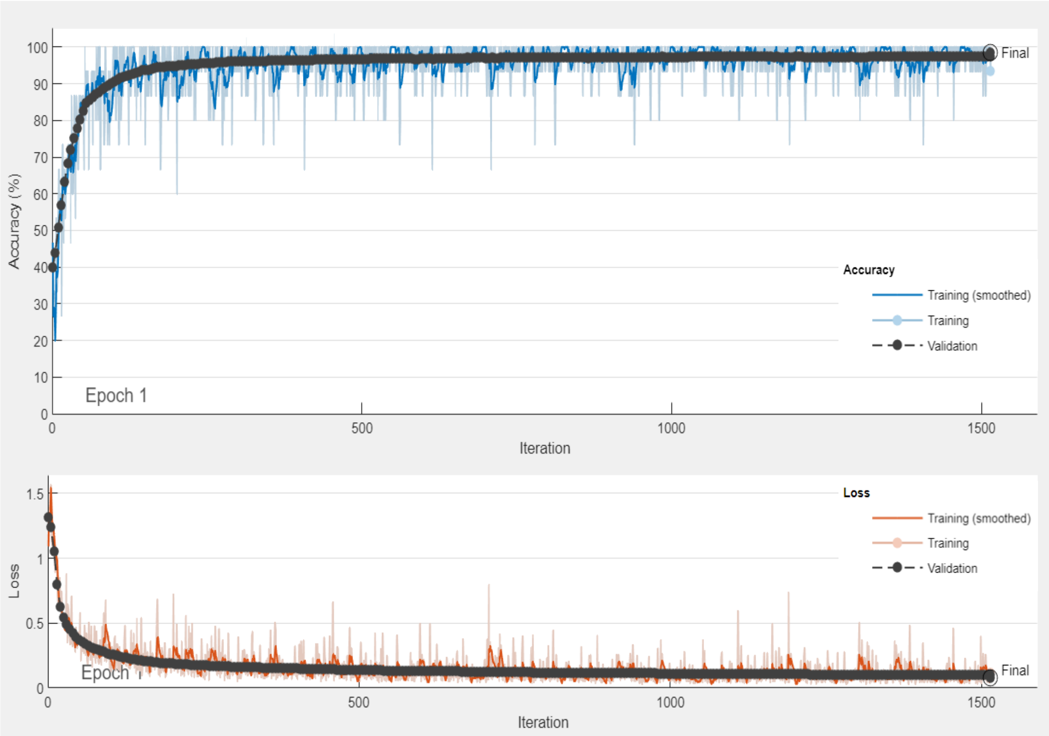


Figure 1: Training and validation accuracy (top) and loss function (bottom).

### 2.2 Laser Relationship and Crack Width Quantification

To build a relationship between the pixel width and millimetre width, a laser was attached to the camera capturing the image of the concrete surface with the crack to be measured. The laser pointer projected a light which was circular in form. The diameter of the laser pointer varies according to the distance the laser is from the measured plane. Figure 2 shows the relationship between the laser diameter and the distance to the measured plane. Figure 2 can be used to convert pixel width to millimetre width and thus convert the crack widths measured in pixels to millimetres.

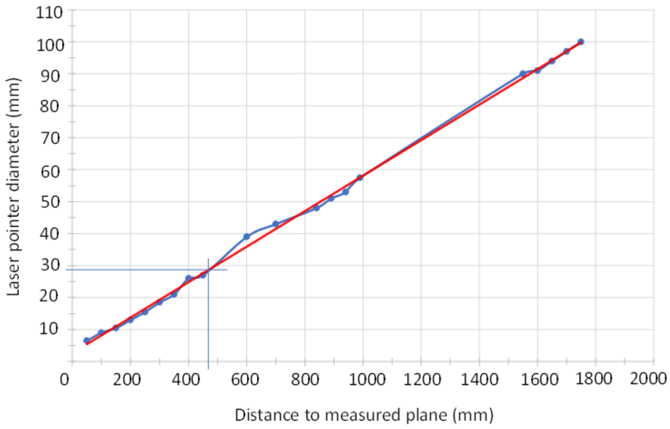


Figure 2: Relationship between the laser pointer diameter and the distance to the measured plane.

To quantify maximum crack widths, the images of cracks were pre-processed in MATLAB by performing operations such as binarisation, applying morphological filters and segmentation. The properties of the cracks were then calculated using the regionprops function, which returns measurements for a set of properties of objects in a binary image, in this case, the segmented cracks. The width of the crack was measured along its entire length and the largest width was chosen as the maximum crack width.

# 3 Results

## 3.1 Crack Detection

The confusion matrix shown in Figure 3 gives a visual interpretation of the performance of the network. From the 2000 cracked images, 1953 were correctly identified as cracked, while 47 were wrongly classified as not cracked. Only 10, not cracked images were misclassified as cracked, while 1990 were correctly classified as not cracked. The performance of the network can be improved by optimising the network by changing the parameters such as filter size, stride, padding and training options as these were initially chosen randomly.

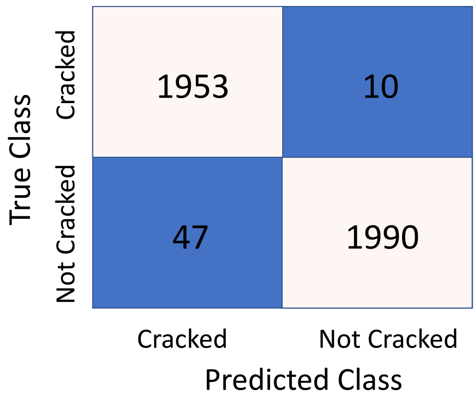


Figure 3: Confusion matrix showing the performance of the 2D convolutional neural network.

### 3.2 Crack Quantification

The diameter of the laser pointer circle was measured in the image and found to be 28 pixels. The laser and camera setup were 460mm away from the measured plane and thus by using Figure 2, the diameter of the laser pointer was found to be 29mm. Using this information, one pixel was found to be equivalent to 1.035mm and hence the crack widths measured in pixels could then be converted to millimetres as shown in Figure 4. The proposed method performed quite well, the widths of crack one and crack two were measured to a percentage error 1.69% and 1.50% respectively.

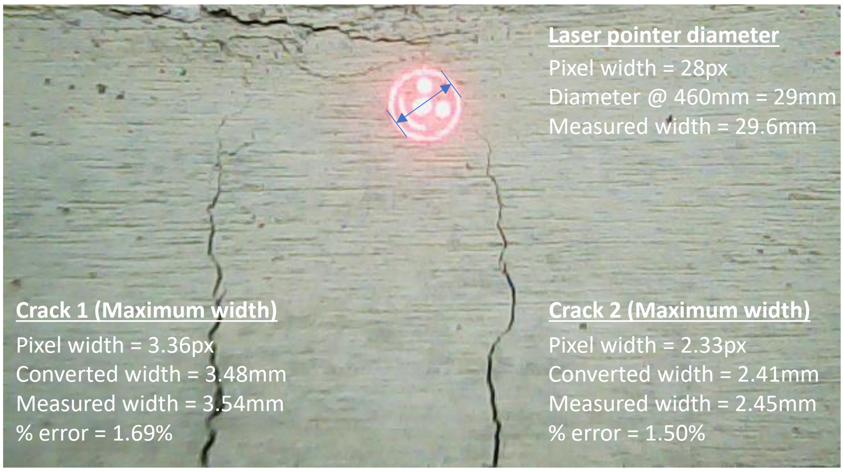


Figure 4: Measurements of two cracks on a beam using the proposed method.

## 4 Conclusions and Contributions

The short paper presented a simple and low-cost method of detecting and measuring crack widths by simply attaching a cheap laser pointer to the device capturing the images of the cracks to be measured. A 2-D convolutional neural network was designed and employed for the detection of the presence of cracks in the captured images. The following conclusions can be drawn from this short paper:

- The 2-D convolutional neural network used to detect cracks in images performed well, achieving an accuracy of 98.58%.
- Attaching a laser pointer that projects a circular light on the plane to be measured enables crack widths to be measured quickly and effectively with ease, while still achieving satisfactory results. The measurements of the two maximum cracks measured here had percentage errors of 1.69% and 1.50%, respectively.

As simple as this proposed method may be, it fills an important gap in the field of structural health monitoring and the inspection of reinforced concrete structures. It allows crack widths measured algorithmically to be converted from pixel widths to millimetre widths and thus adding valuable meaning to them. Knowing the millimetre widths gives a better understanding of the extent of damage in relation to the maximum allowable crack widths specified by various international design guides.

The proposed method will further be developed by using the laser with a stereo camera setup which will enable distance to the measured plane and crack widths to be measured by depth perception of the stereo camera setup. This will make the method more robust, as there will be two crack width measuring techniques which can be compared against each other in addition to the manual measuring method. Different lasers from different manufacturers will also be used to ensure the proposed diameter to measured plane relationship holds for different lasers. The deep learning algorithm will also be trained on images taken under different lighting conditions, angles etc to ensure that it can perform well under any conditions.

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