Toward Automation in Crack Detection and Measurements: Benchmarking of CNN-based Algorithms

D. Ji[a], Y. Turkan[a] and P. Calvi[b]

[a]School of Civil and Construction Engineering, Oregon State University, United States of America
[b]Department of Civil and Environmental Engineering, University of Washington, United States of America
E-mail: jid@oregonstate.edu, yelda.turkan@oregonstate.edu, Pmc85@uw.edu

Abstract

Cracks are one of the main defect features on concrete surfaces, and indicators of concrete structures' condition regarding their state of health. Since traditional methods to identify and assess cracks rely on manual measurements, a significant number of studies to date have focused on identifying ways to automate this process. Accordingly, this study proposes to combine Convolutional Neural Network (CNN)-based algorithms and traditional image morphological operation for crack detection and measurements with a specific goal to benchmark the proposed methodology on data of three images obtained from laboratory experiments in a controlled environment. The proposed methodology performed well, with 92.10% and 90.11% accuracy in crack length and width measurements, respectively. Future research will focus on fine-tuning the proposed crack detection and measurement methodology and evaluate them on a set of images acquired from a real full-scale structure such as a bridge or a building.

Keywords

Crack Detection; Crack Measurement; Image Morphological Operation; Convolutional Neural Network (CNN); Skeletonization

1 Introduction

According to the recent infrastructure report from the American Society of Civil Engineers (ASCE), approximately 231,000 bridges across the United States, or 37.4% of all bridges in the nation, need repair and preservation work, and 46,154, or 7.5% of the nation's bridges, are considered structurally deficient [1]. To prevent infrastructure failures, periodic inspections are needed to determine their condition. One of the most important procedures during periodic inspections are visual inspections carried out to identify and assess surface defects.

Cracks are one of the main defect features on concrete surfaces, and indicators of concrete structures' condition regarding their stability and durability [2]. Thus, the identification and assessment of cracks plays a paramount role in concrete structures' inspections. However, since the traditional methods to identify and assess cracks mostly rely on manual measurements, which are labor intensive and error prone, several recent research efforts have focused on leveraging computer vision and machine learning techniques to automate this process.

Several image-based crack detection and measurement techniques, including deep learning-based algorithms, have been proposed to date to automate crack identification and assessment processes. These studies proposed various image-based crack detection methods that use edge detection algorithms [4]-[6], automatic threshold image segmentation [7], and image morphological operations [8][9]. In recent years, the focus has been on utilizing deep learning-based algorithms due to their robustness and accuracy. These studies utilized convolutional neural networks (CNN) architectures [10]-[13], and performed better compared to previously proposed computer vision-based methods [14]-[20].

Even though image-based methods have been proven to be effective in detecting cracks, most of them perform well when applied to images with well-distinguishable cracks, i.e., cracks with prominent edge-gradient changes, and none to minimal number of non-crack objects such as stains. In addition, deep learning-based crack detection algorithms require large number of training dataset of images and heavy computing resources. Therefore, it can be concluded that the currently available computer vision-based methods to identify and assess surface defects are not mature enough to be used in real-life scenarios, e.g., on data collected from bridges or buildings.

Several studies have focused on fine-tuning the previously proposed algorithms for crack detection and measurement to overcome the limitations summarized above. Moreover, to achieve an acceptable level of accuracy and sensitivity on real-case scenarios, new approaches that combine different methods (e.g., deep learning and 3D point cloud) have been proposed.

Accordingly, this study aims to benchmark CNN based deep learning algorithms for crack detection and measurements on data obtained from a laboratory experiment in a controlled environment. A methodology that combines a CNN-based algorithm and the traditional image morphological operation is presented for crack detection. Next, skeletonization and orthogonal projection algorithms were applied to measure the crack length and width and their overall performance were evaluated.

2 Literature Review

In this section, previous studies on crack detection and measurements are reviewed. First, crack detection methods based on conventional image morphological operations, deep learning algorithms, and the approaches that combine the first two are examined and their strengths and weaknesses are discussed. Next, the studies that focused on crack measurements are analyzed. Finally, the methods selected for crack detection and measurement in this study are introduced.

2.1 Crack Detection

The majority of studies that focused on automating crack detection used digital images as input data. Thus, conventional object detection and segmentation algorithms are very important and play a major role in image-based crack detection. Initially, researchers have focused on detecting crack edges since they are the most distinguishable crack features, and various edge detection methods, such as Sobel, Prewitt, and Canny have been utilized for this purpose [4]-[6]. These methods detect crack edges based on prominent gradient changes in the image, especially the changes in intensity in certain directions along the feature of interest. If the gradient changes are not significant, meaning that the crack is not clearly distinguishable, the overall crack detection performance decreases drastically. Hence, several studies focused on extracting crack edges by applying various image processing algorithms.

To extract cracks, i.e., separate them from the background details in each image, Otsu [7] proposed a segmentation method based on image thresholding approach that uses the maximum grayscale intensity values in the image. Nguyen et al. [8] proposed the Free-Form Anisotropy method, which simultaneously considers various crack features including intensity values, texture, and others to detect cracks more accurately. Following these two approaches, several research studies applied morphological operations to pre/post process images for feature extraction purposes. For example, Xu and Turkan [9] presented an approach for automated crack detection using images of a bridge acquired from an unmanned aircraft system (UAS). They applied Otsu's image gradient segmentation method and additional image pre-processing steps including contrast adjustment and noise reduction for crack detection and reported precision and recall values of 74.6% and 86.2%, respectively.

Although most crack detection methods based on image morphological operations have performed well and yielded meaningful results, issues such as the presence of shadows or stains, features similar to cracks, impact the performance of these methods negatively.

Meanwhile, several studies focused on utilizing deep learning-based object detection methods. The major CNN-based vision architectures, such as AlexNet [10], VGG-Net [11], Inception Network [12], ResNet [13], which performed well in detecting and classifying various objects, were utilized for image-based crack detection in several studies.

Dorafshan et al. [21] compared the performance of conventional edge detectors (Roberts, Prewitt, Sobel, Laplacian of Gaussian, Butterworth, and Gaussian) and a CNN-based crack detector. They tested AlexNet-based crack detector using fully trained, partially re-trained, and pre-trained datasets to determine its performance under different circumstances. They used images from SDNET dataset that include images with various surface defects [22]. The CNN-based crack detector performed well when a fully trained dataset used, with precision value of 99% and recall value of 66%. The precision values for partially trained and pre-trained datasets were 92% and 80% while the recall values were 86% and 84% respectively. In the meantime, the conventional edge detector based on the Laplacian of Gaussian algorithm achieved the precision and recall values of 60%, and 79%, respectively, which was the best performance among conventional methods. Wang et al. [23] tested the crack detection accuracy of six existing CNNs (VGG 16, Inception V2, V3, V4, Inception-ResNet-v2, and ResNet V1 50), using an original image dataset collected from the inspection of a slab element and the highest accuracy was obtained when using the Inception-ResNet-v2 network, with 80.08% of accuracy when utilizing pre-processed dataset.

Recent studies that focused on automatic crack detection proposed to combine different methods to improve the accuracy and reliability of the results. Several studies focused on augmenting digital images with three-dimensional (3D) data such as point clouds acquired using a laser scanner (i.e., lidar) to overcome the issues faced when using image-based methods such as loss of feature (crack) details due to shadows. Chen et al. [2] utilized point cloud data to obtain a depth image, which illustrates features in the image based on their measured depth. The depth image was then combined with the pre-processed image, and by applying Otsu's crack detection algorithm, the proposed approach achieved, on average, 89.0%, 84.8%, and 86.7%, precision, recall and F1, respectively. Yan et al. [3] also utilized point cloud data to identify cracks, which enabled them to exclude background and other non-target segments in data processing, which is one of the most challenging issues for images obtained in real life cases, e.g., images of a bridge. Simultaneously, they processed images including the same crack features, obtained from the three columns of a bridge, using a VGG16-based crack detector. By combining the results obtained from point cloud and image-based methods, they achieved 93% crack detection accuracy on average, and obtained a precision and recall values of 93.9%, and 89.4%, respectively.

2.2 Crack Measurement

Recent studies on image-based crack measurements have focused on implementing a skeletonization algorithm to guarantee the accuracy of the measurements [3][23][24]. Using binary images, which contain the geometry of cracks, the skeletonization algorithm creates the centerline of the crack in one-pixel thickness. From this centerline, referred to as the crack skeleton, the length of a crack can be measured in pixel dimensions by counting the number of pixels along centerline. To measure crack width, the most accurate method proposed in previous studies calculates the continuous width of each pixel on the crack skeleton using the orthogonal projection algorithm [3][23][24], which is explained next. First, the orientation of each crack pixel is computed by fitting a line to the target pixel and its neighboring pixels on the crack skeleton. Then, an orthogonal line, which is perpendicular to the orientation of the crack in the target pixel, is projected to obtain two intersecting points between the orthogonal line and crack boundaries. In the final step, the width of the crack is calculated as the distance between these two intersecting points.

Qiu et al. [24] validated the performance of width measurement based on the skeletonization and the orthogonal projection algorithms. Using images that contained ten different cracks, with widths ranged between 18.1mm and 66.3mm (with an average of 36.4 mm), they calculated 1.4 mm difference, on average, between the ground truth values and their results. A study from Yan et al. [3], which utilized both CNN-based crack detector and point cloud data, presented, and tested their crack measurement approach based on skeletonization and orthogonal projection algorithms. The test datasets they used included cracks with lengths ranged between 44.5mm to 559.0mm and widths ranged between 1.0mm to 5.0mm. They obtained average error rates of ±3% and ±8% for length and width measurements, respectively. Wang et al. [23], who also adopted skeletonization and orthogonal projection methods, mainly focused on classifying crack images into three classes based on their severity levels, i.e., average crack widths. They used an image dataset that contains cracks with an average width of less than 1.0mm and classified the dataset with the average accuracy of 97.41%.

One of the most essential steps in crack measurements is the conversion of measurements into real scale. This process converts the measured pixel dimensions into units such as mm or inches. For example, Wang et al. [23] utilized the width of railhead in the image as a reference. Since the actual geometric width of the railhead can be identified from its specifications document, the conversion factor can be easily calculated. This is a straightforward approach for conversion, but the images must contain a certain target feature with known dimensions in real world units. Also, during data collection an appropriate camera angle must be maintained. Another scale conversion approach is to utilize data from other sources. For example, Yan et al. [3] used values of depth and focal length of the lidar data to compute the scale factor. Kalfarisi et al. [25] utilized dimensions from the 3D mesh model, which was reconstructed from 2D images. The 3D mesh model provided the dimensions in both pixels and metric units.

3 Methodology

3.1 Crack Detection

In this study, a CNN-based crack segmentation algorithm called DeepCrack, which is proposed by Liu et al. [14], and a traditional image morphological operation based on Otsu’s image segmentation algorithm [7] are combined for image-based crack detection. DeepCrack is a CNN-based crack segmentation algorithm that uses the VGG-16 network, one of the major vision architectures in computer vision. In this study, a pre-trained DeepCrack algorithm model, which was trained with 4,800 images and 3,792 images, was used for testing. The overall performance of the pre-trained DeepCrack model is as follows: the global prediction accuracy is 98.73%, while precision, recall and F1 scores are 85.82%, 84.56%, and 85.18%, respectively [14]. In the next step, the image morphological operation, which is based on Otsu’s image segmentation algorithm along with additional pre-processing (e.g., contrast adjustment, smoothing) and post-processing (e.g., area filtering) steps [9] were implemented.

The detailed crack detection procedure followed in this study is provided in Figure 1.

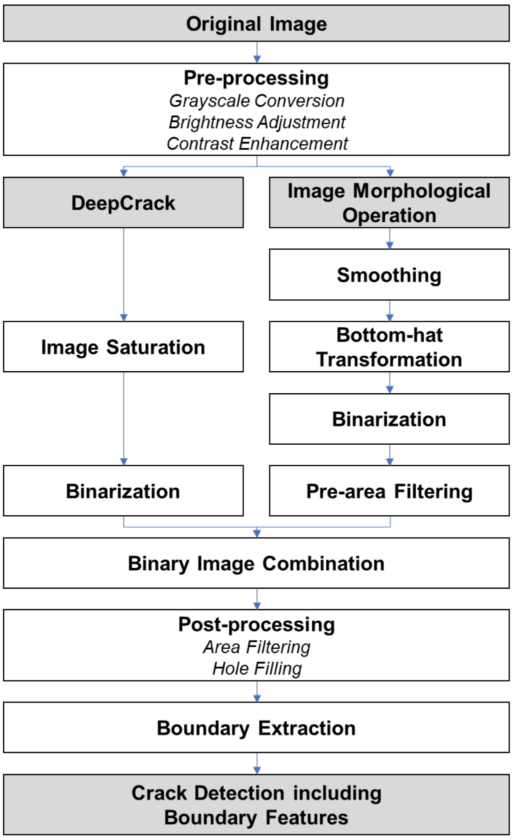

Figure 1. Crack Detection Procedure

First, the original image is pre-processed using grayscale conversion, brightness adjustment, and contrast enhancement techniques, respectively. In the next step, two different methods are applied to the pre-processed images in parallel:

1. The first method involves using the pre-processed image as an input for the pre-trained DeepCrack model. Next, the result from the DeepCrack algorithm is post-processed using image saturation parameters, and binarized to obtain a binary image.
2. The second method used is a conventional image morphological operation process that consists of procedures that include smoothing and discarding unnecessary details of non-crack features, bottom-hat transformation to extract dark regions that are not cracks, and pre-area filtering that uses a certain threshold value to extract detailed features of cracks, which may have been excluded from DeepCrack segmentation results.

After the two-track process based on DeepCrack and image morphological operations, the preliminary results obtained from each step are integrated. Next, the image was post-processed using second area filtering and a hole-filling operation. Lastly, the crack boundaries are extracted using image gradient thresholding technique.

3.2 Crack Measurement

In this study, two prominent crack measurement methods, the skeletonization and orthogonal projection algorithms, are used (Figure 2). The binary image obtained at the end of the crack detection process, is skeletonized. Since the original crack skeleton contains several branches that are not related to the crack length or the main orientation, a post-processing method was used to filter those branches (i.e., pruning). Next, the orthogonal projection algorithm is applied to the crack skeleton. The orientation of the crack skeleton is computed in each pixel, and the target pixel's orthogonal line is projected. By merging these projected orthogonal lines and the binary image of crack boundary from the crack detection step, two intersecting points between the orthogonal line and crack boundaries are obtained. As detailed in section 2, the crack length is measured by counting the number of pixels along the crack skeleton, and the width of the crack is measured by calculating the distance between the orthogonal line and crack boundaries. Finally, the crack length and width dimensions, which were calculated in numbers of pixels are converted into metric dimensions using the dimensions of the specimen that is used in this study.

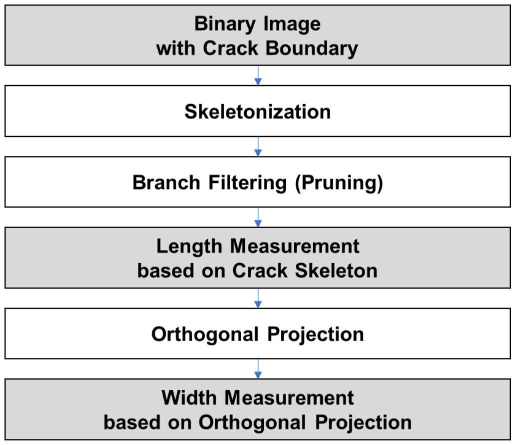

Figure 2. Crack Measurement Procedure

4 Experiment

The crack detection and measurement methods detailed in section 3 were applied to three images taken during a series of shear strength tests conducted at the University of Washington Structures laboratory and the performance of both methods are evaluated. The test data and the experimental procedure are detailed below.

4.1 Test Data

The test data used this study are three images obtained from the shear strength tests on ultra-high-performance concrete (UHPC) [26]. For each test, an 890 × 890 x 70 mm UHPC panel was tested under shear loads using the UW Panel Element Tester. The experimental setup was such that a major crack would form at a pre-selected location. The crack obtained at the end of this test was used as the target crack to be detected and measured in this study (Figure 3, Top).

The original test images were manually cropped and trimmed to extract regions of interests, which contain the target crack (Figure 3, Bottom). The size of the manually cropped test images that contains the regions of interests are 1808 × 1748, 1350 × 1394, and 2044 × 2011 pixels, respectively (left to right, i.e., images 1-3).

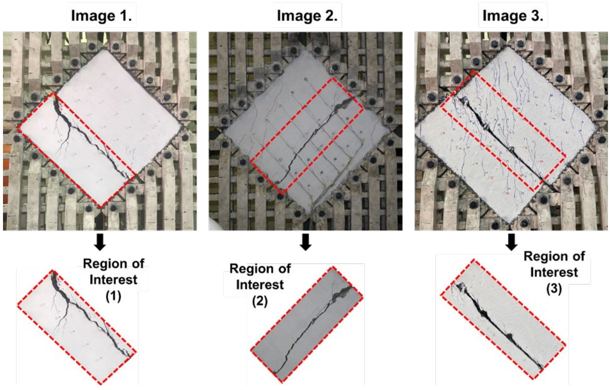

Figure 3. Original Image (Top) and Manually Cropped Test Image (Bottom)

4.2 Experiment Procedure

The images obtained from the laboratory experiments in a controlled environment are processed using the crack detection and measurement methods detailed in section 3. First, the performance of the crack detection method is evaluated based on feature segmentation accuracy that is determined using both the continuity of the feature, and the sensitivity such as preserving the details of the crack. Next, the measured values of length and width are compared with the manually annotated ground truths. More specifically, the length measurements obtained automatically following the procedure described in section 3.1 are directly compared to the manually annotated length from the image. For crack width comparison, five checkpoints along the crack are selected in each image, and the automatically measured widths in the checkpoints are compared with manually annotated widths. This experiment is designed to fine-tune the methodology described in section 3. Once the fine-tuning is achieved, the overall goal of this study is to apply this methodology to real case scenarios, e.g., images collected from bridges.

5 Results

5.1 Crack Detection

The crack detection results based on the methodology proposed in this study are presented in Figures 4 and 5. As can be seen, the cracks in all three images were detected, and their boundaries were extracted successfully. One issue that needs to be discussed here is that there is a loss in details where the crack branches are very thin (Figure 6). These narrow cracks are negligible when assessing reinforced concrete bridges for severe conditions according to North America standards [27], since this type of damage does not affect the integrity of the structure. Note that the average width of the cracks that were lost at the end of the detection process using the proposed methodology is 0.76 mm, which is manually measured at thirty random points and averaged.

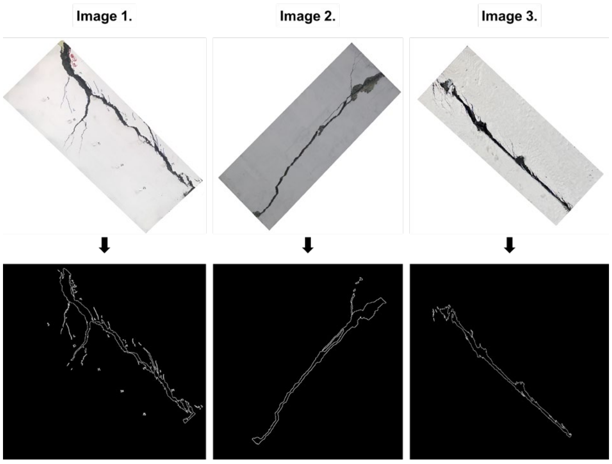

Figure 4. Test Images (Top) and the Crack Detection Results (Bottom)

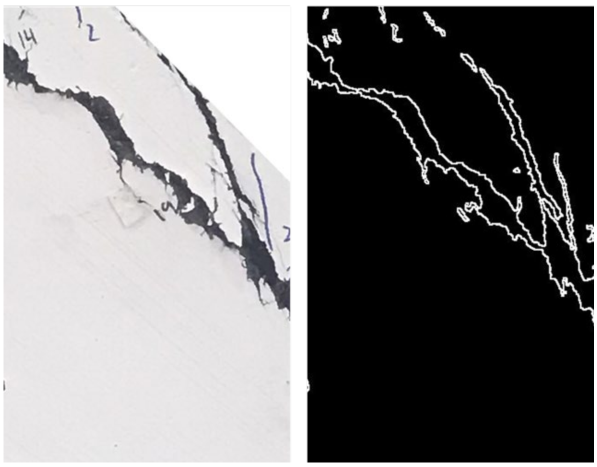

Figure 5. Detailed Detection Results obtained for Image 1

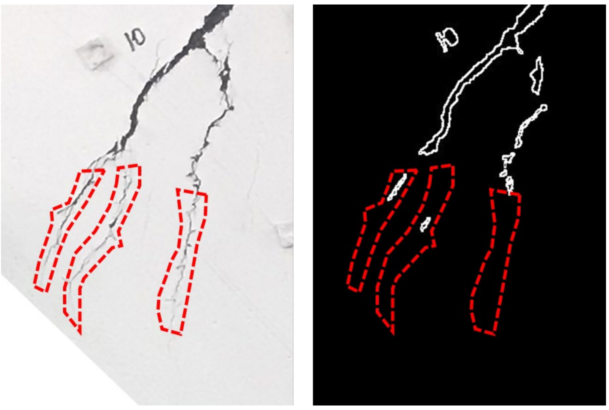

Figure 6. Detail Losses from Crack Detection

5.2 Crack Measurement

First, a real-scale conversion factor is calculated to convert pixel-dimensions into metric dimensions (in millimeter). The widths of the concrete panel in each image were manually measured directly, and the measured values of images 1, 2, and 3 are 1,770.6, 1375.4, and 1939.2 pixels respectively, which equaled to 890 mm. Using these values, the conversion factors for three images were calculated as 0.5027, 0.6471, and 0.4590 mm/pixel, respectively.

Second, the performance of skeletonization and branch filtering algorithms is evaluated. After branch filtering based on the threshold to obtain the proper crack skeleton in a 1-pixel thickness, the losses of pixels on either end of each of the cracks are observed (see Figure 7). The total losses in length along the main crack due to the branch filtering were 28.51, 34.78, and 30.29 mm in images 1 through 3, respectively.

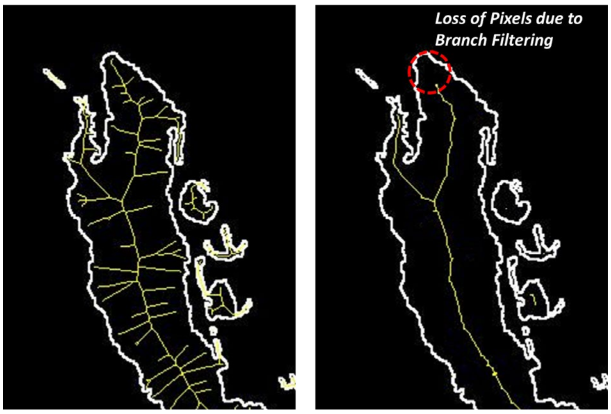

Figure 7. Skeletonization Result and Pixel Loss due to Branch Filtering

Third, the length measurement results are evaluated (Table 1). The measured length along the main crack skeleton in image 1 is 1019.48 mm, which contains 2028 pixels. The main crack skeleton in image 2 is measured as 798.52 mm, or 1234 pixels, and 772.42 mm, or 1683 pixels for image 3. The actual crack length (ground truth) was calculated by dividing each crack into ten segments since the crack is not straight, and then manually measuring each segment and adding them up. At the end of this process, it was determined that the total crack length (ground truth) of each crack in three images are 1071.94, 914.07, and 823.15 mm for images 1 through 3: corresponding to 95.11%, 87.36%, and 93.84% accuracy in length measurement respectively.

Table 1. Length Measurement Results

Image	Proposed method (mm)	Ground Truth (mm)	Accuracy (%)
1	1019.48	1071.94	95.11
2	798.52	914.07	87.36
3	772.42	823.15	93.84
		Average	92.10

Lastly, the crack width measurement result is evaluated by measuring the width from five random checkpoints along each crack in the three images. Using the coordinates of the checkpoints, the width was measured using the method detailed in section 3.2. The actual crack widths (ground truths) at each checkpoint are manually measured directly from the original image. The automatic width measurement results (based on orthogonal projection) as well as the ground truth values for all check points are provided in Table 2. As can be seen, the average width measurement accuracy for each image is 90.54%, 90.78%, and 89.01%, respectively.

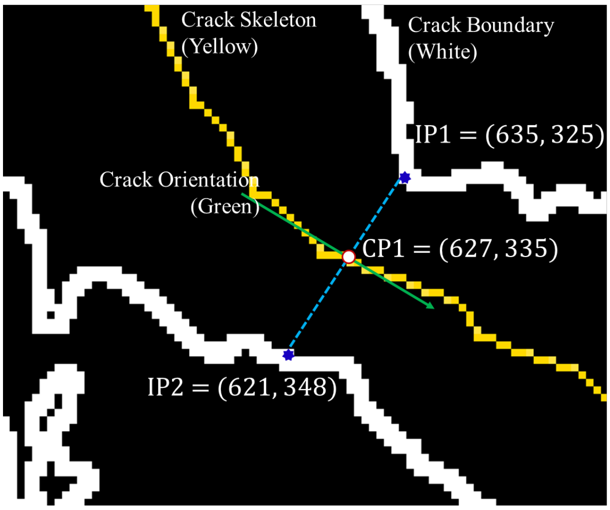

Figure 8. Representation of Width Measurement

Table 2. Width Measurement Results

Checkpoint	Automated Measurement (mm)	Ground Truth (mm)	Accuracy (%)
1.1	13.51	15.29	88.36
1.2	3.83	4.32	88.86
1.3	15.78	16.41	96.16
1.4	12.42	14.00	88.71
1.5	13.05	14.40	90.63
		Average - 1	90.54
2.1	29.77	27.00	89.75
2.2	11.65	13.28	87.73
2.3	10.11	11.45	88.30
2.4	9.15	9.71	94.23
2.5	53.55	50.47	93.88
		Average - 2	90.78
3.1	14.69	15.42	95.27
3.2	12.75	12.22	95.65
3.3	22.03	17.66	75.27
3.4	30.78	37.73	81.58
3.5	25.04	25.74	97.28
		Average - 3	89.01
	Total Average (1, 2, 3)		90.11

6 Conclusions

Visual inspections to identify and assess surface defects are important to ensure structural safety. In particular, dimensions of surface cracks are used to determine concrete structures' condition in terms of their stability and durability. However, the assessment of concrete cracks still relies on manual identification and assessment. Therefore, recent research has focused on leveraging computer vision and machine learning techniques to automate this process.

This study presented a methodology that combined CNN-based algorithms and the traditional image morphological operation for crack detection, and implemented a crack measurement approach based on skeletonization and orthogonal projection algorithms. This approach was tested on using data from three images obtained from the shear strength test on UHPC, which was conducted in a controlled laboratory environment. This was done to evaluate the proposed approach and fine tune it for future applications, including data collected from real-life structures, e.g., bridges, building, etc.

The results showed that the proposed crack detection method detected the crack and its boundary accurately. However, some of the crack details, with an average width of 0.76 mm, were lost. This was considered to be insignificant since those details do not have a major impact on the structural integrity compared to the larger cracks. Next, the results from skeletonization and branch filtering algorithms were tested. Both algorithms could extract the crack skeleton with a thickness of 1-pixel, which is essential for the following measurement procedures. Lastly, the accuracy of the proposed crack measurement method was evaluated with manually measured ground truth values from the original images. The proposed crack measurement method was found to be promising as it measured the crack length with 92.10% accuracy and the crack width with 90.11% accuracy.

To summarize the results, the proposed methodology for crack detection and measurement performs well and is capable of achieving the level of accuracy reported in previous studies. However, since the ground truths used in this study was obtained through manual annotations in the digital image, it is recommended that more precise evaluation based on real crack dimensions (measured physically using a tape) should be performed in future studies.

The study presented in this paper represents an important step in an overall research framework that aims to utilize unmanned aircraft system (UAS) images to automatically identify and measure surface defects of large structures such as bridges and map that information to Building Information Models (BIM), so that inspection reports are integrated with structural drawings and models in a single database. Accordingly, after fine-tuning the crack detection and measurement methods proposed in this paper, they will be evaluated on a set of images acquired from a bridge using an UAS and the results will be mapped to the corresponding BIM.

References

[1] American Society of Civil Engineers (ASCE). *2021 Report card for America's infrastructure*. ASCE, Reston, VA, United States, 2021.

[2] Chen, X., Li, J., Huang, S., Cui, H., Liu, P. and Sun, Q. An Automatic Concrete Crack-Detection Method Fusing Point Clouds and Images Based on Improved Otsu's Algorithm. *Sensors*, 21(5):1581, 2021.

[3] Yan, Y., Mao, Z., Wu, J., Padir, T. and Hajjar, J. F. Towards automated detection and quantification of concrete cracks using integrated images and lidar data from unmanned aerial vehicles. *Structural Control Health Monitoring*, 28(8): e2757, 2021.

[4] Kanopoulos, N., Vasanthavada, N. and Baker, R.L. Design of an image edge detection filter using the Sobel operator, *IEEE Journal of Solid State Circuits*, 23(2):358-367, 2002.

[5] Wang, D. and Zhou, S. Color Image Recognition Method Based on the Prewitt Operator. In *Proceedings of the International Conference on Computer Science & Software Engineering*, pages 170-173, Wuhan, China, 2008.

[6] Li, E.-S., Zhu, S.-L., Zhu, B.-S., Zhao, Y., Xia, C.-

G. and Song, L.-H. An Adaptive Edge-detection Method Based on the Canny Operator. In *Proceedings of the International Conference on Environmental Science & Information Application Technology*, pages 465-469, Wuhan, China, 2009.

[7] Otsu, N. A Threshold Selection Method from Gray-Level Histograms. *IEEE Transactions on Systems, Man, and Cybernetics*, 9(1):62-66, 1979.

[8] Nguyen, T. S., Begot, S., Duculty, F. and Avila, M. Free-form anisotropy: A new method for crack detection on pavement surface images. In *Proceedings of the IEEE International Conference on Image Processing*, pages 1069-1072, Brussels, Belgium, 2011.

[9] Xu, Y. and Turkan, Y. BrIM and UAS for bridge inspections and management. *Engineering, Construction and Architectural Management*, 27(3):785-807, 2020.

[10] Krizhevsky, A., Sutskever, I. and Hinton, G.E. ImageNet classification with deep convolutional neural networks. In *Advanced in Neural Information Processing Systems 25 (NIPS 2012)*, Stateline, Nevada, United States, 2012.

[11] Simonyan, K. and Zisserman, A. Very deep convolutional networks for large-scale image recognition. In *Proceedings of the International Conference on Learning Representations (ICLR 2015)*, San Diego, California, United States, 2015.

[12] Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V. and Rabinovich, A. Going deeper with convolutions. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 1-9, Boston, Massachusetts, United States, 2015.

[13] He, K., Zhang, X., Ren, S. and Sun, J. Deep residual learning for image recognition. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 770-778, Las Vegas, Nevada, United States, 2016.

[14] Liu, Y., Yao, J., Lu, X., Xie, R. and Li, L. DeepCrack: A deep hierarchical feature learning architecture for crack segmentation. *Neurocomputing*, 338:139-153, 2019.

[15] Yang, X., Li, H., Yu, Y., Luo, X., Huang, T. and Yang, X. Automatic Pixel-Level Crack Detection and Measurement Using Fully Convolutional Network. *Comput. Aided Civ. Infrastruct. Eng.*, 33:1090–1109, 2018.

[16] Gopalakrishnan, K., Khaitan, S.K., Choudhary, A. and Agrawal, A. Deep Convolutional Neural Networks with transfer learning for computer vision-based data-driven pavement distress detection. *Constr. Build. Mater.*, 157:322–330, 2017.

[17] Cha, Y.-J., Choi, W. and Buyukozturk, O. Deep Learning-Based Crack Damage Detection Using Convolutional Neural Networks. *Comput. Aided Civ. Infrastruct. Eng.*, 32:361–378, 2017.

[18] Lee, J., Kim, H.-S., Kim, N., Ryu, E.-M. and Kang, J.-W. Learning to Detect Cracks on Damaged Concrete Surfaces Using Two-Branched Convolutional Neural Network. *Sensors*, 19:4796, 2019.

[19] Islam, M.M.M. and Kim, J.-M. Vision-Based Autonomous Crack Detection of Concrete Structures Using a Fully Convolutional Encoder—Decoder Network. *Sensors*, 19:4251, 2019.

[20] Bhowmick, S., Nagarajaiah, S. and Veeraraghavan, A. Vision and Deep Learning-Based Algorithms to Detect and Quantify Cracks on Concrete Surfaces from UAV Videos. *Sensors*, 20:6229, 2020.

[21] Dorafshan, S., Thomas, R.J. and Maguire, M. Comparison of deep convolutional neural networks and edge detectors for image-based crack detection in concrete. *Construction and Building Materials*, 186:1031-1045, 2018.

[22] Maguire, M., Dorafshan, S. and Thomas, R. SDNET2018: A Concrete Crack Image Dataset for Machine Learning Applications, Utah State University, Logan, 2018.

[23] Wang, W., Hu, W., Wang, W., Xu, X., Wang, M., Shi, Y., Qiu, S. and Tutumluer, E. Automated crack severity level detection and classification for ballastless track slab using deep convolutional neural network. *Automation in Construction*, 124:103484, 2021.

[24] Qiu, S., Wang, W., Wang, S. and Wang, K.C.P. Methodology for accurate AASHTO PP67-10–based cracking quantification using 1-mm 3D pavement images. *Journal of Computing in Civil Engineering*, 31(2):04016056, 2017.

[25] Kalfarisi, R., Wu, Z.Y. and Soh, K. Crack Detection and Segmentation Using Deep Learning with 3D Reality Mesh Model for Quantitative Assessment and Integrated Visualization. *Journal of Computing in Civil Engineering*, 34(3):04020010, 2020.

[26] Voytko, D., Calvi, P.M. and Stanton, J. Shear strength of ultra-high-performance concrete. Engineering Structures, 255:113961, 2022.

[27] Calvi, P.M., Proestos, G.T. and Ruggiero, D.M. Toward the development of direct crack-based assessment of structures. ACI Structural Journal, 328:9.1–9.20, 2018.