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Automated Crack Identification, to Ease Maintenance of Reinforced Concrete Bridges

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Abstract

One of the critical factors in the regional economic development and sustainability is the regular maintenance of road infrastructure. The preliminary step in the structural maintenance of bridges is in-situ inspection.
Accurate and reliable infrastructure inspection plays a vital role in making the further steps' decision, whether more assessment needs to put into action or the bridge is in good condition.
The visual assessment, at the moment, is performed manually by the engineers, being therefore a too time-consuming and expensive operation, and in case of inspecting the critical points puts the engineers in danger, otherwise those parts will be missing of data. Overcoming these barriers, over the past few decades, considerable efforts have been made to construct the fundamental of implementing artificial intelligent techniques as a tool, to do autonomous inspection.
This research engages in the data analysis section of the autonomous inspection with segmenting the cracks on the images acquired by them. This goal is achieved by implementing semantic segmentation deep learning development which is being trained on 8192 images and their binary masks as dataset, using the U-Net network. The model prediction shows 98.2% accuracy in crack segmentation. However, the novelty of our research extends beyond these results, we introduce a unique evaluation method named Pixel Average Error Distance (PAED) instead of the commonly used Intersection over Union (IoU) metric for segmentation assessment. Our methodology aims to forego the IoU metrics unreliable results in case of small deviation of crack patterns. It enhances the understanding of our model real performance with the PAED metrics lower than 0.5 which demonstrates a well-designed model, while the average IoU with 0.65 value shows a poor-designed model.
Overall, this method will provide the engineer the possibility to observe all surfaces of a bridge and have a reliable and precise evaluation of the existing cracks.

Keywords: semantic segmentation; deep learning; structural health monitoring; crack identification; maintenance

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1. Introduction

Between 1950 and 1980, the decades following the Second World War, there was a boom in infrastructure construction. In 2021, the American Society of Civil Engineers reported in an infrastructure map that 42% of all bridges are at least 50 years old (ASCE 2021). Therefore, the 2020s era is the golden time for their structural maintenance as they reach their mid-service life (AASHTO 2008). By keeping these infrastructures in optimal condition, it can be ensured the safety and efficiency of transportation systems, promote economic growth, and reduce the need for costly emergency repairs.

Structural maintenance begins with visual inspection, which plays an important role in presenting an optimal final decision. To do a visual inspection, the engineer must have access to all bridge elements and assess the current condition in terms of defects, alignment, and material. The conventional bridge inspection is carried out by expert engineers using snooper trucks. Their use is time-consuming (Stricker et al. 2021), labor-intensive (Eisenbach et al. 2017), high cost, subjective to the engineer's level of knowledge (Zarski et al. 2020) and, in some hard access points, there is a possibility of losing the data or putting the engineer in danger (Devdatt et al. 2018). Conventional-inspection measurements usually take from several weeks to months, which is why the results are outdated at the time of rehabilitation. Nowadays, in many countries with ageing infrastructures, information and communication technologies are being used as a cost-effective tool for the maintenance of structures (Kim and Cho, 2019). With the emergence of Artificial Intelligence (AI) techniques, a new generation of structural damage identification has appeared in the form of the vision that already shows tangible improvements at every step.

Modern AI results allow automated image processing and Machine Learning (ML) to enable the development of accurate and unbiased non-contact automated system as an inspection tool (Dorrafshan et al. 2017). By applying these techniques, it is possible to use the cameras as sensors to do structural monitoring, like deflection measurement (Feng 2016), steel corrosion detection (Leung et al. 2008; Valeti and Pakzad, 2017), and spalling detection (German and Brilakis, 2012; Kim and Cho, 2018). Deep Learning (DL) and Convolutional Neural Networks (CNN) promise to be the next and outperforming step in this direction: these tools have achieved successful results in the field of object detection and localization, facial recognition, 3D visions for autonomous aerial and ground vehicles. Despite several attempts in the field of defects detection and identification, they have still not fulfilled the inspection process desires (Yang et al. 2022). Kim and Cho (2018) discussed some major limitations during training and test phases, such as the number of images and contexts taken as reference, the image exposure the weather and lighting conditions. Other researchers focused on the real usability and the real-time results achievable with these tools (e.g. Eschmann et al. 2012; Morgenthal and Halllermann, 2014; Kim and Lee, 2017).

Considering the point that most of the ageing structures were made of concrete, the focus is on concrete structures and their defects identification (Kim and Cho, 2019). Cracks should have a particular attention since this unavoidable defect in concrete structures can cause further damages, such as reduced durability, corrosion, external damage, and degraded waterproofing performance (Ali et al. 2022; Yao et al. 2014). While relevant progresses have been made in the field of crack detection, accurately detecting the border, the width, the area and the length of the cracks at the pixel level is crucial. This level of evaluation can provide valuable insight into the overall health of the concrete structure (Zhang and Shen, 2020).

Semantic Segmentation is the AI process by which the image pixels are classified (labeled) according to the content they represent (e.g wall, cracks, ...). In this paper, we designed and trained a semantic segmentation network to detect the cracks at pixel-wise level using a U-Net network (Ronneberger et al. 2015). This tool has successfully applied to medical images for the segmentation of relevant medical information such as bones, tumors, vessels. Our model shows 98.2% accuracy both in training and testing stages. The paper is organized as follows: after the introduction, first we pay attention to the relevant works, then we introduce the proposed method and finally we present the experimental set up and show and discuss the achieved results.

Nomenclature

IoU	Intersection over Union
AI	artificial intelligence
ML	machine learning
DL	deep learning
CNN	convolutional neural network
ReLU	rectified linear unit
UAV	unmanned aerial vehicles
PAED	pixel average error distance

2. Related work

One of the initial attempts to apply ML techniques for pavement-crack classification from video frames, was done by Kaseko and Ritchie (1993), the multi-layer feed forward neural network regression was developed with 83.2% accuracy. In 2003, Abdel-Qader (2003) tried an entropy-based thresholding algorithm combined with template matching and morphological operations, which are computer visions techniques, for crack and spalling detection.

With the advancements in AI, particularly in machine learning, there have been significant developments in measuring cracks through the application of DL algorithms (Zhang et al. 2016; Cha and Choi, 2017). Implementing robots equipped with cameras as ground-based vehicles to detect the bridge's deck surface defects had a successful result, like RABIT (Gucunski et al. 2015), Robotics Assisted Bridge Inspection Tool, and Robotic crack inspection and mapping (Lim et al. 2014; Dorrafshan et al. 2017; Kim et al. 2017) allowed to develop a crack identification strategy, combining hybrid image processing with UAV technology equipped with an ultrasonic displacement sensor and a camera. It successfully measured cracks with thickness higher than 0.1 mm and %7.3 error in length measurement. Yokoyama and Matsumoto (2017) developed a CNN to detect the cracks by training 2000 number of images. Kim and Cho (2018) developed a crack detection tool by modifying a famous DL architecture the AlexNet network, with a technique called "transfer learning". According to this technique, they retrained the achieved system with a new dataset completely oriented to the assigned task. They built the dataset as crack and non-crack, in which the non-crack is 4 classes including edges, joints, plant and intact surfaces. According to their initial transfer learning there are confusing objects that cause misclassification in crack detection, which are similar to cracks and cause to reduce the learning accuracy. Later, Kim and Cho (2019) extended their research by applying Mask R-CNN to detect the cracks and measure them using a few morphological operations, which could successfully quantify cracks with width higher than 0.3 mm. Kim and Jeon (2018) use a commercial UAV with high resolution sensor to detect the structural-surface cracks and measure their thickness-and-length with R-CNN transfer learning technique. The technique was applied on an ageing concrete bridge and the results were effective.

Silva and Lucena (2018) trained a VGG16 model using 3,500 images as dataset to detect concrete cracks with 92.27% accuracy. Eslami and Yun (2021) have done pavement cracks classification, by using attention-based CNN, as an improvement to the automated system. Followingly, Yoon and Spencer (2022), used the R-CNN development to do damage detection as a preliminary stage of seismic performance assessment to define the bridge condition. The bridge damage grade was defined based on the detected damages and correspondingly the finite element model was updated.

3. Proposed approach

The analysis of the current trends in research shows that there is a considerable push to move away from traditional inspection methods and move towards AI-based techniques. To achieve this, it is essential to provide detailed and precise information about every kind of defect. The purpose of our work is step forward towards this objective, focusing specifically on cracks. To present information about defects to inspectors and enable them to evaluate and make informed decisions about the structure, a typical convolutional network is not sufficient. While these networks can define the class label of defects, they do not provide information about their location. It is essential to localize the defect in addition to identifying its class label with the final aim of assessing their influence on the structural performance of the component where they are located.

In the following, how to achieve this objective by utilizing the U-net architecture, which was originally developed for biomedical image segmentation (Ronneberger et al. 2015) is presented. Semantic segmentation, as a pixel wise technique, has this potential to create the exact borders of the defects accompanying defining its type.

3.1. Network Architecture

As it is clear from the “U-Net” name, the structure of the network is in U shape format. The objective of a U-Net architecture is to recreate a new image having the same size of the original one, but having pixel value changed according to the kind of information they represent. This network type has two components, as shown in Fig. 1: an encode stage (left side) and a decoder stage (right side).

Whilst the encoder extracts multilevel features of the original image, the decoder generates the final output. Illustrated in Fig. 1., in each step two 3x3 convolutions accompany with a rectified linear unit (ReLU) (Agarap 2018) as an activation function is applied. Between each step, to reduce the spatial dimensions, a 2x2 max pooling operation is applied. On the other side, to do up sampling, in each step a 2x2 transpose convolution is applied. An important aspect of U-Net is the combination of the down sampling with the up sampling by using concatenation, it is usually a 3x3 convolutional (each followed by a ReLU). Finally, a 1x1 convolution which outputs the desired number of classes in channels format. Sigmoid as a pixel wise loss function is being applied in the U-net architecture.

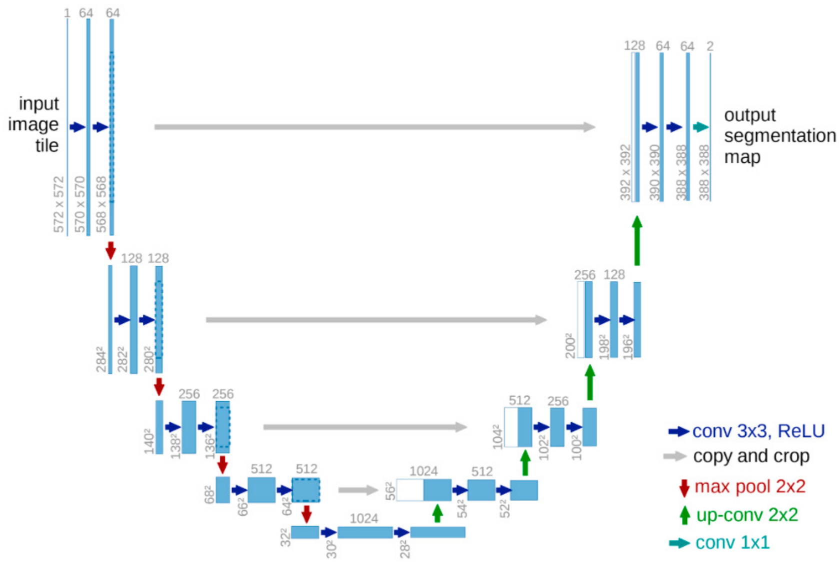


Fig. 1. U-Net network architecture Ronneberger et al. (2015).

3.2. Dataset and training

To do semantic segmentation, 8192 numbers of images and their corresponding binary masks were selected from CrackSeg9K (Kulkarni et al. 2022) and CFD (Shi et al. 2016; Cui et al. 2015), which are available dataset for segmentation. CrackSeg9k is a collection of 9255 image datasets showcasing cracked and uncracked surfaces of various building materials which itself is a combination of 10 different opensource datasets, resizing to 400x400 pixel resolution. Crack Forest Dataset (CFD) is a road crack image database with tiny shapes that can be difficult to recognize. All the 8192 images and their binary masks are resized into 256x256 pixels. 80 percent of the dataset is dedicated to training and the remaining 20 percent is used for validation. The neural network was trained for 25 epochs and 512 iterations for each.

4. Experimental results

We initially examined transfer learning accuracy and loss results for the training and testing, as illustrated in Fig.2. The model has demonstrated 98.2% accuracy rate in both phases. In the segmentation domain, Intersection over Union (IoU) is one of the most used metrics to evaluate the model performance. This value measures the overlap between predicted and ground truth masks and is defined by the following formula (1):

$$IoU = \frac{Area\ of\ \ Intersection}{Area\ of\ \ Union} \tag{1}$$

Being 'Area of Intersection' the number of pixels that are common between the predicted segmentation mask and the ground truth mask, therefore representing the overlapping region; 'Area of Union' the total number of pixels encompassed by both the predicted and ground truth segmentation masks, counting each pixel only once.

Although IoU is widely used as a segmentation metrics, it may not be the most appropriate option in scenarios where the area of interest is a fine line like cracks.

To illustrate this point, please consider Fig. 3, where the ground truth mask and predicted mask are shown. It can be seen that the model predicts the object with great precision, but due to a minor shift, just one pixel to the right in the prediction stage the IoU for this segmentation is 0.26. This IoU indicates poor model performance, despite the model has correctly segmented the object.

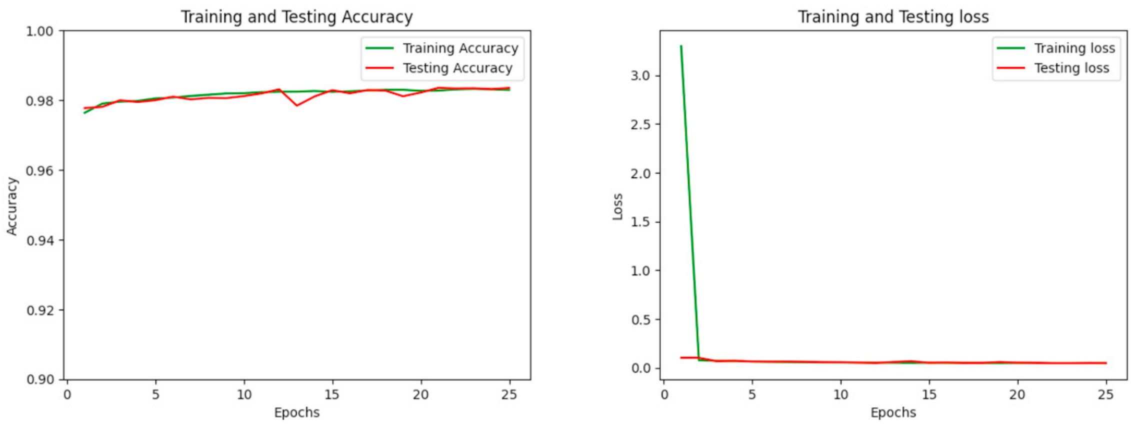
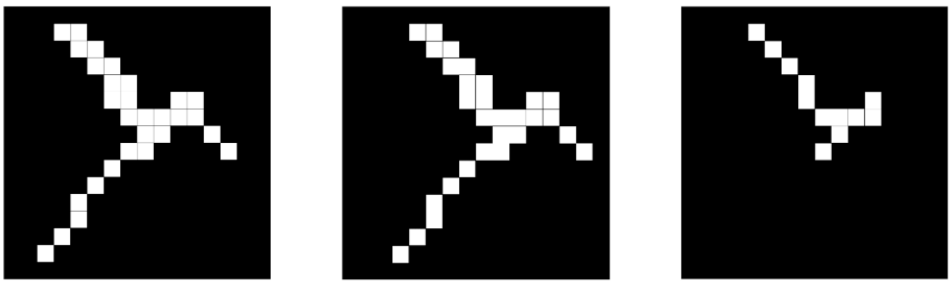


Fig. 2. Training and Testing accuracy loss



(a) (b) (c)

Fig. 3. (a) as ground truth mask, (b) as predicted mask and (c) as overlapping region

To address this challenge, we introduce a novel evaluation approach which considers both pixel-wise accuracy and spatial relationships, allowing for small variations in crack locations. It aims to provide a more realistic assessment of the model's performance, considering that, in practical applications, cracks may not always be predicted precisely in the same spot. We presented a numerical metric to validate the model and name it as Pixel Average Error Distance

(PAED). The brief concept of this metric is based on the distance of the predicted pixel as a crack to the original position of the corresponding crack pixel. The smaller the PAED metrics, the more precise the model.

For this goal, we considered the shape of the crack in the original mask as S_1, and in the predicted mask as S_2. We considered the $d(P, S_1)$ function as the minimum distance of the point "P" to the shape S_2, then we extend this function to all the points on the S_1 to calculate the distance of shape S_1 to the S_2.

$$d(P, S_1) = min_{x \in S} |P - x| \tag{2}$$

$$d(S_1 - S_2) = \sum_{x \in S_1} d(x, S_2) \tag{3}$$

$$PAED = \frac{(d(S_1, S_2) + d(S_2, S_1))}{A(S_1) + A(S_2)} \tag{4}$$

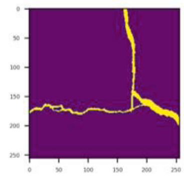
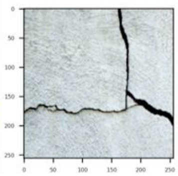
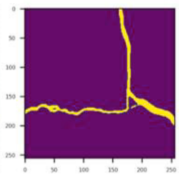
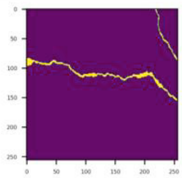
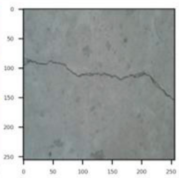
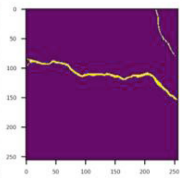
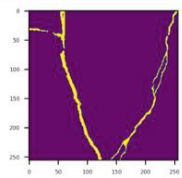
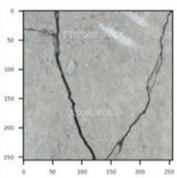
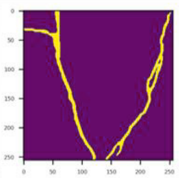
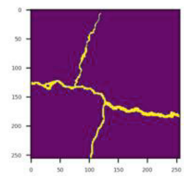
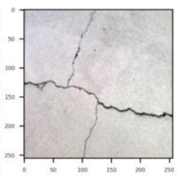
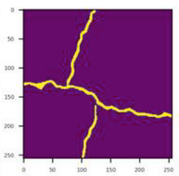
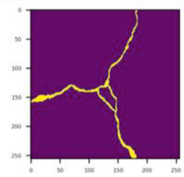
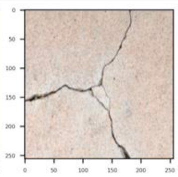
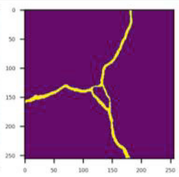
Original Mask	Image	Predicted Mask	IoU	PAED
			0.8	0.12
			0.59	0.29
			0.6	0.37
			0.68	0.24
			0.67	0.22

Fig. 4. Development result for the image and its corresponding IoU and PAED metric.

To make more adequate inter shape definition once we considered the distance from the original crack shape to the predicted shape and once in a reverse direction. These two distances were combined and then normalized by calculating it per crack area to achieve the average pixel errors. Fig.4. illustrates our development results for selected images and presents the original and predicted masks along with their corresponding PAED and IoU metrics.

Notably, the first row of Fig.4 depicts an image with a thick crack, where both the IoU and PAED metrics indicate that the model performs efficiently. Conversely, for images with fine cracks, the IoU metric suggests poor model performance, while the cracks are, in fact, accurately predicted as shown in the figure. In such cases, the PAED metric emerges as a reliable evaluation of the model's proficiency, as it provides accurate values that closely align with reality, as demonstrated in Fig.4.

5. Conclusion

This research presents a deep learning development to do crack semantic segmentation of concrete structures. In the other words, the primary objective of this implementation was to accurately identify and locate crack defects at the pixel level, to gather the maximum possible information from the images, which could then be utilized for further structural health monitoring purposes. The proposed approach employs semantic segmentation modeling using a U-net network architecture. The model was trained and validated on a dataset of 8192 images, each with a resolution of 256x256 pixels.

The model's performance in achieving an accuracy of 98.2% during both the training and validation phases was highly satisfactory and will meet the expectations of the structural inspector.

Our research presents a validation metric to evaluate the model proficiency, addressing the limitation of the IoU metric. The approach has this potential to neglect small deviations in the prediction stage, which leads to an unrealistic reduction in IoU results. With the PAED metric lower than 0.5, our model demonstrates powerful efficiency in segmenting even the finest cracks.

References

ASCE's 2021 Infrastructure Report Card | GPA: C-. https://www.infrastructurereportcard.org/ [accessed 2021]

AASHTO LRFD bridge design specifications. (2008). Washington, D.C.: American Association of State Highway and Transportation Officials.

Stricker, R., Aganian, D., Sesselmann, M., Seichter, D., Engelhardt, M., Spielhofer, R., Hahn, M., Hautz, A., Debes, K., & Gross, H.-M. (2021). Road Surface Segmentation - Pixel-Perfect Distress and Object Detection for Road Assessment. In 2021 IEEE 17th International Conference on Automation Science and Engineering (CASE). 2021 IEEE 17th International Conference on Automation Science and Engineering (CASE). IEEE. https://doi.org/10.1109/case49439.2021.9551591

Eisenbach, M., Stricker, R., Seichter, D., Amende, K., Debes, K., Sesselmann, M., Ebersbach, D., Stoeckert, U., & Gross, H.-M. (2017). How to get pavement distress detection ready for deep learning? A systematic approach. In 2017 International Joint Conference on Neural Networks (IJCNN). 2017 International Joint Conference on Neural Networks (IJCNN). IEEE. https://doi.org/10.1109/ijcnn.2017.7966101

Żarski, M., Wójcik, B., & Miszczak, J. A. (2020). KrakN: Transfer Learning framework for thin crack detection in infrastructure maintenance. arXiv. https://doi.org/10.48550/ARXIV.2004.12337

Devdatt P. Purohit, N.A. Siddiqui, Abhishek Nandan, Bikarama P. Yadav, Hazard identification and risk assessment in construction industry, Int. J. Appl. Eng. Res. 13 (10) (2018) 7639–7667

Kim, B., & Cho, S. (2019). Image-based concrete crack assessment using mask and region-based convolutional neural network. In Structural Control and Health Monitoring (p. e2381). Hindawi Limited. https://doi.org/10.1002/stc.2381

Dorafshan, S., Maguire, M., Hoffer, N. V., & Coopmans, C. (2017). Challenges in bridge inspection using small unmanned aerial systems: Results and lessons learned. In 2017 International Conference on Unmanned Aircraft Systems (ICUAS). 2017 International Conference on Unmanned Aircraft Systems (ICUAS). IEEE. https://doi.org/10.1109/icuas.2017.7991459

Feng, D., & Feng, M. Q. (2015). Vision-based multipoint displacement measurement for structural health monitoring. In Structural Control and Health Monitoring (Vol. 23, Issue 5, pp. 876–890). Hindawi Limited. https://doi.org/10.1002/stc.1819

Leung, C., Wan, K., & Chen, L. (2008). A Novel Optical Fiber Sensor for Steel Corrosion in Concrete Structures. In Sensors (Vol. 8, Issue 3, pp. 1960–1976). MDPI AG. https://doi.org/10.3390/s8031960

Valeti, B., & Pakzad, S. (2017). Automated Detection of Corrosion Damage in Power Transmission Lattice Towers Using Image Processing. In Structures Congress 2017. Structures Congress 2017. American Society of Civil Engineers. https://doi.org/10.1061/9780784480427.040

German, S., Brilakis, I., & DesRoches, R. (2012). Rapid entropy-based detection and properties measurement of concrete spalling with machine vision for post-earthquake safety assessments. In Advanced Engineering Informatics (Vol. 26, Issue 4, pp. 846–858). Elsevier BV. https://doi.org/10.1016/j.aei.2012.06.005

Kim, B., & Cho, S. (2018). Automated Vision-Based Detection of Cracks on Concrete Surfaces Using a Deep Learning Technique. In Sensors (Vol. 18, Issue 10, p. 3452). MDPI AG. https://doi.org/10.3390/s18103452

Yang, G., Liu, K., Zhang, J., Zhao, B., Zhao, Z., Chen, X., & Chen, B. M. (2022). Datasets and processing methods for boosting visual inspection of civil infrastructure: A comprehensive review and algorithm comparison for crack classification, segmentation, and detection. In Construction and Building Materials (Vol. 356, p. 129226). Elsevier BV. https://doi.org/10.1016/j.conbuildmat.2022.129226

Eschmann, C., Kuo, C.H., Kuo, C., & Boller, C. (2012). Unmanned Aircraft Systems for Remote Building Inspection and Monitoring. In Proceedings of the 6th European Workshop on Structural Health Monitoring, Dresden, Germany, Volume 2, pp. 1–8.

Morgenthal, G., & Hallermann, N. (2014). Quality Assessment of Unmanned Aerial Vehicle (UAV) Based Visual Inspection of Structures. In Advances in Structural Engineering (Vol. 17, Issue 3, pp. 289–302). SAGE Publications. https://doi.org/10.1260/1369-4332.17.3.289

Kim, H., Lee, J., Ahn, E., Cho, S., Shin, M., & Sim, S.-H. (2017). Concrete Crack Identification Using a UAV Incorporating Hybrid Image Processing. In Sensors (Vol. 17, Issue 9, p. 2052). MDPI AG. https://doi.org/10.3390/s17092052

Ali, R., Chuah, J. H., Talip, M. S. A., Mokhtar, N., & Shoaib, M. A. (2022). Structural crack detection using deep convolutional neural networks. In Automation in Construction (Vol. 133, p. 103989). Elsevier BV. https://doi.org/10.1016/j.autcon.2021.103989

Yao, Y., Tung, S.-T. E., & Glisic, B. (2014). Crack detection and characterization techniques-An overview. In Structural Control and Health Monitoring (Vol. 21, Issue 12, pp. 1387–1413). Hindawi Limited. https://doi.org/10.1002/stc.1655

Zhang, L., Shen, J., & Zhu, B. (2020). A research on an improved Unet-based concrete crack detection algorithm. In Structural Health Monitoring (Vol. 20, Issue 4, pp. 1864–1879). SAGE Publications. https://doi.org/10.1177/1475921720940068

Kaseko, M. S., and Ritchie, S. G. (1993). A neural network-based methodology for pavement crack detection and classification. Transp. Res. Part C Emerg. Technol. 1, 275–291. doi:10.1016/0968-090x(93)90002-w

Abdel-Qader I, Abudayyeh O, Kelly ME (2003) Analysis of edge-detection techniques for crack identification in bridges. J Comput Civ Eng 17:255–263. https://doi.org/10.1061/(asce)0887-3801(2003)17:4(255)

Zhang, L., Yang, F., Daniel Zhang, Y., & Zhu, Y. J. (2016). Road crack detection using deep convolutional neural network. In 2016 IEEE International Conference on Image Processing (ICIP). 2016 IEEE International Conference on Image Processing (ICIP). IEEE. https://doi.org/10.1109/icip.2016.7533052

Cha, Y., Choi, W., & Büyüköztürk, O. (2017). Deep Learning-Based Crack Damage Detection Using Convolutional Neural Networks. In Computer-Aided Civil and Infrastructure Engineering (Vol. 32, Issue 5, pp. 361–378). Wiley. https://doi.org/10.1111/mice.12263

Gucunski, N., Kee, S.-H., La, H., Basily, B., Maher, A., & Ghasemi, H. (2015). Implementation of a Fully Autonomous Platform for Assessment of Concrete Bridge Decks RABIT. In Structures Congress 2015. Structures Congress 2015. American Society of Civil Engineers. https://doi.org/10.1061/9780784479117.032

Lim, R. S., La, H. M., & Sheng, W. (2014). A Robotic Crack Inspection and Mapping System for Bridge Deck Maintenance. In IEEE Transactions on Automation Science and Engineering (Vol. 11, Issue 2, pp. 367–378). Institute of Electrical and Electronics Engineers (IEEE). https://doi.org/10.1109/tase.2013.2294687

Yokoyama, S., & Matsumoto, T. (2017). Development of an Automatic Detector of Cracks in Concrete Using Machine Learning. In Procedia Engineering (Vol. 171, pp. 1250–1255). Elsevier BV. https://doi.org/10.1016/j.proeng.2017.01.418

Kim, I.-H., Jeon, H., Baek, S.-C., Hong, W.-H., & Jung, H.-J. (2018). Application of Crack Identification Techniques for an Aging Concrete Bridge Inspection Using an Unmanned Aerial Vehicle. In Sensors (Vol. 18, Issue 6, p. 1881). MDPI AG. https://doi.org/10.3390/s18061881

Silva, W. R. L. da, & Lucena, D. S. de. (2018). Concrete Cracks Detection Based on Deep Learning Image Classification. In The 18th International Conference on Experimental Mechanics. The International Conference on Experimental Mechanics. MDPI. https://doi.org/10.3390/icem18-05387

Eslami E, Yun HB (2021) Attention-Based Multi-Scale Convolutional Neural Network (A+MCNN) for Multi-Class Classification in Road Images. Sensors 21(15):5137. https://doi.org/10.3390/S21155137

Yoon, S., Spencer, B. F., Jr., Lee, S., Jung, H., & Kim, I. (2022). A novel approach to assess the seismic performance of deteriorated bridge structures by employing UAV-based damage detection. In Structural Control and Health Monitoring (Vol. 29, Issue 7). Hindawi Limited. https://doi.org/10.1002/stc.2964

Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation (Version 1). arXiv. https://doi.org/10.48550/ARXIV.1505.04597

Agarap, A. F. (2018). Deep Learning using Rectified Linear Units (ReLU) (Version 2). arXiv. https://doi.org/10.48550/ARXIV.1803.08375

Kulkarni, S., Singh, S., Balakrishnan, D., Sharma, S., Devunuri, S., & Korlapati, S. C. R. (2023). CrackSeg9k: A Collection and Benchmark for Crack Segmentation Datasets and Frameworks. In Lecture Notes in Computer Science (pp. 179–195). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-25082-8_12

Shi, Y., Cui, L., Qi, Z., Meng, F., & Chen, Z. (2016). Automatic Road Crack Detection Using Random Structured Forests. In IEEE Transactions on Intelligent Transportation Systems (Vol. 17, Issue 12, pp. 3434–3445). Institute of Electrical and Electronics Engineers (IEEE). https://doi.org/10.1109/tits.2016.2552248

Cui, L., Qi, Z., Chen, Z., Meng, F., & Shi, Y. (2015). Pavement Distress Detection Using Random Decision Forests. In Data Science (pp. 95–102). Springer International Publishing. https://doi.org/10.1007/978-3-319-24474-7_14