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Crack Detection based on Crack Types Using Machine Learning Techniques

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1. ABSTRACT

Due to severe deterioration of concrete surface infrastructure assets require frequent inspection and repair. Furthermore, unavoidable circumstances such as road accidents may occur because of defected infrastructure. Therefore, a proper civil infrastructure inspection system is essential to avoid unwanted circumstances as well as prevent traffic disruption. Manual inspection has been employed for a long time using heavy and large equipment by civil engineers to assess the structural defects. The time- consuming and labor-intensive nature of this type of inspection system causes traffic disruption. Furthermore, the manual assessment procedure is perilous for humans in inaccessible regions of civil infrastructures such as under bridge decks and underwater beams. On the contrary, an autonomous civil infrastructure inspection system monitors structural health continuously with the least human intervention [11]. Such an autonomous robotic system can capture data for surface-level visual inspection and defect identification of civil infrastructures [3].

Keywords: Crack Detection, Machine Learning, CNN.

2. INTRODUCTION

A fully functional and healthy infrastructure is the heart of the modern transportation system. The main element of these infrastructures is concrete. A mixture of several different types of rocks, limestone, clay, and water is known as concrete. The water in the concrete evaporates over time due to environmental factors and continuous usage. As a result, the concrete surface hardens over time, leading to severe deterioration such as cracking, spalling, abrasion, etc. [7]. There are other factors responsible for concrete surface deterioration such as overloaded vehicles, chemical exposure, corrosion with the metals infused in concretes, and improper dying as reported in [10].

3. RESEARCH OBJECTIVES

1. **Semi-automatic detection of cracks:** We propose to detect cracks when the user provides an arbitrary point on the cracks. Figure displays different types of cracks that we want to detect using our algorithm.

2. **Detection of continuous cracks for crack sealing applications:** We pro- pose to detect continuous cracks that extend over several miles by just providing the starting point on a crack as input to the algorithm. Figure shows two consecutive images that have a continuous crack. Once, the algorithm detects

4. LITERATURE REVIEW

Structural monitoring is needed for on-site inspection of critical structures like bridges, dams and sewer pipes. The potentially catastrophic consequences of fatigue crack- ing can be avoided by the early detection of fatigue cracks in on-site structures such as bridges. The frequently used method of inspecting bridge components for fatigue damage has been the elementary method of visual inspection. The most revealing sign of a crack is the existence of rust, oxide film and powder. However, since rust does not always appear immediately after a crack is formed, cracks may go undetected during visual inspection. Once a crack is observed or suspected, the structure is further tested to determine the extent or severity of the damage. A number of techniques arecurrently used to confirm the existence of a crack. Among them are vibration based methods, eddy current imaging, ultrasonic techniques [71], holographic interfere- try, acoustic emission, photo elasticity, and Electronic Speckle Pattern Interferometry(ESPI). Of late, wireless sensor networks [22] and mobile sensor networks [77] have been designed to monitor structures. Moreover, concrete defect images are affected by environmental non-uniformity such as illumination, noise, shading, and many more. The image processing methods are highly sensitive to these environmental factors [2].Machine learning architectures were employed for crack detection to achieve ro- bustness toward crack detection. Machine learning architectures such as Support Vector Machines (SVM) [20], Adaboost [28] and Multi-Layer Perceptron (MLP) [35] networks, were used preliminary for concrete crack

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Identification. Later a combination of machine learning and image processing techniques were employed to improve the defect detection result [36]. Although the accuracy of defect detection improves with these methods, they inherit the complexity of appropriate parameter selection.

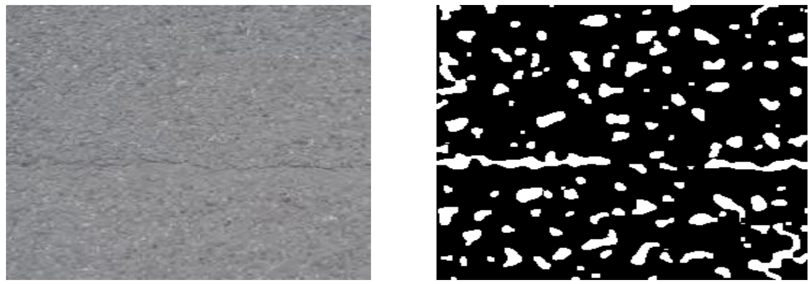

Figure 1: Example of crack detection: (a) Original image, (b) Image processing technique

4.1 MACHINE LEARNING

Machine learning is an application of artificial intelligence that studies the use of algorithms and statistical methods that improve automatically using sample data to perform predictions on new data. Among the different types of machine learning algorithms, the most common algorithms are support vector machines, decision trees, forests, and deep learning.

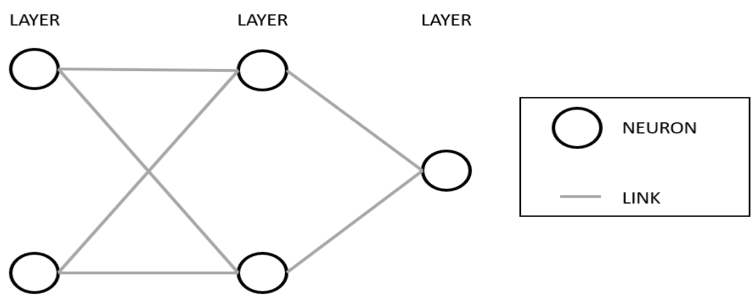

Figure 2 General structure ANN

In Figure we can see an ANN with three layers, the first two with two nodes and the last layer with only one node.The literature review will be divided into three parts. The first part will define and introduce the framework of the Visual Pattern Recognition (VPR) model and current state of pothole detection.

4.2 CONVOLUTIONAL NEURAL NETWORKARCHITECTURE

CNN [40] architectures are a composition of various connected layers such as in- put, convolution, pooling, activation, and output layers. Some auxiliary layers such as batch normalization and drop out layer are also associated according to appli- cation purpose. This arrangement of various layers and their functionality extracts discernible feature sets for each object on CNN. Among all the layers of CNN, the convolutional layer is primarily responsible for the salient feature extraction of a specific object. Each convolutional layer performs multiple convolution operations using receptive fields (kernels) of fixed size and variable weights.

5. METHODOLOGY

An in-depth convolutional neural network of crack fragmentation is introduced into this work. A framework to eliminate the impact of the problem is to reduce the unequal arrangement of data sharing in the categories presented in this work. Reducing unnecessary feature space improves the accuracy of our framework and reduces the impact of the gradient collapse problem. In addition, the sensitivity formation of biodiversity is reduced by the FSM module. As a result, our structure is much more accurate than the methods found in the literature. The experimental results in this study also show that a large proportion of unnecessary calculations are performed in deep structures. Completion of these statistics improves the speed and processing of very deep networks, which is important in the real-time use of these structures.

5.1 IMAGE COLLECTION

Photo collection is an important step in the crack discovery model. The purpose of this process is to compile photogrammetry of model images in order to detect fractures. Memon et al. (2005) argued that photogrammetry is a well-established and commonly used method of architects and engineers to monitor highways.

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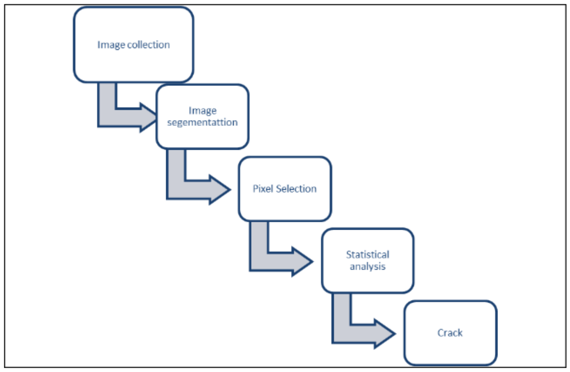

Figure 3. Crack detection model

All the images were collected under the same situation. Furthermore, this study uses image segmentation to transform the original image into a binary image. In this process, the image is converted into a 0 and 1 matrix. The R (Red) value is treated as primary threshold in this phase.

5.2 MINOR CRACKS

Small cracks are very small or very small cracks with three small, small and linear types. These cracks are common in RC bridges, underwater dams, plastics, cars and planes. Small cracks are common in RC bridges and can be obtained using the stereo triangulation method, a small square method and a visual flow analysis method. These techniques are capable of capturing concrete surface cracks with a width of 0.2 pixels using Regional of Interest (ROI) and control area, and for best results images should be shot using a single camera without any change in lighting effect. In an underwater lake it is difficult to see and divide the cracks into small, medium, and large cracks so a photo of the sun is used.

5.3 MODERATE CRACKS

The middle cracks are not strong cracks so corrective action is required. Typically, these cracks occur in an underwater dam and on a concrete road with types such as medium, sealed and hard crack. Pengfeishi et al., 2017; said that it is difficult to find and divide the crack into a small, medium, and large crack to use the image of the sun.

5.4 SEVERE CRACKS

Large cracks are very large and dangerous so quick repairs are needed. This crack is most common in underwater dam, underground tunnel, bridges, road, concrete road and public building. Larger cracks include larger, simpler and more complex cracks. Large cracks [Pengfeishi et al., 2017] can be easily identified, but cracks found in an underwater dam are difficult to detect and distinguish, so solar images are used.

5.5 COMPLEX CRACKS

Complex cracks are complex in shape and structure so additional details are needed to separate them. Complex cracks are common on bridges, tarred roads, concrete roads, and public buildings. Complex cracks include crocodile, reflexive, block and mixed crack. Alligator cracks are common on bridges, paved concrete roads and can be found using migration method, separation, morphological operations, EMD method, binarization, radon conversion, regional growth method, small square path and separated by SVM, random forest and adaboost [Mojtaba et al. ., 2016; Salari and Ouyang, 2016; Chen et al., 2016; Weili et al., 2017].

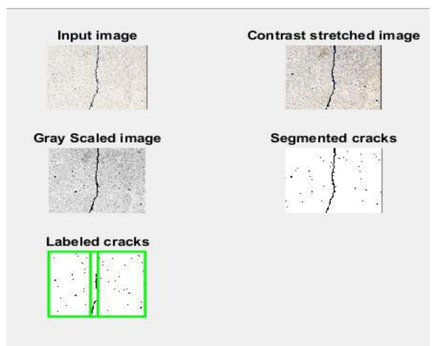

Figure 4.a) Preprocessing module **b)** Resize the image **c)** Normalizing the intensity value **d)** Segmentation by thresholding **e)** Extracting crack region (labeledcracks are highlighted in green color)

6. PROPOSED SYSTEM

Automatic detection and partition system is proposed to capture invisible images. In the pre-processing step, the image blur is removed, using the Wiener filter. Cracks that do not fit well with bright images are not easy to spot and may produce erroneous results. To overcome these problems, a Wavelet modification and Automatic Value Addition (SVD) is proposed. Analysis of the gray images of the available cracks looks good enough, but the unaffected areas also look like cracks. To address this issue, morphological and KD-tree functionality has been included in the

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construction. Morphological function is used to enhance the fragmentation image while the KD tree is used to connect color variations in cracks. Dividing the cracks into a kind based on structures found in the random forest algorithm was chosen, as it resulted in better accuracy in the literature. Finally, it is calculated to analyze the length, width, location and number of cracks. The design of the proposed system is shown in Fig.5.

7. EXPERIMENT RESULTS

Finding excess cracks is an important task in monitoring the health of concrete structures. If cracks grow and continue to grow, it reduces the area carrying the active load and over time can cause structural failure. The manual process of crack detection is time consuming and suffers from direct judgment by inspectors. Manual inspections can be difficult to do if there are tall buildings and bridges. In this blog, we use in-depth reading to create a simpler but more accurate classification model. In addition, we evaluate the model from real-world data and determine whether the model is accurate in determining spatial distribution in concrete and non-concrete structures.The rest of the research network in the table achieved 94% accuracy after testing in a test set of 627 images of crack and non-crack classes. The proposed CNN structure [2] and [3] achieved 89.8% and 96% accuracy (trained with the same set of data). In addition, six images of 3486 × 5184 × 3 size were taken and included in the program.

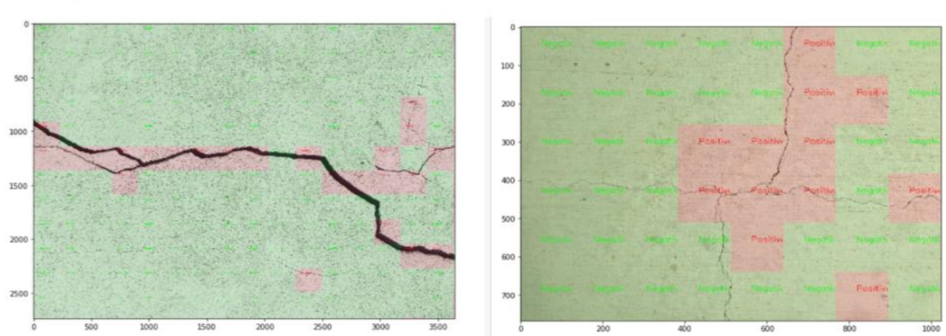

Figure 5: Proposed CNN Structure Result

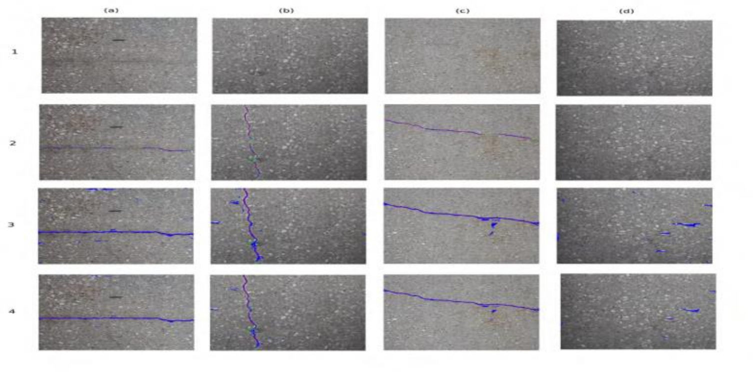

Figure 6: Comparison of different contains non-cracked concrete image

On the other hand, the architecture maintains a stable precision, recall, specificity, and sensitivity scores (all are assigned the same rank in table. Consequently, its F1 score is better than SegNet-SO and less than inspection because of lower sensitivity. However, the ANet-FSM architecture with a low threshold achieves exceptional recall scores with relatively low specificity

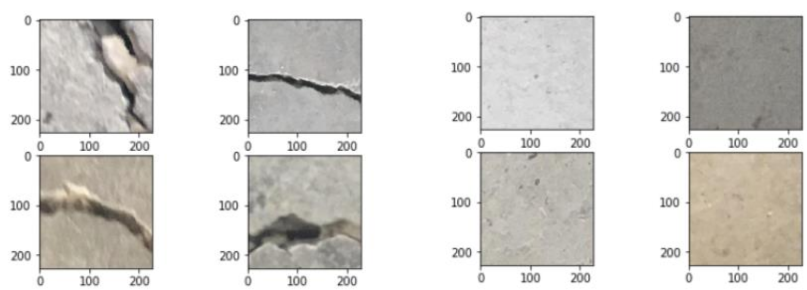

Figure 7: Accuracy of cracked concrete image

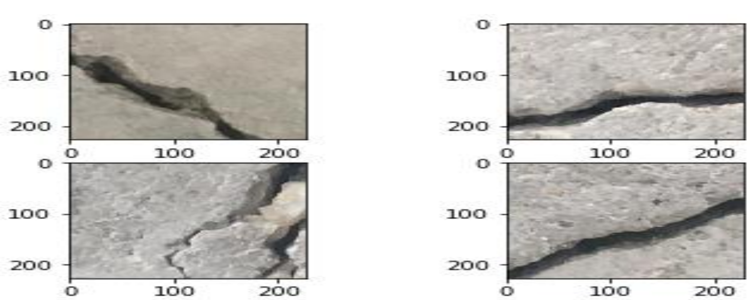

Figure 8: Random Images with Cracks

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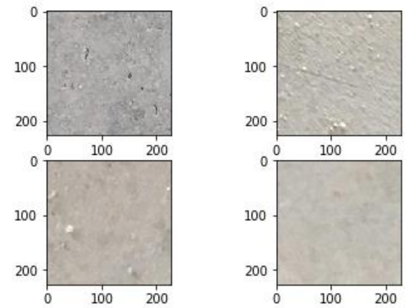

Figure 9: Random Images with Cracks Negative and Positive Predictions

The model was surprisingly confident on a few of the errors. One could decrease the false negative rate by filtering predictions with low probabilities (after calibration). In this context, the consequences of a false negative are high compared to those of a false positive, so a implemented system should err on the side of caution. Depending on the type of inspection a system like this would be used to improve, a single false negative could have serious consequences. Let's take a closer look:

8. CONCLUSION

An in-depth convolutional neural network of crack fragmentation is introduced into this work. Framework to eliminate the impact of the problem of reducing the grading of the unequal portion of data in the categories presented in this work. Reducing unnecessary feature space improves the accuracy of our framework and reduces the impact of the gradient collapse problem. In addition, the sensitivity formation of biodiversity is reduced by the FSM module. As a result, our structure is much more accurate than the methods found in the literature. The experimental results in this study also show that a large proportion of unnecessary calculations are performed in deep structures. Completion of these statistics improves the speed and processing of very deep networks, which is important in the real-time use of these structures.

8.1 FUTURE WORK

Although the proposed framework achieves the highest precision in crack detection, the silencing policy is handcrafted. As a result, the framework is highly sensitive to a certain type of data-set. This sensitivity can be alleviated by designing anoptimization framework, enabling the network to choose policies based on data-set criteria. Another future direction of this work would be

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exploring the area of other concrete distress identification such as spalling detection using an optimized featuresilencing module.

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