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Crack Detection And Classification Using Deep Learning

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ABSTRACT:

Crack detection and characterization is a fundamental part of road intelligent maintenance systems. Due to the high non-uniformity of cracks, topological complexity, and similar noise from crack texture, the challenge arises in this domain with automated crack detection and classification in a complex environment. In this work, an overarching framework for a universal and robust automatic method that simultaneously characterizes the type of crack and its severity level was developed. For crack detection, we propose a novel and efficient crack detection network that captures the crack context information by establishing a multi scale dilated convolution module. On this foundation, an attention mechanism is introduced to further refine the high-level features. Moreover, the rich features at different levels are fused in an up sampling module to generate more detailed crack detection results. For crack classification, a novel characterization algorithm is developed to classify the type of crack after detection. The crack segment branches are then merged and classified into four types: transversal, longitudinal, block, and alligator; the severity levels of cracks are assessed by calculating the average width and distance between the crack branches.

KEYWORDS: crack detection, crack classification, resnet.

1. INTRODUCTION

1.1 Motivation:

In addressing the challenges of crack detection, this research endeavors to revolutionize road maintenance systems

with a pioneering deep learning approach. Motivated by the intricacies of non-uniform cracks and topological complexities, our innovative framework combines a novel crack detection network with an attention mechanism for refined feature extraction. By

introducing a groundbreaking characterization algorithm, we aim to classify cracks into distinct types and assess severity levels, contributing to a universal and robust solution for intelligent maintenance. This pursuit of excellence in convolutional neural networks underscores our commitment to advancing infrastructure sustainability.

1.2 Problem Statement:

Cracks, if not detected and addressed in a timely manner, can lead to deteriorating road conditions, causing safety concerns and costly repairs. Traditional methods of identifying these cracks, which often involve manual inspections, are labor-intensive, time-consuming, and prone to human error.

1.3 Objective of the Project:

To design and deploy a deep learning-powered system capable of autonomously detecting and highlighting cracks from image data. The aim is to offer transportation departments and municipalities a state-of-the-art tool that can significantly improve the efficiency and effectiveness of road maintenance strategies, thereby enhancing road safety and longevity.

1.4 Scope:

1. Collection and preprocessing of high-resolution road surface images from various terrains and conditions.
2. Design and training of a deep learning model specifically optimized for crack detection.
3. Validation of the model's accuracy and efficiency in diverse real-world scenarios.
4. Integration of the system into current infrastructure management tools, ensuring ease of use and immediate alerts.

1.5 Project Introduction:

Automatic detection and classification of cracks is an important part of intelligent transportation systems and acts as a primary rapid analysis of distresses. The implementation of a fast and accurate automatic crack detection system is essential for maintaining and monitoring complex transportation networks, and is an effective way to improve the road service quality. crack automatic detection and characterization systems perform three primary tasks: data acquisition, crack detection, and crack classification. With the

development of mobile mapping technology and hardware storage devices, fast acquisition devices are becoming more widely used in distress screening as they can quickly obtain road distress data. Shows a road surface image acquisition device installed on a roof, whereas Fig. 1(b) is a image taken vertically, which can be used to measure the crack location and for qualitative analysis. In recent years, a numerous experts and scholars have devoted themselves to researching automatic detection of cracks, and have obtained promising research results. At present, the research on automatic detection of cracks is roughly divided into three methods: traditional image processing methods, machine learning methods, and deep learning methods.

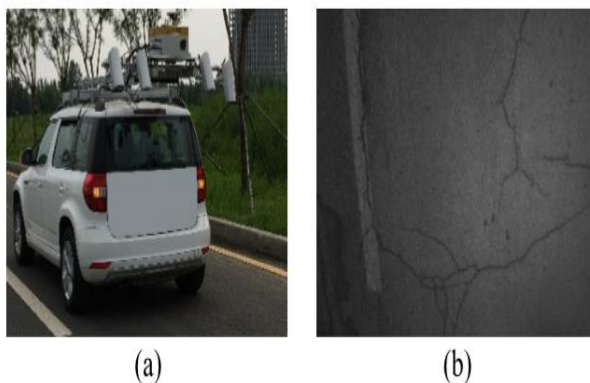


FIGURE 1. Road surface distress acquisition image: (a) road surface image acquisition device installed on the roof; (b) road surface distress image data after collection.

In the traditional methods, the crack region was usually detected using the threshold approach. These algorithms can quickly detect the results in the input image by setting different thresholds. Ideally, cracks can be detected easily, as cracks always absorb more light than other areas and typically appear as darker areas in the image. However, when there is a certain amount of noise, the pixels with intensity is lower than that of the cracked pixels seriously degrade the overall detection performance. These methods lack a description of the global information, are sensitive to noise, and rely primarily on the choice of thresholds. Other researchers use artificially designed feature descriptors to detect cracks in images. For example, Gabor filters and wavelet transforms show significant progress in detecting simple cracks. However, due to complexity, diverse topologies, arbitrary shapes and widths, as well as oil spots, weeds, stains, and other strong disturbances on the road, the performance is still limited.

Upon further development, the machine learning method became widely adopted

in the field of crack detection. The improved active contour model and greedy search-based Support Vector Machine (SVM) have been used to study the detection of bridge cracks. Ai proposed an SVM-based approach to calculate probability maps using information from multi-scale neighborhoods. Through the fusion algorithm, multiple probability maps obtained from the Probabilistic Generation Model (PGM) and SVM methods are merged into a fusion map, which can detect cracks with higher precision than any original probability map. Prasanna classified multiple spatially adjusted visual features using the random forest method. However, these detection methods are limited to detecting learned cracks, and therefore have difficulty detecting new cracks. To overcome the above problems, Crack Forest was proposed based on randomly structured forest for automatic crack detection; it effectively suppresses noise by selecting crack features manually and learning the internal structure. However, it fails to consider the different categories of damage under the complex situation of crack extraction. As

traditional methods simulate cracks by setting color or texture features manually, the features set manually can only satisfy crack extraction in some specific situations. The main weakness of these methods is their failure to address robust detection in the changeable environment. Therefore, manual design features are inefficient for extracting cracks from different road images in complex situations.

Recent theoretical developments have revealed that deep learning can solve complex problems by learning features at different levels automatically. The rich hierarchical features of Deep Convolutional Neural Network (DCNN), and the end-to-end trainable framework, have made significant progress in pixel-level semantic segmentation tasks. Recently, several crack detection methods based on object detection and image block segmentation and utilizing deep learning have been proposed. However, because these rough estimate methods fail to extract cracks at the pixel-level, they cannot accurately characterize crack classification and severity level assignment in the

subsequent step. Huang et al. Proposed a solution to this problem that uses the FCN network for pixel-level crack extraction. However, this method did not consider that cracks with different widths and topologies require different sizes of context information. Moreover, in this method, the different contributions of crack features to crack detection were ignored, and all crack features treated in the same manner. Several studies in the literature have proposed 3D crack detection networks based on DCNN for automatic pixel-level crack detection from 3D asphalt. However, as the network uses a convolutional layer with uniform convolution kernels, this can lead to confusion between the target and the context. Zou et al. implemented the Deep Crack network on the encoder-decoder architecture of SegNet, and merged the convolution features generated in the encoder and decoder network in pairs on the same scale to achieve pixel-level crack detection. However, based on the SegNet network structure, the characteristics of learning in the encoding-decoding stage are relatively simple, and most of the spatial

information that is lost during the up sampling process cannot be restored through shallow layers. Song et al. Developed a crack segmentation network with the DeepLabv3 framework to achieve pixel-level precise segmentation of tunnel cracks. Although this method makes full use of the Atrous Spatial Pyramid Pooling (ASPP) module to obtain multi-scale information, it fails to fully acknowledge the significance of the up sampling operating for refining detection results. In general, deep-learning based methods produce better results than traditional methods. However, there is still a lack of research on robust pixel level crack detection for trainable DCNN models that utilize rich semantic information. The above crack detection based on DCNN methods does not consider crack classification and damage severity levels.

2. LITERATURE SURVEY

- [1] Q. Zou, Z. Zhang, Q. Li, X. Qi, Q. Wang, and S. Wang, "DeepCrack: Learning hierarchical convolutional features for crack detection," IEEE

Trans. Image Process., vol. 28, no. 3, pp. 1498–1512, Mar. 2019.

Cracks are typical line structures that are of interest in many computer-vision applications. In practice, many cracks, e.g., cracks, show poor continuity and low contrast, which brings great challenges to image-based crack detection by using low-level features. In this paper, we propose DeepCrack - an end-to-end trainable deep convolutional neural network for automatic crack detection by learning high-level features for crack representation. In this method, multi-scale deep convolutional features learned at hierarchical convolutional stages are fused together to capture the line structures. More detailed representations are made in larger-scale feature maps and more holistic representations are made in smaller-scale feature maps. We build DeepCrack net on the encoder-decoder architecture of SegNet, and pairwise fuse the convolutional features generated in the encoder network and in the decoder network at the same scale. We train DeepCrack net on one crack dataset and evaluate it on three others. The experimental results demonstrate that DeepCrack achieves F-Measure over 0.87

on the three challenging datasets in average and outperforms the current state-of-the-art methods.

[2] Q. Song, Y. Wu, X. Xin, L. Yang, M. Yang, H. Chen, C. Liu, M. Hu, X. Chai, and J. Li, “Real-time tunnel crack analysis system via deep learning,” IEEE Access, vol. 7, pp. 64186–64197, 2019.

Cracks in the tunnel become an unavoidable problem in tunnel construction and tunnel using. Cracks will affect the stability of the tunnel and have a negative impact on the operation of the train. It is a crucial part of rail safety as well as rail defects and train defects. Therefore, cracks in the tunnel must be identified and repaired in time. At present, the detection of tunnel cracks in the domestic railways relies on the manual inspection mainly. It is difficult to satisfy the requirements of the rapidity and the accuracy of railway inspection by the manual inspection due to the subjective judgment of the inspection personnel. At the same time, tunnel images have some complex situations such as water stains, scratches, structural seams, uneven illumination, and a lot of noise, which have brought bottlenecks to the development of traditional image processing methods. It is

necessary to adopt more effective methods to detect the tunnel cracks in time. This paper builds the first tunnel crack dataset with semantic segmentation annotation and proposes an objective and fast tunnel crack identification algorithm using semantic segmentation in computer vision to construct a complete tunnel crack identification and analysis system. The system applies advanced semantic segmentation to the railway tunnel image analysis to achieve precise segmentation of tunnel crack locations, thereby saving the railway department a lot of manpower and material resources and improving efficiency.

[3] L.-C. Chen, G. Papandreou, I. Kokkinos, K. Murphy, and A. L. Yuille, "DeepLab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected CRFs," *IEEE Trans .PatternAnal. Mach. Intell.*, vol. 40, no. 4, pp. 834–848, Apr. 2018.

In this work we address the task of semantic image segmentation with Deep Learning and make three main contributions that are experimentally shown to have substantial practical merit. First, we highlight convolution with up sampled filters, or

'atrous convolution', as a powerful tool in dense prediction tasks. Atrous convolution allows us to explicitly control the resolution at which feature responses are computed within Deep Convolutional Neural Networks. It also allows us to effectively enlarge the field of view of filters to incorporate larger context without increasing the number of parameters or the amount of computation. Second, we propose atrous spatial pyramid pooling (ASPP) to robustly segment objects at multiple scales. ASPP probes an incoming convolutional feature layer with filters at multiple sampling rates and effective fields-of-views, thus capturing objects as well as image context at multiple scales. Third, we improve the localization of object boundaries by combining methods from DCNNs and probabilistic graphical models. The commonly deployed combination of max-pooling and down sampling in DCNNs achieves invariance but has a toll on localization accuracy. We overcome this by combining the responses at the final DCNN layer with a fully connected Conditional Random Field (CRF), which is shown both qualitatively and quantitatively to improve localization performance. Our proposed "Deep Lab" system sets the new state-of-art at the PASCAL VOC-2012

semantic image segmentation task, reaching 79.7 percent mIOU in the test set, and advances the results on three other datasets: PASCAL-Context, PASCAL-Person-Part, and Cityscapes. All of our code is made publicly available online.

[4] W. Wang, A. Zhang, K. C. P. Wang, A. F. Braham, and S. Qiu, “ crack width measurement based on Laplace’s equation for continuity and unambiguity,” *Comput.-Aided Civil Infrastruct. Eng.*, vol. 33, no. 2, pp. 110–123, Feb. 2018.

Crack is one of the most important condition indicators that are immediately relevant to water ingress and deterioration. In practices of management, crack width has been extensively referenced by highway agencies to determine crack severity. Accurate measurement of crack width is meaningful for highway agencies in understanding the mechanism of crack formation, and in predicting crack propagation. This article presents a new automatic method for measuring crack width using the binary crack map images. The proposed method introduces a new crack width definition and formulates it using the Laplace's Equation so that crack width can

be continuously and unambiguously measured. Two algorithms, including the crack blob extraction algorithm and the crack boundary extraction algorithm, are developed to implement the proposed formulation in an automated fashion. Experimental tests using both synthetic data and field data are conducted to demonstrate the accuracy and reliability of the proposed method. A case study on crack width propagation is also performed to demonstrate the practical capacity of the proposed method. The results of the experimental tests and the outcome of the case study have demonstrated that the proposed method, together with the existing crack map extraction algorithms, provides a promising means for consistent and unambiguous crack width measurement supporting automated condition evaluation.

[5] A. Zhang, K. C. P. Wang, B. Li, E. Yang, X. Dai, Y. Peng, Y. Fei, Y. Liu, J. Q. Li, and C. Chen, “Automated pixel-level crack detection on 3d asphalt surfaces using a deep-learning network,” *J. Comput.-Aided Civil Infrastruct. Eng.*, vol. 32, no. 10, pp. 805–819, Oct. 2017.

The CrackNet, an efficient architecture based on the Convolutional Neural Network

(CNN), is proposed in this article for automated crack detection on 3D asphalt surfaces with explicit objective of pixel-perfect accuracy. Unlike the commonly used CNN, CrackNet does not have any pooling layers which downsize the outputs of previous layers. CrackNet fundamentally ensures pixel-perfect accuracy using the newly developed technique of invariant image width and height through all layers. CrackNet consists of five layers and includes more than one million parameters that are trained in the learning process. The input data of the CrackNet are feature maps generated by the feature extractor using the proposed line filters with various orientations, widths, and lengths. The output of CrackNet is the set of predicted class scores for all pixels. The hidden layers of CrackNet are convolutional layers and fully connected layers. CrackNet is trained with 1,800 3D images and is then demonstrated to be successful in detecting cracks under various conditions using another set of 200 3D images. The experiment using the 200 testing 3D images showed that CrackNet can achieve high Precision (90.13%), Recall (87.63%) and F-measure (88.86%) simultaneously. Compared with recently developed crack

detection methods based on traditional machine learning and imaging algorithms, the CrackNet significantly outperforms the traditional approaches in terms of F-measure. Using parallel computing techniques, CrackNet is programmed to be efficiently used in conjunction with the data collection software.

3. SYSTEM ANALYSIS

3.1 Existing System

In existing system, it focus on automatic detection and classification algorithms for cracks mainly focus on pixel-based analysis of the road image to generate a global image analysis result, and then classify the type of crack detected in the image.

3.2 Disadvantages

1. **Time-Consuming:** Inspecting large stretches of road manually is labour-intensive.
2. **Subjectivity:** Different inspectors might have varying judgments on the severity or even the presence of cracks.
3. **Delayed Intervention:** Due to the periodic nature of inspections, cracks

might only be noticed when they have already worsened, leading to more extensive repairs.

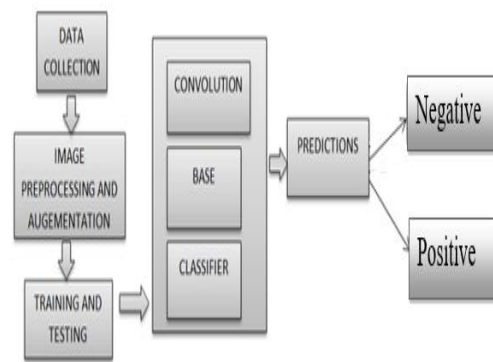
4. **Higher Costs:** Late detections typically translate to more expensive repairs and maintenance.

4. **Proactive Maintenance:** Early detection allows for timely repairs, potentially extending the lifespan of the and saving on repair costs.

3.3 Proposed System:

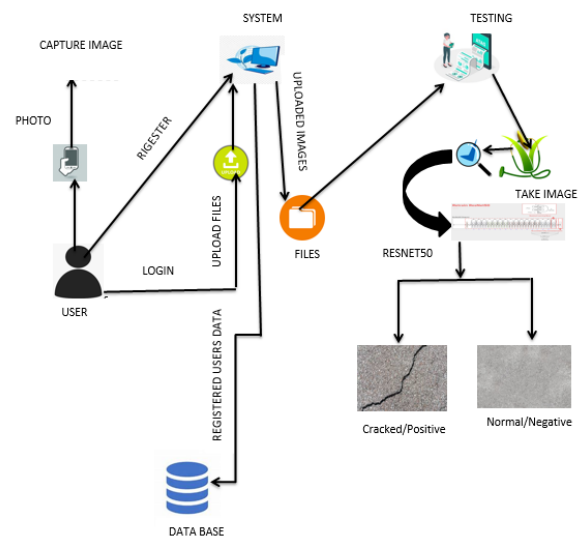
In proposed system, we classify the crack detection network using TensorFlow, which is an open source platform for deep learning. To improve the robustness of the model, several transformations were applied to the data, including random flip, color enhancement, and enlargement. We also utilized the Adam optimizer to converge the network.

3.5 Block Diagram:



3.4 Advantages

1. **High Accuracy:** Capable of detecting subtle cracks that might be missed during manual inspections.
2. **Consistency:** Provides consistent results, eliminating the subjectivity of human inspections.
3. **Efficiency:** Speeds up the crack detection process, making large-scale inspections more feasible.



1.System:

1.1 Create Dataset:

The dataset containing images of the desired objects to be recognize is split into training and testing dataset with the test size of 20-30%.

1.2 Pre-processing:

Resizing and reshaping the images into appropriate format to train our model.

1.3 Training:

Use the pre-processed training dataset is used to train our model using CNN algorithm with transfer learning model.

2. User:

2.1 Register

The user needs to register and the data stored in MySQL database.

2.2 Login

A registered user can login using the valid credentials to the website to use a application.

2.1 About-Project

In this application, we have successfully created an application which takes to classify the images.

2.2 Upload Image

The user has to upload an image which needs to be classify the images.

2.3 Prediction

The results of our model is displayed as either crack positive (Cracked) or Negative (Normal).

2.6 Logout

Once the prediction is over, the user can logout of the application.

6.2 ALGORITHM:

RESNET

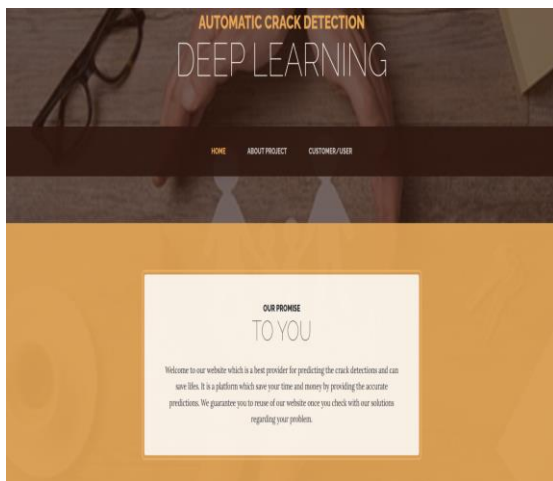
In this research project, we aim to address the critical issue of crack detection and classification by leveraging the power of deep learning. Specifically, we employ the ResNet (Residual Network) algorithm, a state-of-the-art convolutional neural network architecture known for its ability to effectively train deep networks while mitigating the vanishing gradient problem.

Our study focuses on developing a robust model that can accurately detect and classify various types of cracks, contributing to the advancement of automated infrastructure inspection and maintenance. The utilization of ResNet ensures efficient feature extraction and learning capabilities, enhancing the overall performance of the deep learning model in handling complex crack patterns.

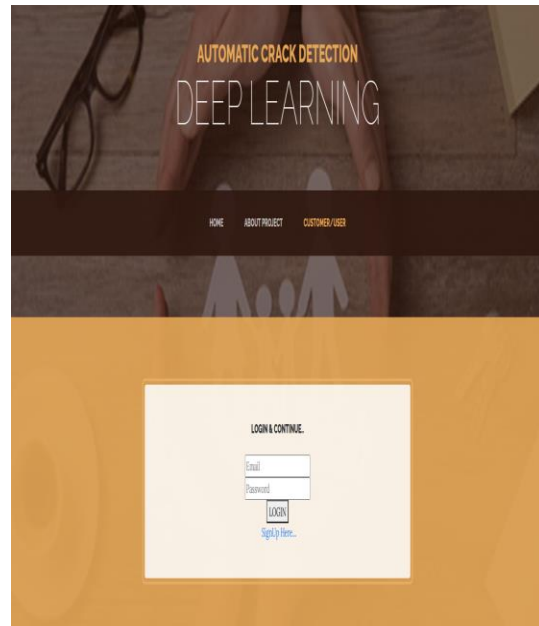
Through this research, we aim to provide a reliable and scalable solution for identifying and categorizing cracks, ultimately contributing to the improvement of road safety and the longevity of transportation infrastructure.

6.3 OUTPUT SCREENS

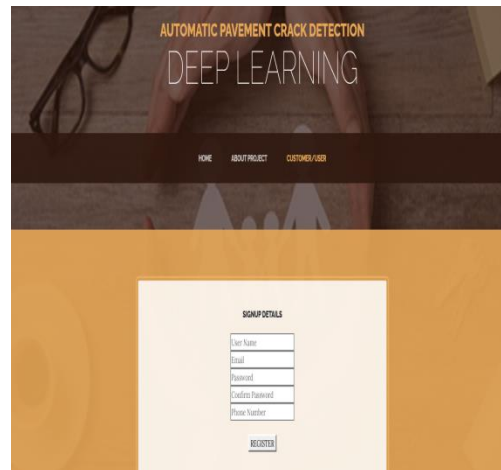
HOME PAGE:



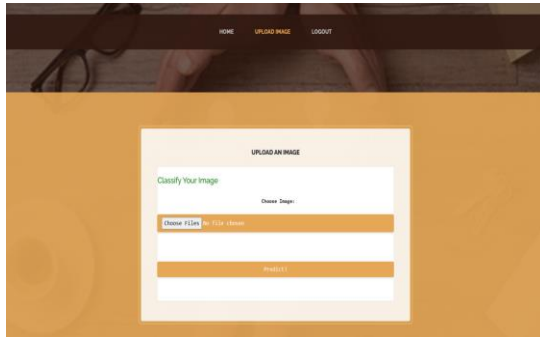
USER LOGIN PAGE:



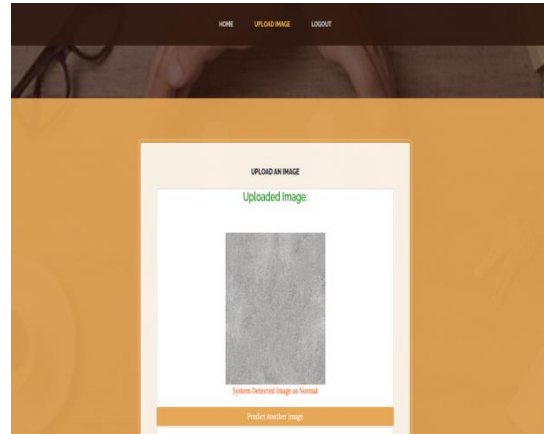
USER REGISTRATION PAGE:



UPLOAD AN IMAGE:

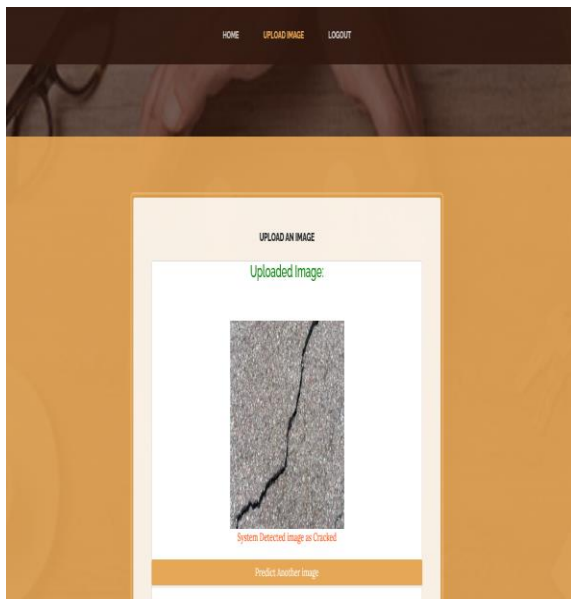


System predicted image as Cracked:



1. CONCLUSION:

In this paper, a novel trainable convolutional network was proposed for automatic detection of cracks in complex environments. In consideration of the different characteristics of different level features, we designed an MDA feature extraction module containing different dilated convolutions at multiple scales and a channel-wise attention module to capture the semantic high-level features. Then, crack pixel-level prediction is achieved by an FFU module that is combined with low-level features and continuous convolution. The experimental results show that both the MDA module and the FFU module contribute to the improvement of crack detection performance.



System predicted image as Normal:

FUTURE WORK

For future developments in research, we will continue to investigate the influence of the attention mechanism on crack feature extraction. Likewise, the crack classification algorithm will be optimized, especially for classification of the block and alligator cracks. Additionally, other types of distress, such as potholes and crack sealings will be taken into account to improve the procedure of automatic crack detection.

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