# Automatic Crack Detection using Image Processing

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**Abstract**— *Robust automatic pavement crack detection is critical to automated road condition evaluation. However, research on crack detection is still limited and pixel-level automatic crack detection remains a challenging problem, due to heterogeneous pixel intensity, complex crack topology, poor illumination condition, and noisy texture background. Crack detection and parameter estimation in roads helps the pavement management in finding the cracks in the roads. In this article, the algorithm is composed of two parts; image processing and image classification. In the first step, cracks are distinguished from background image easily using the filtering, the improved subtraction method, and the morphological operation. The particular data such as the number of pixel and the ratio of the major axis to minor axis for connected pixels area are also extracted. In the second step, the existence of cracks is identified. But if these cracks are detected with the help of some computerized system, then it will take less time. So, this project contains the information regarding the techniques that is used for detection and classification of the cracks on the wall images. This detection and classification is done in MATLAB tool with the help of digital image processing techniques.*

## I. INTRODUCTION

Surveys and analysis of pavement distress is important for the maintenance and evaluation of pavement safety, which requires accurate information about the state of the pavement surface. The most direct manifestation and important indicator to evaluate the condition of the pavement distress is the production of cracks. Thus, accurately and timely detection and quantization of cracks, which usually have complex topology in physical form, can provide important information for quantifying the quality of pavement surfaces as well as preventing and controlling the pavement distress. As such, crack detection is an essential part of road maintenance systems and is attracting more and more attentions in recent years. Moreover, automatic crack detection will also benefit a wide range of applications in other industrial fields, including civil infrastructures like tunnels, bridges, and dams, as well as metallic surface and rock surface. In this paper, we focus on pavement crack detection at pixel-level, which produce the details about the borders and the widths of the cracks. It supports ne-grained characterization of the cracks, thus can provide more critical information for pavement distress analysis. In particular, with the accurate detection of pavement cracks, it is easy to achieve accurate result on various types of pavement cracks, e.g., longitudinal, transverse, diagonal, block, alligator and even some irregular shapes. Also, crack geometric features like width, length, and orientation are also important indicators to identify the road distress level. In this work, we aim to design efficient methods to achieve pixel-level pavement crack detection. We propose novel probability-based methods that jointly consider pixel intensity and multi-scale neighborhood information. The probability based on pixel intensity is calculated using Probabilistic Generative Model (PGM) based approach, while probabilities based on neighborhood information are calculated using Support Vector Machine (SVM) based method. The multiple probabilities of each pixel are further fused together to improve detection accuracy. In addition, the probability information is also used to enhance the recognition of borderline pixels through a weighted dilation operation.

### 1.1 Crack Detection

Road cracks characterize the state of the road and are an important measure for road maintenance. Early crack detection and road reparation enable efficient cost allocation. Moreover, road safety depends on the pavement quality. Asphalt pavements are affected by various types of pavement distresses, like cracking and raveling etc. Therefore, improved road crack detection system can be automatized by recognition and classification algorithms that enhance, speed up and reduce the costs of the road inventory. Road safety is one of the main concerns nowadays. Due to their intensive general use, to keep road pavement in good conditions is a critical point to decrease accidents and, as a direct consequence, to decrease mortal victims. Once roads are built, cracks in the asphalt surface may arise due to several different problems. Depending on the severity, those cracks in the road can be aggravated if they are not quickly repaired.

### 1.1.1 Types of Cracks

***Transverse Cracks:*** Transverse cracks are perpendicular to the centreline of the pavement. They are usually caused by thermal changes. Other causes are asphalt binder hardening or reflexion cracks provoked by other cracks beneath the asphalt surface.

***Longitudinal Cracks*:** Longitudinal cracks have two main causes: fatigue and poor joints. Fatigue cracks are produced by a continuous over-load due to heavy vehicles. Joints are generally the least dense areas of the pavement. If joints are located in a high stressed region, a crack could appear.

***Alligator Cracks:*** Alligator cracks are a combination of fatigue causes and unstable asphalt bases. Walker states that unstable asphalt bases occur when base or sub base cannot support adequately the surface layer. This instability is usually caused by a poor drainage or heavy thaws.

## 1.2 Pavement Crack Detection

Cracking is the most common type of pavement distress. Rapid and accurate detection of pavement cracks is helpful for evaluating the integrity of pavement, improving the level of road maintenance, and has important significance for ensuring traffic safety. Pavement crack detection relies on humans to manually extract image features to detect and identify pavement cracks. This method is inaccurate and errors are easy to occur because different people provide different judgments. Therefore, it is difficult to judge the defective road objectively and scientifically. Also, human visual inspection consumes a lot of manpower and time. In order to achieve the goal of efficient, rapid and accurate detection of pavement cracks, human visual inspection can be replaced by automatic defect detection methods. Automatic crack detection and classification system capable of identifying and retrieving pavement surface images containing cracks from a road pavement image of the system. Pavement surface visual inspection the main objective is to collect image data to use in pavement condition analysis. The captured images must be geographically referenced by automatic methods. This image data allows the posterior identification of both the extent and the severity of the pavement distresses, grouping them into different classes such as cracking, break up and loss of materials (raveling, bares and potholes), movement of materials (climbing of fine aggregates and bleeding), deformations (rutting, abatement and localized deformations) and repairs of the system.

## 1.3 Probabilistic Generative Model

A model is generative if it places a joint distribution over all observed dimensions of the data. A Generative Methods can be obtained in the class-conditional pdfs and prior probabilities. “Generative” sampling can generate synthetic data points.

Probabilistic graphical models (PGMs) are a rich framework for encoding probability distributions over complex domains: joint (multivariate) distributions over large numbers of random variables that interact with each other. These representations sit at the intersection of statistics and computer science, relying on concepts from probability theory, graph algorithms, machine learning, and more. They are the basis for the state-of-the-art methods in a wide variety of applications, such as medical diagnosis, image understanding, speech recognition, natural language processing, and many, many more. They are also a foundational tool in formulating many machine learning problems

Probalistic Generative models: beyond P(Y/ X) can be obtained some functions.

- Compute arbitrary conditionals and marginals.
- Compare the probabilities of different examples.
- Reduce the dimensionality of the data.
- Identify interpretable latent structure.
- Fantasize completely new data

A Popular models can be obtained in the probalistic generative models are Gaussians, Naïve Bayes, Mixtures of multinomials, Mixtures of Gaussians, Mixtures of experts, Hidden Markov Models (HMM), Sigmoid belief networks, Bayesian networks, Markov random fields. PGM based method is used to calculate the probability of a crack pixel for each pixel using intensity information, and illustrate and analyze the detection capability using only pixel information of the system. Generative models consider prior information about the structure of the observed data and exploit such information to estimate latent structure from new data.

### 1.4 Support Vector Machine

A support-vector machine constructs a hyper plane or set of hyper planes in a high- or infinite-dimensional space, which can be used for classification, regression, or other tasks like outliers' detection. A good separation is achieved by the hyper plane that has the largest distance to the nearest training-data point of any class (so-called functional margin), since in general the larger the margin, the lower the generalization error of the classifier.SVM (support vector machine) based approach is used to calculate the probability of a crack pixel using neighborhood information, and then compare the detection capability using information of different scale neighborhoods. Multi-scale neighborhood information are constructed using an SVM method. We develop an SVM method to calculate obtained from the SVM. To solve problems based on a straightforward idea to construct a hyper plane that sets apart the classes of data. We describe a block by extracting block features such as mean value, standard deviation matrix, histogram of oriented gradient (HOG), local binary pattern (LBP) etc., we rely on the original intensity of each pixel of the neighborhood block to characterize the neighborhood information. Support vector machines (SVMs) are a general class of statistical learning architectures that perform structural risk minimization on a nested set structure of separating hyper planes. SVM based method to generate probability maps based on multi-scale neighborhood information. SVM can be viewed as a maximum likelihood estimate of a class of probabilistic models. This model class can be viewed as a reparametrization of the SVM in a similar vein to the ν-SVM reparametrizing the classical (C) SVM. It is not discriminative, but has a non-uniform marginal.

## II. LITERATURE SURVEY

**Recognition And Evaluation Of Bridge Cracks With Modified Active Contour Model And Greedy Search Based Support Vector Machine**

*G. Li, X. Zhao, (2018)*

In this article, we propose the method consists of three steps. First, we build a high-precision image acquisition framework, which can automatically collect image sequences from the lower bridge slab and fuse the multiple sensor data for computing crack parameters. Second, we develop a modified region-based active contour model combined with the iterated Canny operator for the concrete image segmentation. Finally, we utilize the novel feature selection approach based on the linear support vector machine with a greedy search strategy for noise elimination. After that, we provide a crack width calculation method which combined the binary image with the gray scale image information. We evaluate the proposed method on a collection of 1200 real bridge images, which gathered from 10 existing bridges on various weathers, and the experimental results show that the proposed method achieves a better performance than several up-to-date algorithms.

**Automated Pixel-Level Pavement Crack Detection On 3D Asphalt Surfaces Using A Deep-Learning Network**

*A. Zhang (2017).*

In this article, we implement the CrackNet, an efficient architecture based on the Convolutional Neural Network (CNN), for automated pavement crack detection on 3D asphalt surfaces with explicit objective of pixel-perfect accuracy. 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 pavement images and is then demonstrated to be successful in detecting cracks under various conditions using another set of 200 3D pavement 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 other system.

**Automatic Pavement Crack Detection by Multi-Scale Image Fusion.**

*H. Li, D. Song, Y. Liu, and B. Li. (2017).*

In this article, we implement the new unsupervised multi-scale fusion crack detection (MFCD) algorithm that does not require training data. First, we develop a windowed minimal intensity path-based method to extract the candidate cracks in the image at each scale. Second, we find the crack correspondences across different scales. Finally, we develop a crack evaluation model based on a multivariate statistical hypothesis test. Our approach successfully combines strengths from both the large-scale detection (robust but poor in localization) and the small-scale detection (detail-preserving but sensitive to clutter). We analyze and experimentally test the computational complexity of our MFCD algorithm. We have implemented the algorithm and have it extensively tested on three public data sets, including two public pavement data sets and an airport runway data set. Compared with six existing methods, experimental results show that our method outperforms all counterparts.

**Detection of Cracks in Nuclear Power Plant Using Spatial-Temporal Grouping of Local Patches**

*S. J. Schmugge (2016)*

In this article, we propose a crack detection method for nuclear power plant inspection videos by fine tuning a deep neural network for detecting local patches containing cracks which are then grouped in spatial-temporal space for group-level classification. We evaluate the proposed method on a data set consisting of 17 videos consisting of nearly 150,000 frames of inspection video and provide comparison to prior methods.

**Automatic Crack Detection on Two-Dimensional Pavement Images: An Algorithm Based on Minimal Path Selection**

*R. Amhaz, S. Chambon (2016)*

In this article, we implement the new algorithm for automatic crack detection from 2D pavement images. It strongly relies on the localization of minimal paths within each image, a path being a series of neighboring pixels and its score being the sum of their intensities. The originality of the approach stems from the proposed way to select a set of minimal paths and the two post processing steps introduced to improve the quality of the detection. Such an approach is a natural way to take account of both the photometric and geometric characteristics of pavement images. An intensive validation is performed on both synthetic and real images (from five different acquisition systems), with comparisons to five existing methods. The proposed algorithm provides very robust and precise results in a wide range of situations, in a fully unsupervised manner, which is beyond the current state of the art.

**Automatic Road Crack Detection Using Random Structured Forests**

*Y. Shi, L. Cui, Z. Qi, F. Meng (2016).*

In this article, we propose CrackForest, a novel road crack detection framework based on random structured forests, to address these issues. Our contributions are shown as follows: 1) apply the integral channel features to redefine the tokens that constitute a crack and get better representation of the cracks with intensity in homogeneity 2) introduce random structured forests to generate a high-performance crack detector, which can identify arbitrarily complex cracks and 3) propose a new crack descriptor to characterize cracks and discern them from noises effectively. In addition, our method is faster and easier to parallel. Experimental results prove the state-of-the-art detection precision of CrackForest compared with competing methods.

**Road Crack Detection Using Deep Convolutional Neural Network**

*L. Zhang, F. Yang (2016)*

In this article, we implement the deep-learning based method for crack detection. A supervised deep convolutional neural network is trained to classify each image patch in the collected images. Quantitative evaluation conducted on a data set of 500 images of size 3264 $\chi$ 2448, collected by a low-cost smart phone, demonstrates that the learned deep features with the proposed deep learning framework provide superior crack detection performance when compared with features extracted with existing hand-craft methods.

**Extraction of Micro Cracks In Rock Images Based On Heuristic Graph Searching And Application**

*Z. Luo, Z. Zhu, H. Ruan (2015)*

In this article, we propose a new method, based on a graph searching technique, for micro crack extraction from scanning electron microscopic images of rocks. This method mainly focuses on how to detect the crack and extract it, and then quantify some basic geometrical features. The crack can be detected automatically with the aid of two endpoints of the crack. The algorithm involves the following process: the A graph searching technique is first used to find a path throughout the crack region, defined by the initial two endpoints; the pixels of the path will be used as the seeds for the region growing method to restore the primary crack area; then, an automatic filling holes' operation is used to remove the possible holes in the region growing result; the medial axis and distance transformation of the crack area are acquired, and then the final crack is rebuilt by painting disks along a medial axis without branches. The crack result is separated without interaction. In the remaining parts, the crack features are quantified, such as the length, width, angle and area, and error analysis shows that the error percentage of the proposed approach reduces to a low level with actual width increases, and results of some example images are illustrated.

**Automatic Crack Detection And Classification Method For Subway Tunnel Safety Monitoring**

*W. Zhang, Z. Zhang, D. Qi, (2014)*

In this article, we present an automatic crack detection and classification methodology for subway tunnel safety monitoring. With the application of high-speed complementary metal-oxide-semiconductor (CMOS) industrial cameras, the tunnel surface can be captured and stored in digital images. In a next step, the local dark regions with potential crack defects are segmented from the original gray-scale images by utilizing morphological image processing techniques and thresholding operations. In the feature extraction process, we present a distance histogram-based shape descriptor that effectively describes the spatial shape difference between cracks and other irrelevant objects. Along with other features, the classification results successfully remove over 90% misidentified objects. Also, compared with the original gray-scale images, over 90% of the crack length is preserved in the last output binary images. The proposed approach was tested on the safety monitoring for Beijing Subway Line 1. The experimental results revealed the rules of parameter settings and also proved that the proposed approach is effective and efficient for automatic crack detection and classification.

**Road Crack Detection Using Visual Features Extracted By Gabor Filters**

*E. Zalama, J. Gómez-García-Bermejo (2014)*

In this article, we presents a solution based on an instrumented vehicle equipped with an imaging system, two Inertial Profilers, a Differential Global Positioning System, and a webcam. Information about the state of the road is acquired at normal road speed. A method based on the use of Gabor filters is used to detect the longitudinal and transverse cracks. The methodologies used to create Gabor filter banks and the use of the filtered images as descriptors for subsequent classifiers are discussed in detail. Three different methodologies for setting the threshold of the classifiers are also evaluated. Finally, an AdaBoost algorithm is used for selecting and combining the classifiers, thus improving the results provided by a single classifier. A large database has been acquired and used to train and test the proposed system and methods, and suitable results have been obtained in comparison with other reference works.

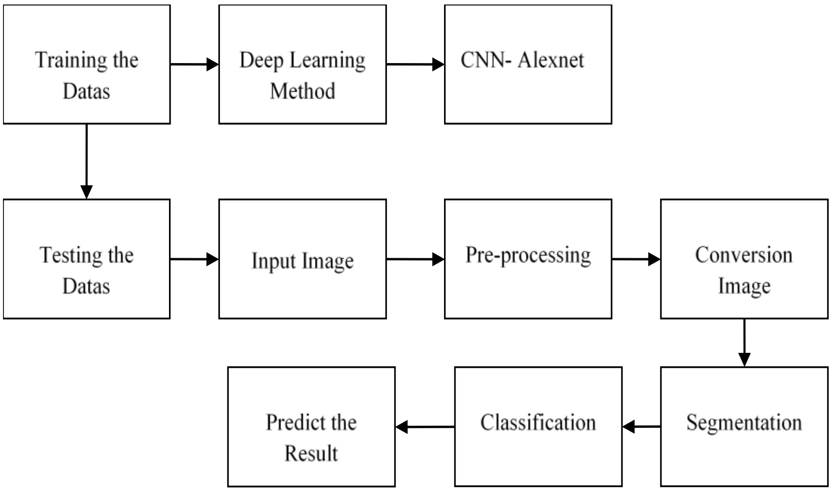
## III. METHODOLOGY

Robust automatic pavement crack detection is critical to automated road condition evaluation. However, research on crack detection is still limited and pixel-level automatic crack detection remains a challenging problem, due to heterogeneous pixel intensity, complex crack topology, poor illumination condition, and noisy texture background. In our proposed method, we aim to design efficient methods to achieve pixel-level pavement crack detection. We propose novel probability-based methods that jointly consider pixel intensity and multi-scale neighborhood information. That is, for each pixel, we estimate the probability of each pixel being a crack using different point of views, i.e. based on the pixel intensity, and based on information of neighborhoods with sizes of $7 \times 7$, $13 \times 13$, $19 \times 19$ and $25 \times 25$, respectively. The probability based on pixel intensity is calculated using Probabilistic Generative Model (PGM) based approach, while probabilities based on neighborhood information are calculated using Support Vector Machine (SVM) based method. The multiple probabilities of each pixel are further fused together to improve detection accuracy. In addition, the probability information is also used to enhance the recognition of borderline pixels through a weighted dilation operation. We develop a fusion algorithm to merge the multiple probability maps, obtained from both PGM and SVM approaches, into a fused map, which can detect cracks with accuracy higher than any of the original probability maps. We also propose a weighted dilation operation that relies on the fused probability map to enhance the recognition of borderline pixels and improve the crack continuity without increasing the crack width improperly. Experimental results demonstrate that our algorithm achieves better performance in terms of precision, recall, f1-score, and receiver operating characteristic, in comparison with the state-of-the-art pavement crack detection algorithms.

**Advantages**

- Better Performance.
- Clear Pixel intensity.

- Accurate.
- Better illumination condition.




### 3.1 Input Data

A collection of data is called as datasets. An input data can be obtained from the datasets. A collection of Crack images can be obtained from the datasets. Given an input image to associate a binary label (where 0 represents non-crack and 1 represents crack in this paper) with each pixel in the image, to indicate whether this pixel belongs to a crack or not, based on the observed data at each pixel. Example 4 pixels with neighborhood information of different scales can be considered of the system.

### 3.2 Pre-Processing:

Pre-processing data is a common first step in the deep learning workflow to prepare raw data in a format that the network can accept. For example, you can resize image input to match the size of an image input layer. You can also preprocess data to enhance desired features or reduce artifacts that can bias the network. For example, you can normalize or remove noise from input data.

You can preprocess image input with operations such as resizing by using datastores and functions available in MATLAB® and Deep Learning Toolbox™. Other MATLAB toolboxes offer functions, datastores, and apps for labelling, processing, and augmenting deep learning data. Use specialized tools from other MATLAB toolboxes to process data for domains such as image processing, object detection, semantic segmentation, signal processing, audio processing, and text analytics.

### 3.3 Image Analysis:

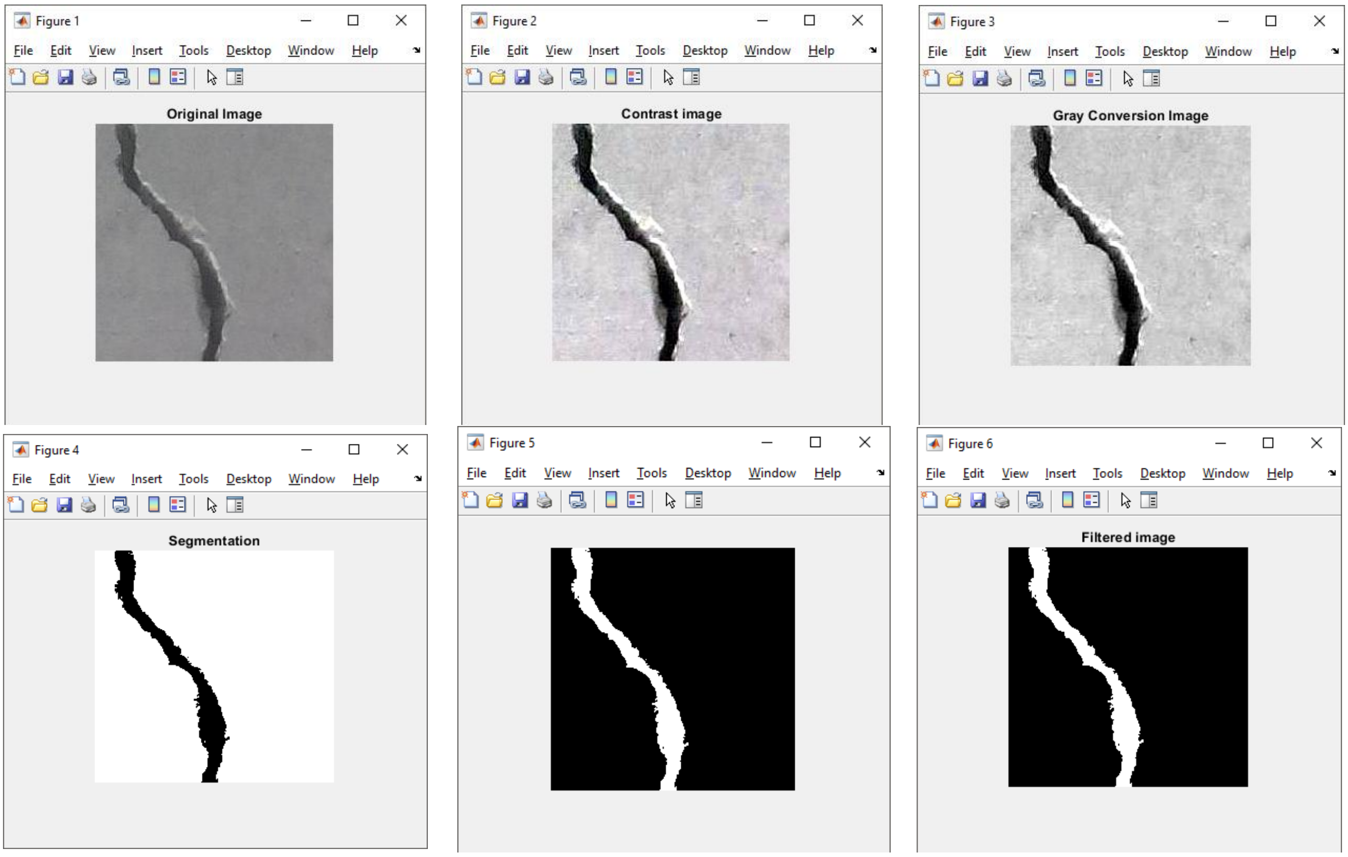
Deep Learning enables remarkable advancements in the medical imaging field. This type of automated algorithm helps in providing a valuable second opinion to the healthcare professionals during the screening process. Deep Learning using MATLAB helps in quickly prototyping and developing algorithms.

- Easily manage large image dataset using datastores
- Interactively use apps to semi-automate the process of generating ground-truth labels from images
- Efficiently train and evaluate a semantic segmentation model using labelled images
- Automatically generate optimized code to deploy on a medical device

### 3.4 Detection Result

Finally, all the process can be obtained to detect the results based on the Crack detection. A ROC curve is used to display the result in the graphical form of the system. Experimental results have demonstrated the superiority of our approach in terms of Deep Learning Algorithm to predict the results.

## IV. IMPLEMENTATION




***label = categorical***
***Crack***

## V. CONCLUSION

Automatic pixel level pavement crack detection problem by leveraging on multi-scale neighborhood information as well as the pixel intensity, to meet the challenges posed by heterogeneous pixel intensity, complex crack topology, poor illumination condition, and noisy texture background such as oil spots, water stains, shadow casting etc. We have demonstrated that neighborhoods contain critical information for crack detection and different size of neighborhoods have significant impact on the detection results. We developed novel PGM based method to generate probability map based on pixel intensity information, and SVM based method to generate probability maps based on multi-scale neighbourhood information. We also compared the results of probability fusion strategies and designed a novel fusion algorithm to merge the multiple probability maps into a fused map that can detect cracks with high accuracy. To enhance the recognition of borderline pixels as well as improve the crack continuity, we have proposed a weighted dilation operation to further optimize the detected cracks, which also relies on the fused probability maps. Experimental results have demonstrated the superiority of our approach in terms of precision, recall, f1-score and ROC, over the state-of-the-art pavement crack detection algorithms.

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