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# AN DEEP LEARNING BASED SHADOW REMOVAL AND PAVEMENT CRACK DETECTION

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Abstract—The goal is to develop an efficient method for the automatic detection of asphalt roads, which involves removing shadows with the same intensity as cracks. This shadow can interfere with the accuracy of fracture detection. Currently, there is a lack of efficient algorithmic models and training data to solve this problem. Our methodology consists of three steps. First, we use pre-processing techniques to improve image quality. Second, we detect and remove shadows and classify intersections using deep learning methods. The system uses intensity values for accurate detection and supports multiple image formats. Advanced filtering techniques are used to eliminate noise. Biasing and padding improve race detection using lateral edge detection. Small parts are extracted to isolate important features and a CNN-based feature extraction system is used to detect intersec-tions. To solve the challenges related to seasonality and climate change, we propose a data augmentation method based on the difference in light values. This method allows the system to adapt to different lighting conditions. In addition, we present a residual feature augmentation algorithm to detect small cracks that may indicate a potential disaster. This algorithm significantly improves the overall performance of the model. In addition, we present a deep learning Convolution Neural Network method to classify cracks, which can predict unexpected disasters by classifying them as either positive or negative. The proposed system uses a shadow crack database to train and test different databases. The classification accuracy of the best system reached 94% with the lowest mean squared error (MSE). The test and training accuracy of our model is higher than other advanced methods.

Index Terms—Automatic pavement crack detection, deep learning, shadow removal, shadow-crack dataset.

## I. Introduction

Visual inspection and image processing are becoming increasingly important in civil and construction engineering. The condition of structures must remain consistent throughout their lifespan, although this can be affected by natural aging, environmental factors, and unforeseen events. Early inspection of deteriorating structures is crucial for their repair, as damage can worsen over time. Concrete degradation primarily occurs due to earthquakes, frost damage, salt erosion, rainwater, and dry shrinkage. Cracks on concrete surfaces are early indicators of deterioration. Detecting cracks is essential for inspecting, diagnosing, and repairing concrete structures, but traditional methods may not provide accurate results due to various types of noise in concrete images. Detecting wall cracks is vital for

Fig. 1. some typical images from mendeleys dataset of concrete crack images for classification. Top row shows without crack whereas bottom rows shows crack images of concrete surfaces

maintaining structural integrity and building safety. Manual inspection is time-consuming and prone to errors. This project utilizes image processing to automatically detect wall cracks, overcoming these challenges. MATLAB is used to process images and identify cracks efficiently. Early identification enables proactive measures to be implemented in order to prevent harm and potential breakdown. The process of identifying cracks in structures can be achieved through various processing techniques. Detection of cracks can be carried out in two main ways: Destructive Testing and Non-Destructive Testing. Monitoring and detecting surface cracks is crucial for assessing the structural integrity of concrete structures. If cracks are left unchecked and continue to spread, they can diminish the load-bearing capacity of the structure over time, ultimately leading to structural failure. The introduction of a research paper acts as a guide for the reader, offering background information, emphasizing the importance of the research issue, and outlining the objectives and contributions of the study. In the case of a paper focusing on road crack detection using deep learning methods, the introduction would typically follow a structure similar to the one described above.

The main objective of this project is to develop a pavement crack detection system using image processing techniques while eliminating the presence of shadows. By implementing preprocessing techniques and advanced algorithms, the accuracy of crack detection will be significantly improved through training and testing. The ultimate goal is to automate the process of detecting pavement cracks, reducing the possibility of human error and increasing efficiency. Additionally, the proposed system aims to detect both major and minor cracks, enabling early identification and resolution of structural issues. The problem involves the detection of cracks in images, specif-ically in the context of infrastructure or material inspections. With a dataset consisting of images that contain both cracked and intact surfaces, the objective is to train a convolutional neural network (CNN) to accurately classify these images as either having cracks or being crack-free.

## II. Literature Survey

To gain a comprehensive understanding of pavement crack detection, it is important to review the existing literature on the subject. This includes examining previous methods and techniques that have been used for crack detection. It is also important to analyze the strengths and weaknesses of traditional approaches, which typically involve manual feature extraction combined with machine learning algorithms. Furthermore, it is necessary to highlight the recent progress in crack detection methods based on deep learning, such as Convolutional Neural Networks (CNN). Zhang et al. (2016): This work presents a method for detecting road cracks using deep convolutional neural networks (CNNs). However, it is important to note that the effectiveness of the proposed CNN model may depend on the quality and variety of the training data. In addition, model performance may vary under different light and weather conditions, as well as on roads with different textures and surface materials. Shi et al. (2016): This work pro-poses a method for automatic pavement crack detection using random structured forests. While random structured forests can offer robustness to changes in the appearance of road cracks, their performance can depend on the choice of features and the quality of the training data. Furthermore, the accuracy of this method may decrease in the presence of complex backgrounds or overlapping cracks. Schmugge et al. (2017): This work presents a crack segmentation method that uses multiple images of different illumination. However, it is important to consider the limitations of this approach. The effectiveness of crack segmentation using multiple images can be affected by factors such as motion blur, occlusion, and changes in lighting conditions between images. Additionally, the computational complexity of the method may limit its applicability in real-time scenarios. By understanding the strengths and weaknesses of these previous works, researchers can build on existing knowledge and strive to develop more robust and accurate pavement crack detection methods. A study by Benedetto et al. (2014) primarily focuses on the use of finite-difference time-domain (FDTD) simulation to effectively investigate pavement damage using ground-penetrating radar (GPR). In research conducted by Zou et al. (2012), a method called Crack Tree is presented that automates the detection of cracks in pavement images. The performance of CrackTree largely depends on the efficiency of feature extraction and the robustness of the classification algorithm used. In addition, this method may encounter difficulties in detecting small or weak cracks and distinguishing cracks from other types of pavement anomalies. Huyan et al. (2020) present a new lighting compensation model that uses a k-means algorithm to detect cracks on the road surface, especially in the presence of shadows. Limi-tations: Although the proposed model effectively solves the problem of shadow interference in crack detection, its perfor-mance depends on the accuracy of illumination compensation and the effectiveness of the k-means algorithm in shadow segmentation. Additionally, the robustness of the model under different lighting conditions and road textures requires further investigation. Shelhamer et al. (2017) pioneered the use of fully convolutional networks (FCNs) for semantic segmenta-tion. While FCNs offer promising results, their performance can be limited by factors such as image size, complexity, and label ambiguity. Hu et al. (2020) introduced direction-oriented spatial context features for shadow detection and removal. Despite their potential to increase accuracy, these features can struggle with complex scenes and variable lighting conditions, especially when distinguishing shadows from other dark areas. Xie and Tu (2015) proposed a holistic nested edge detection for generating detailed edge maps. However, the effectiveness of this method may decrease in noisy environments and may require careful tuning of parameters to achieve optimal results, especially when detecting weak or ambiguous edges. Zhou et al. (2003) proposed a wavelet approach for pavement distress detection that is effective in capturing texture and structure information. However, sensitivity to noise and the need for careful parameter selection can hinder its performance. pic-tures on the sidewalk. However, its performance may depend on the image quality, resolution, and complexity of crack patterns, which may have problems detecting fine or weak cracks. Nguyen et al. (2011) introduced free anisotropy for crack detection, which can be effective in optimal parameter selection. However, its generalization to different pavement types and crack patterns along with performance under dif-ferent lighting conditions remains a challenge. Ieracitano et al. (2021) proposed a hybrid unsupervised and supervised machine learning system for nanofiber classification, but areas for consideration are its direct applicability to pavement stress detection and computational complexity.Prasanna et al. (2016) discussed automated crack detection on concrete bridges, confronting challenges related to lighting conditions, surface textures, and environmental factors that can affect detection accuracy. Li et al. (2022) investigated UAV-based image gen-eration for change detection, although its direct relevance to pavement disturbance detection, particularly crack detection resolution, remains uncertain. Gopalakrishnan et al. (2017) advocated deep CNNs with transfer learning in pavement distress detection, despite challenges related to dataset size, computational resources, and detection of fine or weak cracks. Zhang et al. (2022) conducted a survey of deep learning-based attack detection, which, while comprehensive, lacks concrete insight into crack detection techniques and appli-cations. Hacıefendioglu˘ and Bas¸aga˘ (2022) proposed a deep learning-based method for concrete pavement crack detection using a faster R-CNN approach. However, its performance may depend on dataset quality and computational complexity, especially in real-time scenarios. Hu et al. (2021) presented a deep learning-based pavement crack detection method, with challenges including variability in lighting conditions, pavement materials, and crack types, along with generalization to different road environments. Lv et al. (2021) focused on the regression of lane markings using deep learning techniques, facing obstacles in accurately detecting markings under adverse weather conditions or in complex traffic scenarios.Fan et al. (2022) proposed RAOUNet for road crack detection, but its deployment may be limited by significant computational resources, limiting its practicality in real-time applications. Pauly et al. (2017) discussed the use of deeper networks for pavement crack detection, with concerns of possible overfitting and computational complexity.

## III. Methodology

In the proposed methodology, there are two main parts.They are A)Shadow Removal and Pavement Crack Detection and B) Neural Network for Concrete Crack Detection. These methods make sure that the result is accurate, correct and Perfect.They also provide the output which gives the clear and accurate result.

### A. Shadow Removal and Pavement Crack Detection

To ensure accurate crack detection, image processing techniques are often used to overcome problems with image noise and shadows that have similar intensities and can interfere with crack detection. This technique improves image quality and removes shadows by comparing intensities. Finally, the system analyzes the intensity of the image to identify cracks and facili-tate their detection by viewing the image in two directions. The system fills the image holes to increase the visibility of cracks. Clump analysis is used to remove insignificant small particles that may interfere with fracture detection. By analyzing image correlation, the system can distinguish real intersections from image artifacts. Finally, the reproduction of concrete fracture images is done by combining images using the superposition technique. This involves blending one image (shadow mask) with another image (concrete surface) using a multi-rendering process. The resulting composite image creates the illusion of a single image containing features from the two source images. This expansion strengthens the database for more reliable breach detection.

### B. Neural Network for Concrete Crack Detection

Advanced methods greatly improve the performance of neural networks for concrete crack detection. The corrected linear unit (ReLU) function is used to solve the vanishing gradient problem, speeding up the learning process. Two-dimensional convolutional layers produce feature maps with trained kernels, which are most helpful in feature reduction. Normalizing local responses helps generalization, and detraining prevents overtraining and accelerates learning. Modified architecture for discrete image classification problem using 2-way Softmax activation in the output layer. In addition, adjustments are made to fully connected layers and training level parameters to optimize predictive performance. The network is retrained using augmented data using stochastic gradient descent optimization with carefully chosen parameters such as batch size, number of epochs, and initial training rate determined by extensive numerical computation.

### C. Block Diagram

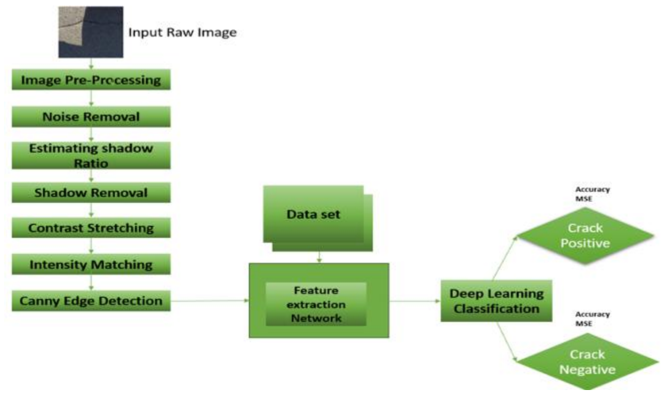


Fig. 2. Proposed Block Diagram

### D. Steps for Crack Detection

1) Acquisition of RGB Image: Begin by capturing the RGB image directly from the camera.
2) Conversion to Grayscale: Convert the RGB image to grayscale to simplify processing.
3) Median Filtering: Apply a median filter to the grayscale image to smooth the surface and reduce noise.
4) Edge Detection: Utilize Sobel's edge detectors to en-hance edges in the image, highlighting potential crack locations.
5) Thresholding: Apply Otsu's thresholding method to con-vert the grayscale image into a binary image, separating cracks from the background.
6) Removal of Small Components: Identify and remove connected components with an area less than a specified threshold (e.g., 200 pixels) to eliminate noise.
7) Removal of Certain Orientations: Identify and remove connected components with orientations of 0, 90, and -90 degrees, which are less likely to represent cracks.
8) Morphological Operations: Apply morphological operations, such as the "majority" operation, to connect disconnected crack segments and fill holes within them.
9) Additional Component Removal: Detect and remove objects with a total pixel count less than a specified threshold (e.g., 50 pixels) to further eliminate noise.

### E. Crack Image Pre-processing

To improve crack extraction accuracy, pre-processing steps including noise elimination, crack enhancement, and shadow removal are necessary. Algorithms for shadow and noise removal, as well as crack enhancement, were studied for this purpose.

### F. Crack Extraction

Following pre-processing, crack extraction involves two main steps: crack detection on grayscale images and final-ization of crack information on binary images. The first step utilizes an improved level set algorithm, while the second step involves noise elimination and gap linking to finalize crack detection.

### G. Data Preparation

Image data is loaded from a directory utilizing imageDatastore, then split into training and testing sets using splitEachLabel.

### H. CNN Architecture

The architecture comprises several layers:

- Input layer: Accepts 128x200 pixel images with 3 color channels.
- Convolutional layers (conv_1, conv_2, conv_3): Ex-tract features, with 16 filters in the first layer and 32 in subsequent layers.
- Batch normalization layers (BN_1, BN_2, BN_3): Nor-malize convolutional layer activations.
- ReLU activation layers (relu_1, relu_2, relu_3): Introduce non-linearity.
- Addition layer (add): Implements a skip connection from relu_1 to conv_3.
- Average pooling layer (avpool): Reduces feature map dimensions.
- Fully connected layer (fc): Generates final feature vector.
- Softmax layer: Computes class probabilities.
- Classification layer: Assigns class labels.

### I. Training

The CNN is trained using the training data with speci-fied training options (e.g., adam optimizer, mini-batch size, epochs). Input images undergo histogram equalization and noise removal. Shadow detection and removal are achieved through shadow ratio calculation and thresholding. Edge de-tection is performed using the Canny method. Post-processing involves adjusting intensity levels, filtering, and image combi-nation. Crack length is calculated using a calibration factor to convert from pixels to real-world units. Heat maps visualize CNN activation on input images.

### J. Classification and Evaluation

The trained CNN classifies individual images (classify) and the entire test data set. Evaluation metrics such as precision, accuracy, recall, and F1 scores were calculated from the confusion matrix. The confusion matrix and classification criteria are represented by a confusion diagram.

This approach integrates CNN-based feature extraction with traditional image processing techniques for crack detection. From data preparation to evaluation, it follows a comprehen-sive methodology aiming for accurate results.

## IV. Results and Discussions

The following information shows the output in every step and in every section such as shadow detection, highlighted edge, shadow removal,heated image, crack detection etc. the outputs are more accurate when compared previous methods.

### A. Result Analysis

Based on the algorithm for image pre-processing and crack detection, we conducted extensive testing on a diverse dataset comprising hundreds of pavement images. The step-by-step testing procedure for crack extraction is depicted in Figures 3 to 13. The model demonstrates impeccable accuracy in both scenarios—images with and without cracks, which focuses on images with shadows but without cracks. In particular, images containing large shadow areas with high intensity are correctly identified, demonstrating the effectiveness of classification using networks trained on long images containing shadows and concrete surfaces.

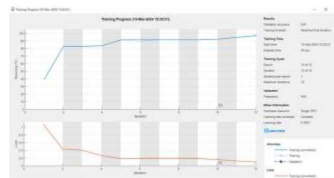

Fig. 3. Training Plot

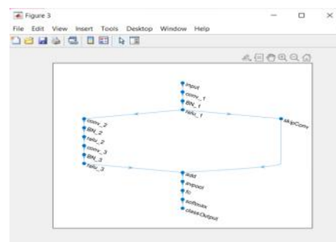

Fig. 4. Layers of CNN

### B. Training Progress

This section shows the progress of the training process. It lists the epoch number, iteration number, time elapsed, mini-batch accuracy, mini-batch loss, and base learning rate. Each epoch represents a full pass through the entire training dataset.

### C. Performance Metrics

The performance metrics are presented below:

- Accuracy: 0.88333
- Precision: 0.89796
- Recall: 0.95652
- F1 Score: 0.92632

Finally, the results presented in our paper show that the extended data set helps to retrain the network to achieve a high level of accuracy for image classification. However, multiplication alone does not always lead to improved results. The reproduction algorithm introduced in this paper is based on a realistic simulation of optical effects in a virtual digital environment. Therefore, such an approach can be improved if existing data sets are replicated and then applied to deep learning algorithms based on real environmental conditions. This is demonstrated in our paper and is a key differentiator for the success of such an approach.

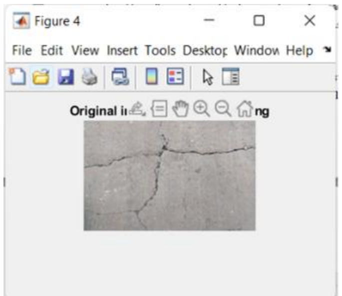


Fig. 5. Original Image Before Pre-Processing

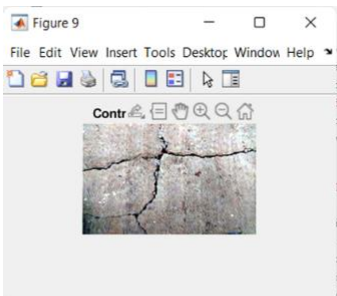


Fig. 6. Contrast Enhanced image

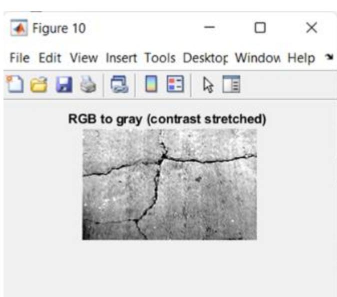


Fig. 7. Another Contrast Enhanced image

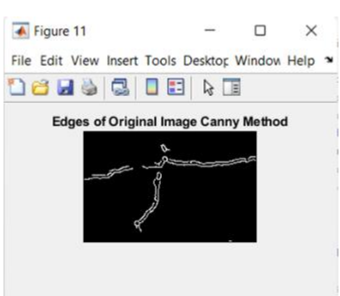


Fig. 8. Canny Edge Detected image

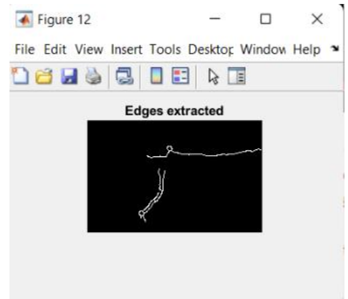


Fig. 9. Edges Extracted Image

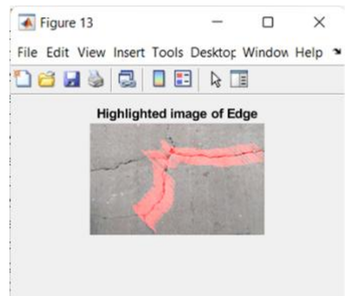


Fig. 10. Highlighted Image Of Edge

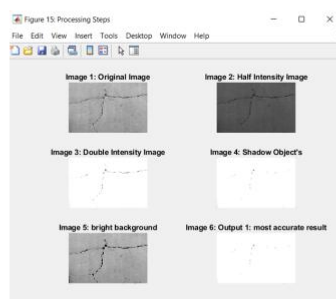


Fig. 11. Processing Steps For Shadow Identification And Removal

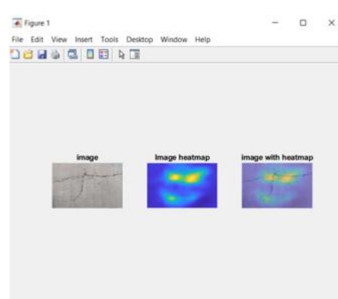


Fig. 12. Heat Map Image

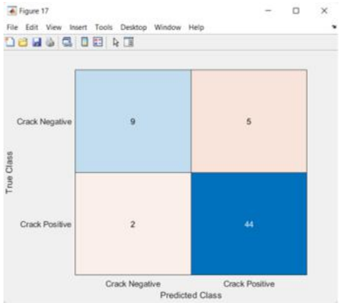


Fig. 13. Confusion Matrix


Fig. 14. Final Result

Fig.5 above is the original image before image processing, while Fig. 6 and Fig.7 are contrast enhanced images and in images 8, 9 and 10 along with edge detection it removes edges and highlights the edge.In Fig.11 we can see the processing steps for shadow identification and removal.The Fig.12 shows the heat map of the crack. The final result can be seen in Fig.13. We can get a clear vision about results by seeing the Confusion matrix which is shown in Fig.14. These results suggest that the model is relatively good at identifying cracks (high recall) and is reasonably precise in its predictions. However, there are many ways to improve, especially in terms of accuracy.

## V. Conclusion

Our research introduces a novel approach within the shadow removal network, where we implement a unique data aug-mentation method based on discrepancies in brightness val-ues. This technique allows our system to adapt effectively to fluctuations in lighting caused by seasonal changes and varying weather conditions. Through this augmentation, our method achieves superior performance across diverse datasets, accurately identifying both minor and severe cracks through advanced image processing techniques. By leveraging so-phisticated deep learning algorithms, our system successfully suppresses noise, enhances image quality, and isolates crucial features essential for effective crack detection. We highlight the considerable challenges associated with accurately classi-fying real-world concrete crack images taken under complex lighting conditions. Our experiments on images containing shadows clearly reveal the limitations of existing deep learning models in accurately identifying cracked surfaces in shadowy environments. To address this challenge, we propose a novel image augmentation technique comprising three consecutive steps: shadow ray-tracing, augmentation of shadow datasets, and shadow blending. Evaluation of our model trained on the augmented dataset demonstrates a significant improvement in both robustness and accuracy, achieving an impressive accuracy rate of 0.9941 compared to the baseline accuracy of 0.9045. Our proposed augmentation approach presents a practical solution to enhance neural network training for crack detection on concrete surfaces under shadowy conditions, effectively utilizing existing datasets. These advancements hold great promise for applications in structural monitoring and health assessment of concrete structures using unmanned aerial vehicles or drones, ensuring adaptability to real-world scenarios characterized by diverse environmental conditions, including shadows, shading, blemishes, and concrete spall.

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