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A Machine Learning Approach for Pavement Crack detection and Classification

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Abstract-Pavement cracking, a common issue affecting road infrastructure, significantly impacts road performance and longevity. This article employs MATLAB software to process pavement crack image detection, aiming at a machine learning approach for pavement crack detection and classification. A comprehensive model is utilized for categorizing various cracks and evaluating detection confidence. Additionally, a dedicated crack segmentation network is employed to achieve precise pavement crack segmentation. This approach incorporates advancements that improve precision in crack classification and segmentation. Based on the segmentation results, computations were performed to determine the length of linear cracks and the area of alligator cracks. Research findings demonstrated exceptional accuracy in recognizing block cracks, alligator cracks, transverse cracks, and longitudinal cracks. Notably, longitudinal and transverse cracks exhibited high detection rates, while alligator and block cracks have lower detection rates.

Keywords: Longitudinal crack, Alligator crack, Block crack, Transverse crack, Crack classification, Pavement crack

1. Introduction

Pavement cracks pose a significant challenge in road maintenance, as they have a profound impact on the structural integrity and lifespan of roads. These cracks, often indicative of various pavement issues, can lead to structural damage if left unattended, underscoring the importance of early detection and prompt repair (Zhang & Li, 2015). While traditional methods for crack detection have been effective to some extent, they are characterized by time-consuming procedures, labor-intensive requirements, and limited accuracy, necessitating the exploration of more advanced detection methods (Menghe et al., 2013).

In response to this imperative, recent years have witnessed a surge in scientific research aimed at harnessing modern technological advancements to extract crack information accurately and efficiently from images (Liu & Zhang, 2012). Various techniques for detecting pavement cracks have been documented in the literature, including the valley bottom boundary extraction approach (Wang & Wu, 2014) and the Prim minimal spanning tree-based crack connection algorithm (Ren et al., 2015). However, these conventional methods, originally tailored for specific databases or scenarios, may not yield satisfactory results in evolving conditions.

With the advent of artificial intelligence, deep learning techniques have gained prominence in pavement crack detection (Anjun et al., 2018). While these techniques have significantly enhanced detection accuracy (Zou et al., 2018), several challenges persist, such as reliance on complex feature extraction methods, limited adaptability to diverse image sources and road segments, susceptibility to environmental factors affecting algorithm stability and accuracy, and the inability of current models to directly access road conditions (Xu et al., 2008).

The present study introduces an innovative approach that combines the deep machine learning approach for pavement crack recognition to address these limitations. The goal is to provide a versatile solution applicable in various crack detection scenarios, offering simultaneous detection and segmentation, which enhances the model's effectiveness (Zhang & Li, 2015).

In light of the escalating concerns surrounding pavement distresses, the importance of developing intricate image processing algorithms for pavement crack inspection becomes evident. This study delves into previous research, including the utilization of moment invariants and neural networks (Cao, 2014), the application of histogram projection (Cao, 2014), and the use of neural networks for crack detection and classification (Menghe et al., 2013), contributing to the comprehensive understanding of this field.

2. Objectives of the Study

- Develop an image preprocessing technique to improve the visibility of pavement cracks.
- Implement the A Machine Learning Approach to effectively detect and segment pavement cracks in preprocessed images.
- Extract pertinent features from detected cracks to enable classification into distinct types, including block cracks, alligator cracks, longitudinal cracks, and transverse cracks.

3. Crack classification standard

Table 1. The characteristics of different types of cracks

Types of cracks	Crack angle Ω	branches
Block	$\Omega \geq 60°$	NO
Longitudinal	$\Omega \leq 30°$	NO
Transverse	$60° > \Omega > 30°$	NO
Alligator	-	YES

4. Method

The Machine learning approach was used to analyze images of pavement cracks in the recommended method. The images were preprocessed to enhance crack visibility and then subjected to the machine learning approach for detection and segmentation of cracks. Relevant features were extracted from the detected cracks, and a classification model was trained to classify the cracks into four main types. Also, this article utilized 1000 images procured from cement and asphalt roads.

Table 2. Four main types of cracks used

Crack Types	Images
Block	250
Longitudinal	250
Transverse	250
Alligator	250

5. Algorithm flow

Machine learning approach can be used to identify images based on pavement crack features. Figure 1 shows the fundamental method

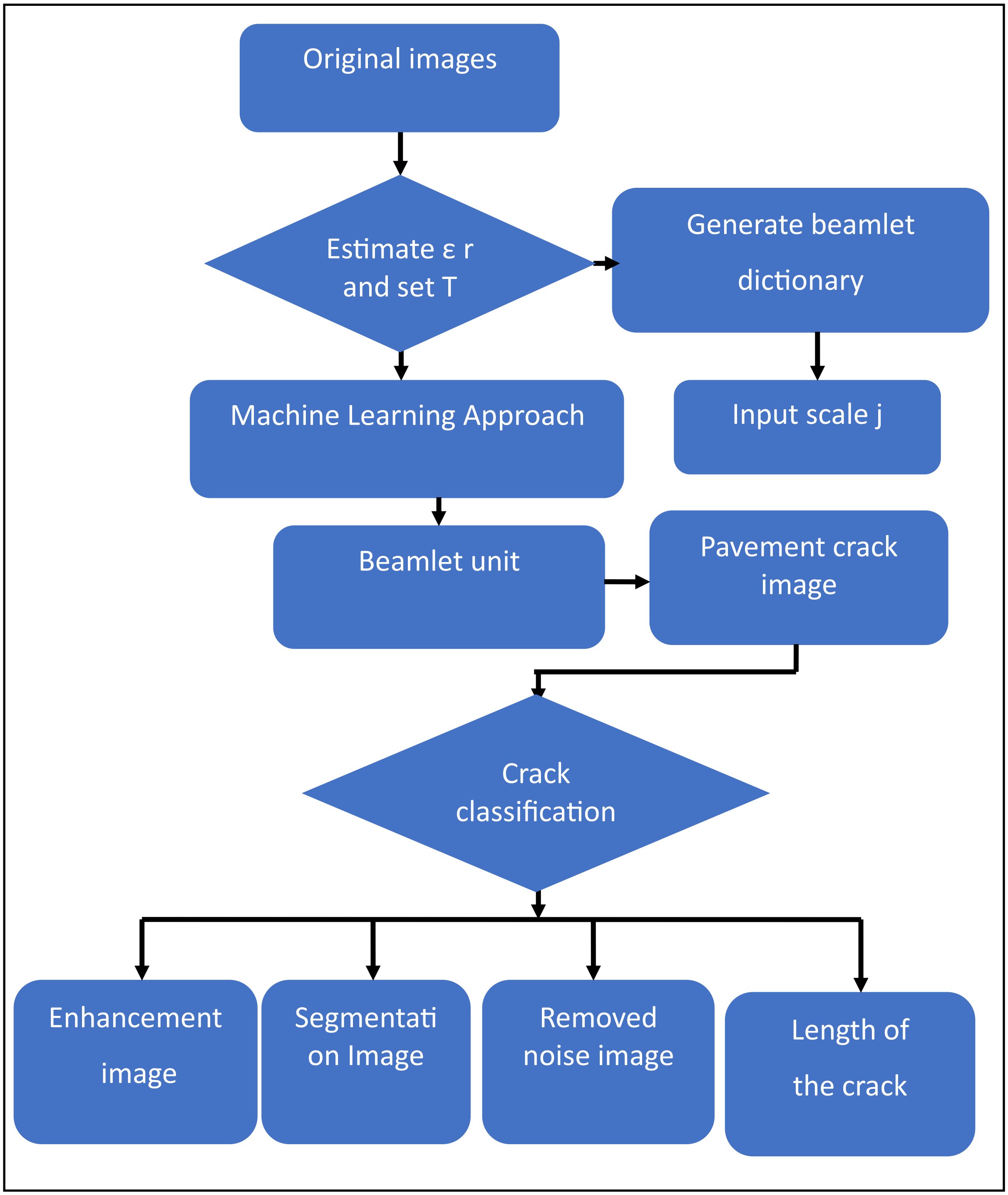

Figure 1. Processing steps algorithm flowchart

6. Result and Discussion

Asphalt pavement crack detection was performed by using the steps of image enhancement, segmented image, thresholding, eliminated denoising processing, and image improvement according to the algorithm flow (figure 1). The results are displayed in figures 2- 29. The following figures display the outcomes of applying the Beamlet algorithm to the various types of pavement crack images.

Figure 2 Original of longitudinal crack image

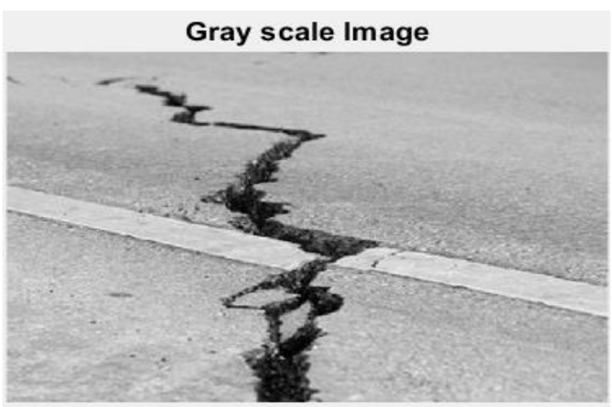

Figure 3 Gray scale of longitudinal crack image

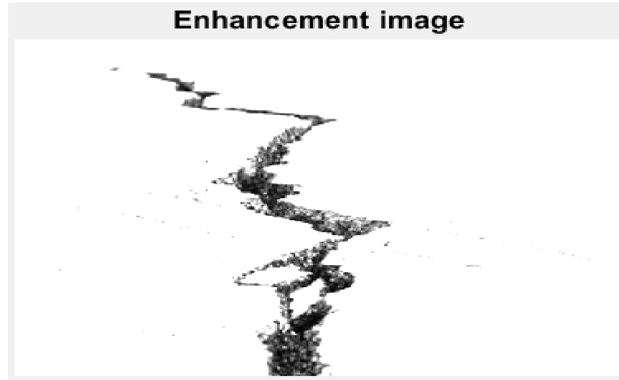

Figure 4 Enhancement of longitudinal crack image

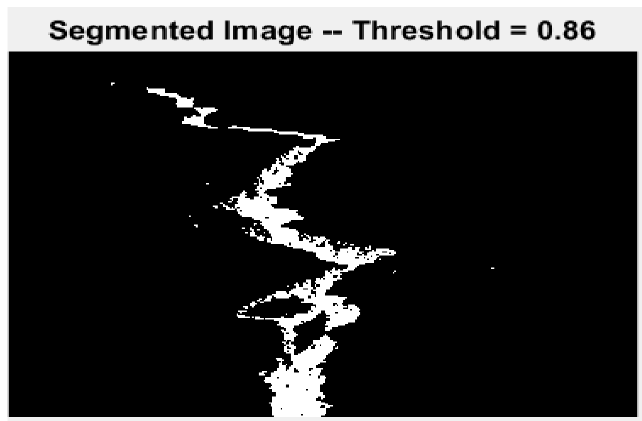

Figure 5 Segmented of longitudinal crack image and thresholding

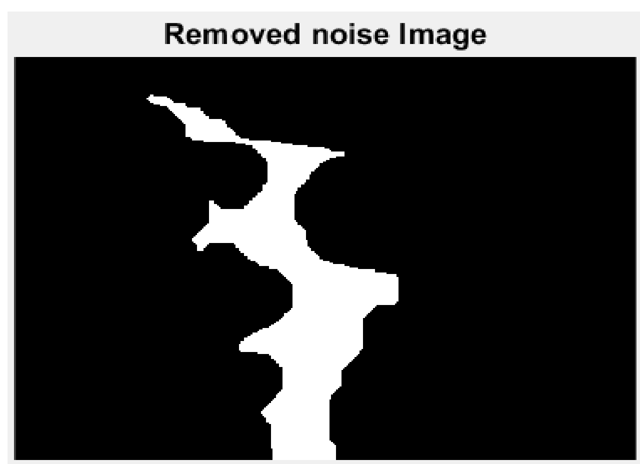

Figure 6 Removed noise of longitudinal crack image

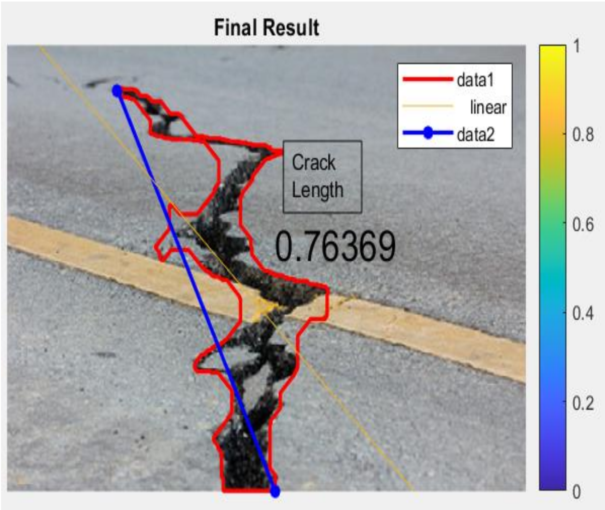

Figure 7 Crack length result for longitudinal crack

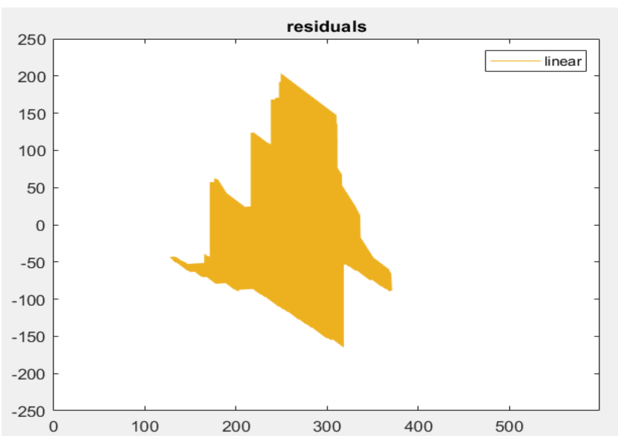

Figure 8 Residuals result for longitudinal crack

Table 3 Longitudinal crack classification

Crack angle Ω	Crack length	Threshold	Crack types
9°	0.76369 m	0.86 m	Longitudinal

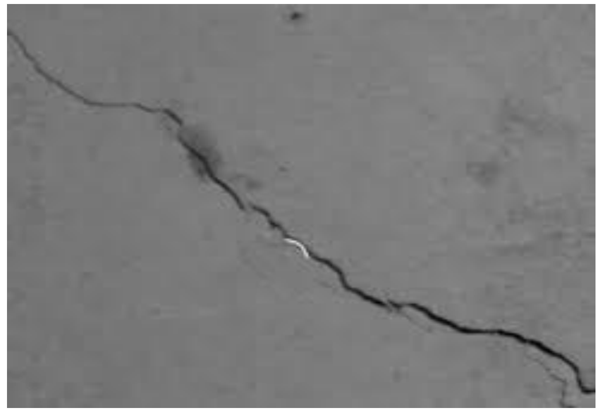

Figure 9 Original of transverse crack image

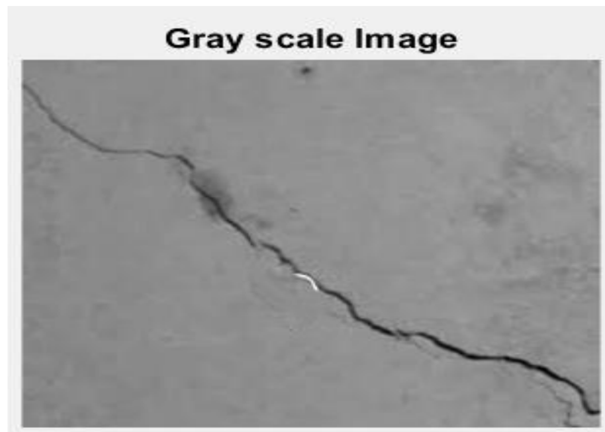

Figure 10 Gray scale of transverse crack image

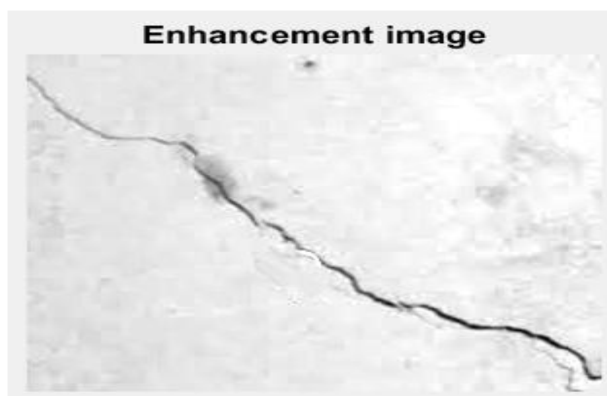

Figure 11 Enhancement of transverse crack image

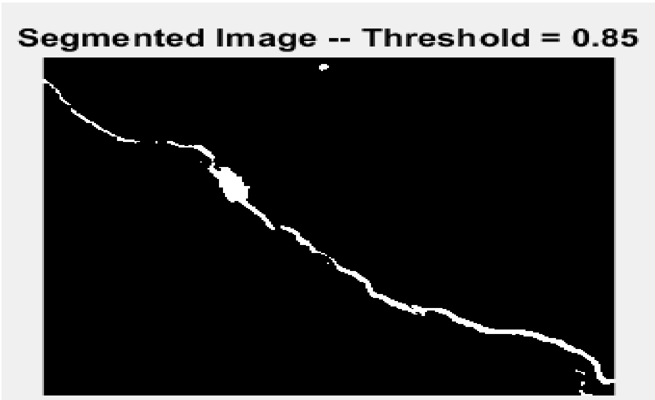

Figure 12 Segmented of transverse crack image and thresholding

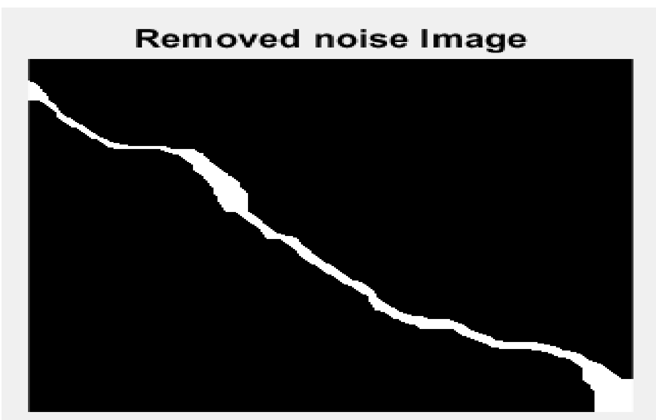

Figure 13 Removed noise of transverse crack image

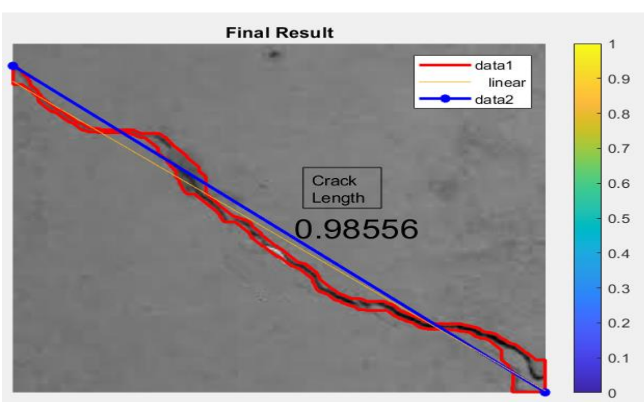

Figure 14 Crack length result for transverse crack

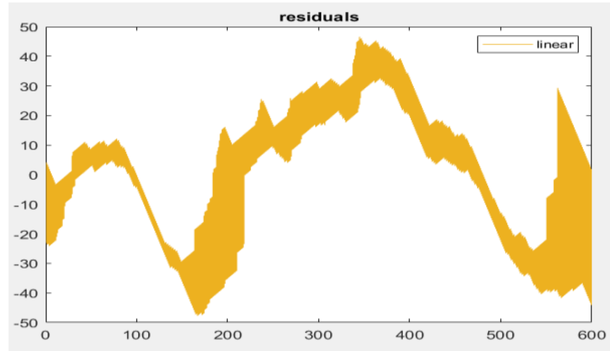

Figure 15 Residuals result for transverse crack

Table 4. Transverse crack classification

Crack angle Ω	Crack length	Threshold	Crack types
11°	0.98556 m	0.85 m	Transverse

Figure 16 Original of alligator crack image

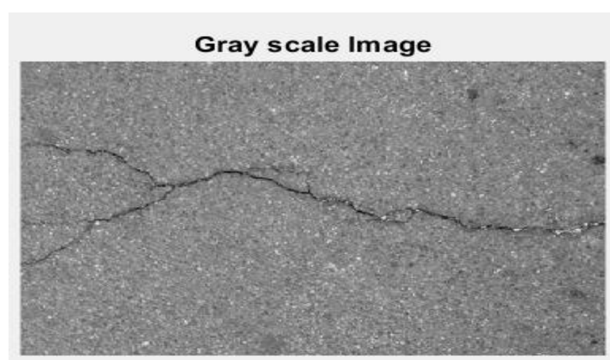

Figure 17 Gray scale of alligator crack image

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Figure 18 Enhancement of alligator crack image

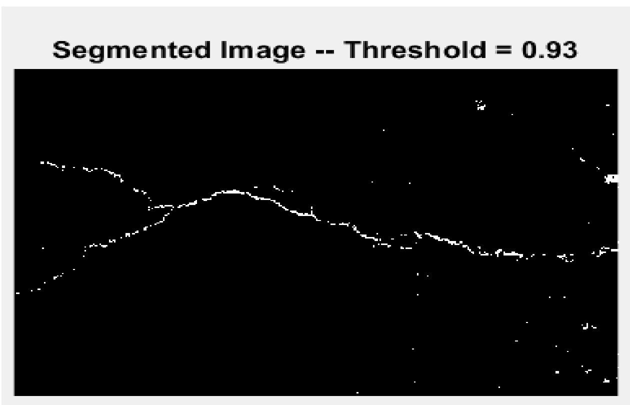

Figure 19 Segmented of alligator crack image and thresholding

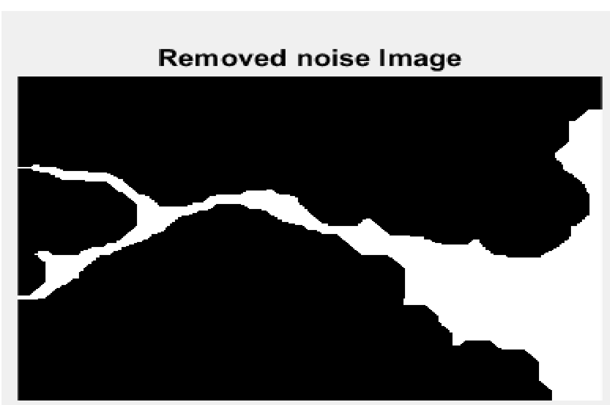

Figure 20 Removed noise of alligator crack image

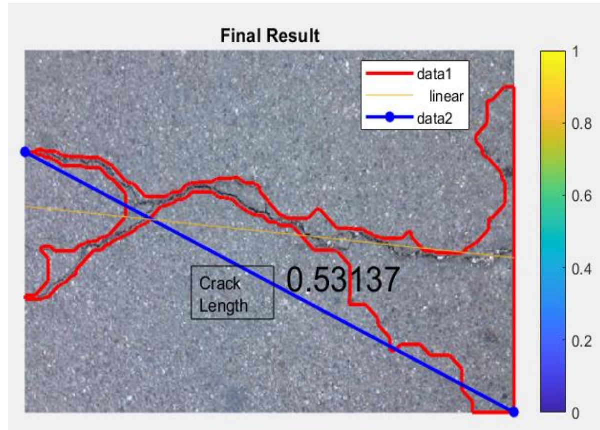

Figure 21 Crack length result for alligator crack

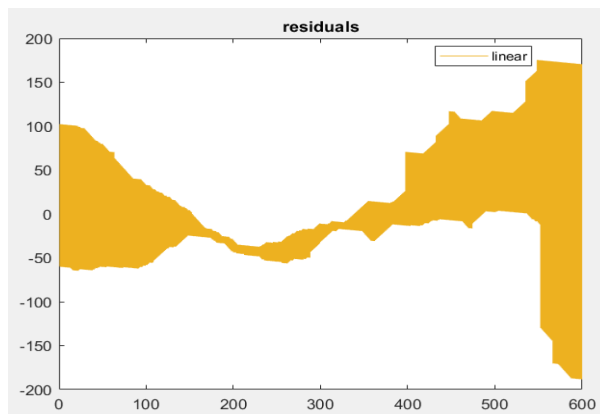

Figure 22 Residuals result for alligator crack

Table 5 Alligator crack classification

Crack angle Ω	Crack length	Threshold	Crack types
14°	0.53137 m	0.93 m	Alligator

Figure 23 Original of block crack image

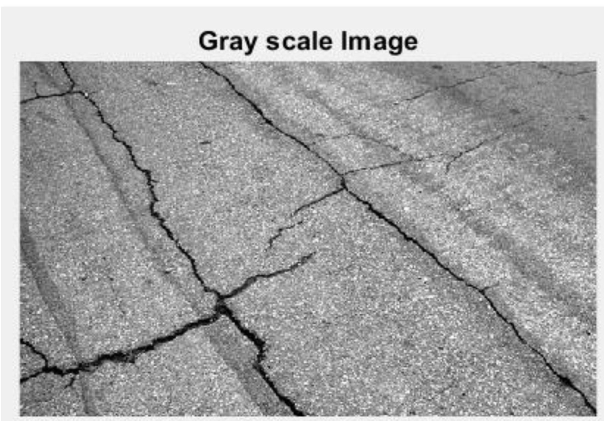

Figure 24 Gray scale of block crack image

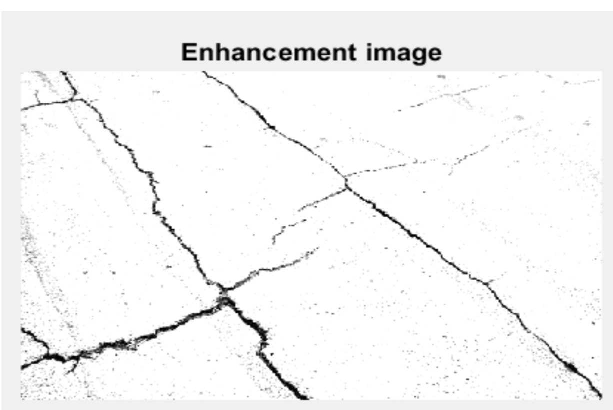

Figure 25 Enhancement of block crack image

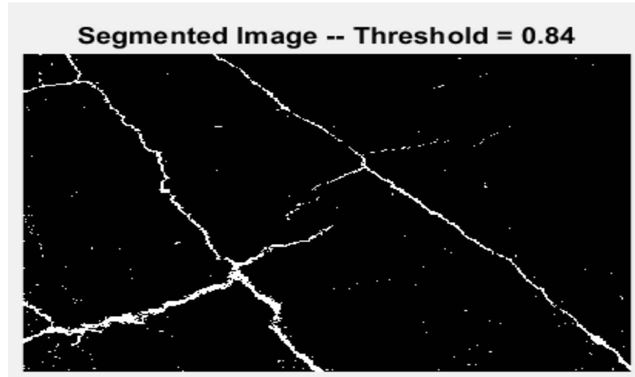

Figure 26 Segmented of block crack image and threshold

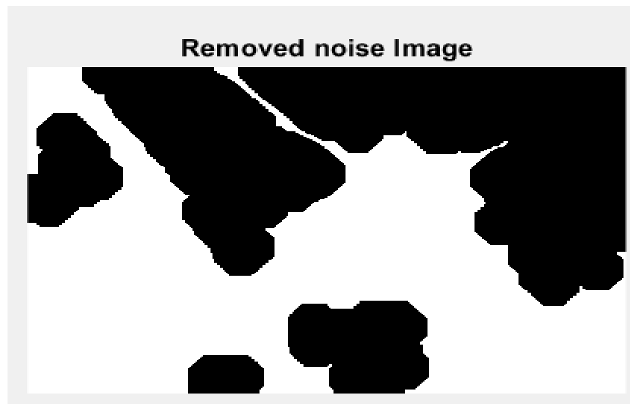

Figure 27 Removed noise of block crack image

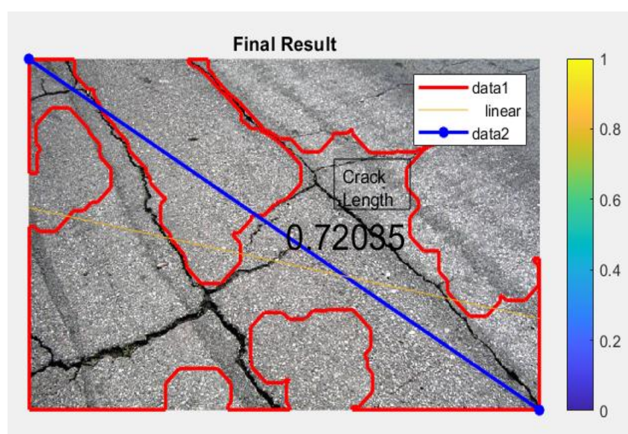

Figure 28 Crack length result for block crack

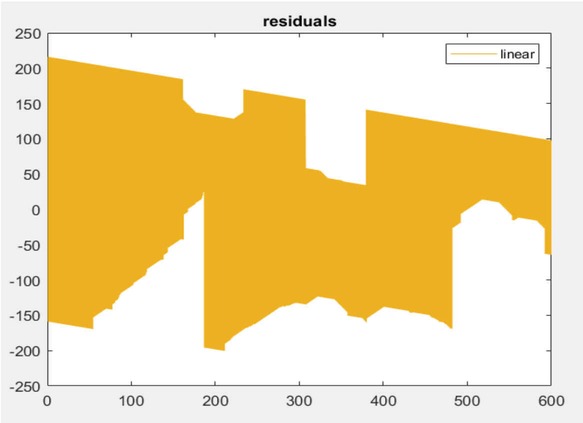

Figure 29 Residuals result for block crack

Table 6 Block crack classification

Crack angle Ω	Crack length	Threshold	Crack types
15°	0.72035 m	0.84 m	Block

Longitudinal Crack:

A single longitudinal crack was initially detected in Figure 2. Image processing techniques were employed to enhance visibility and reduce noise, resulting in a clear fracture edge for precise detection and classification. The grayscale image in Figure 3 simplified subsequent processing steps. An image enhancement technique improved fracture details (Figure 4), followed by segmentation using a thresholding technique (Figure 5). Denoising further improved accuracy (Figure 6).

The longitudinal crack was classified with a length of 0.76369 m and a crack angle of 9° using the Machine Learning Approach. Table 3 summarizes the findings, including threshold value, crack length, crack angle, and crack number, confirming its classification as a longitudinal crack. However, further research with a larger dataset is suggested for evaluating the model's performance in diverse crack scenarios.

Transverse Crack:

The original image (Figure 9) contained both transverse and lengthy cracks. Image enhancement, segmentation, and denoising techniques were applied to isolate the transverse crack. A grayscale image (Figure 10) simplified processing, while image enhancement (Figure 11) improved visibility.

Segmentation with a threshold value of 0.85 m (Figure 12) isolated the transverse crack. Denoising (Figure 13) enhanced fracture detection. The transverse crack was classified with a length of 0.98556 m and a crack angle of 11° using the Machine Learning Approach. Table 4 provides detailed classification results, confirming it as a transverse crack.

Alligator Crack:

The first crack image (Figure 16) displayed an alligator fracture with four branches. Efficient techniques, including segmented image thresholding, denoising, and image enhancement, produced a distinct depiction. A grayscale image (Figure 17) was created for processing, and image enhancement (Figure 18) further highlighted crack features.

Segmentation with a threshold value of 0.93 m (Figure 19) isolated the alligator crack. Denoising (Figure 20) improved fracture classification. The alligator crack was classified with a length of 0.53137 m and a crack angle of 14° using Machine Learning

Approach. Table 5 summarizes the findings, confirming it as an alligator crack.

Block Crack:

For block crack detection, the original image was converted to grayscale (Figure 23), and image enhancement (Figure 24) improved fracture details. Segmentation with a threshold value of 0.84 m (Figure 25) separated the fracture sections. Denoising (Figure 26) eliminated noise.

The block crack was determined to have a length of 0.72035 m and a crack angle of 15° using the Machine Learning Approach. Table 6's categorization findings illustrate that the fracture is a block crack.

7. Conclusion

In this research, an improved model for detecting and classifying asphalt pavement cracks was built using the Machine Learning Approach technique. The suggested model in this study showed a high degree of accuracy in accurately identifying and classifying various types of pavement cracks. These included block fractures, alligator cracks, transverse cracks, and longitudinal cracks. The advantageous findings demonstrated the model's potential in this circumstance. The model was able to maintain crack information, enhance crack visibility, and provide precise crack measurements by utilizing the Machine Learning Approach.

The Machine Learning Approach ability to detect very small or minute cracks may be constrained, and outside influences like lighting conditions can affect the model's performance. To determine the model's applicability to various road conditions and environmental variables, more research is required.

8. Recommendation

The recommended Pavement Crack Detection and Classification using the Machine Learning Approach should be expanded upon and validated further, in my opinion. The model has shown great promise in accurately identifying and classifying different pavement crack types, such as block, alligator, and longitudinal cracks. It is crucial to evaluate its performance on a broader, more varied dataset that includes a greater range of real-world fracture events in order to increase its practical usefulness. It would also be beneficial to assess how resilient the model is to noise interference and changes in pavement conditions. These measures will support infrastructure management and road safety initiatives by establishing the model as a trustworthy instrument for automated pavement care and safety assessment.

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