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The Classification of Asphalt Pavement Crack Images Based on Beamlet Transform

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Abstract: Pavement cracking is a common road infrastructure issue which significantly affects road performance, safety and longevity. This article employed a Beamlet Transform algorithm to detect and classify different types of flexible asphalt concrete pavement cracks. Additionally, a dedicated crack segmentation network was employed for precise segmentation of pavement crack. This approach incorporates advancements that has improve precision in crack classification and segmentation. Based on the results of the beamlet transform, significant improvements in the gray scale representation of crack, enhanced crack detection, reduced noise in crack images and a more precise measurement of cracks length were achieved. Computations were performed to determine the length of linear cracks and the area of block cracks. A total of 1000 pavement images were used for training and testing the accuracy of asphalt pavement crack detection and classification models. The research results showed that block cracking, alligator cracking, transverse cracking, and longitudinal cracking can all be recognized with a remarkable accuracy. Alligator cracks and block cracks achieved detection rates more than 90%, while detection rates for the longitudinal and transverse cracks reached more than 95% accuracy.

Keywords: Pavement crack detection, Crack classification, Longitudinal crack, Alligator crack, Block crack, Transverse crack, Beamlet transform.

Introduction

Pavement cracks pose a significant challenge in road maintenance, as they have a profound impact on the structural integrity, functional performance and lifespan of roads. These cracks, which are frequently a sign of several pavement problems, can cause structural damage if ignored, highlighting the significance of early diagnosis and timely repair (Ying & Salari, 2010).

The investigation of enhanced means of crack detection is necessary. Although, the traditional methods for crack detection have proven to be somewhat effective, they are labor intensive, include lengthy procedures, and provide limited accuracy (Safaei et al., 2021). In response to this need, recent years have seen a proliferation of scientific research aimed at leveraging modern technological advancements to achieve accurate and efficient extraction of crack information from images (Zhang et al., 2017). The valley bottom boundary extraction methodology (Safaei et al., 2022) and the Prim minimum spanning tree-based crack connection algorithm (Yang et al., 2022) were the two major methods for identifying pavement cracks that have been described in the literature. These traditional procedures, which were initially designed for particular databases or scenarios, might not produce satisfactory results under changing circumstances.

Deep learning algorithms have become more popular in pavement crack identification after the development of artificial intelligence (Hu et al., 2021). Despite the fact that these methods have significantly improved detection accuracy (Zhang et al., 2017), a number of problems still existed. For example, current models were unable to directly access road conditions due to their reliance on complicated feature extraction techniques and their limited adaptability to a variety of image sources and road segments (Alayat & Omar, 2023). To overcome these constraints, the current study offered a novel methodology that combines the deep learning and Beamlet algorithms for classification of asphalt pavement deterioration. The simultaneous crack detection and segmentation provided by this approach was a special benefit that boosted the model effectiveness.

The significance of developing complex image processing algorithms for pavement crack assessment becomes clear in light of the growing issues regarding pavement distresses. This study further explored the earlier work, such as the application of histogram projection (Zhao & Wang, 2010), the use of moment invariants and neural networks (Zhao & Wang, 2010), and the use of neural networks for crack detection and classification (Safaei et al., 2022), adding to the overall understanding of this field.

Beamlet Transform Algorithm

The implementation of the beamlet transform occurs within image sections that are dynamically divided into squares. Visual representations of images occur within the continuous square $[0, 1]^2$, in this scenario, pixels are arranged in a grid of 1/n by 1/n squares throughout the $[0, 1]^2$ area. The compilation of beamlets constitutes a diverse range of line segments, encompassing a broad spectrum of orientations, positions, and scales. This variation is visually portrayed in Figure 1. (Ouyang et al., 2014)

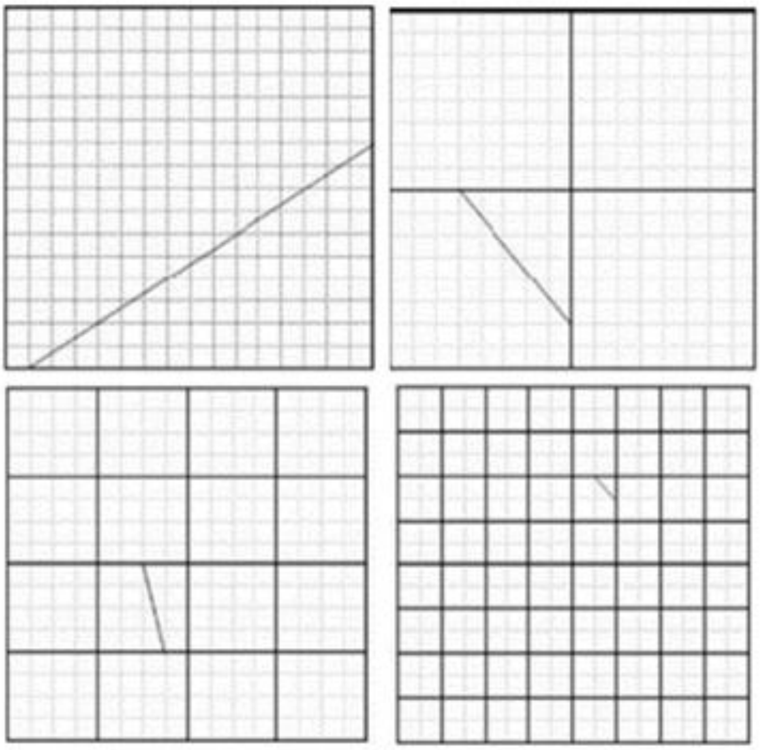

Figure 1. Different in size, location, and orientation, four beamlets

The beamlet transform is characterized as the summation of line integrals calculated across the entirety of the beamlet set. Consider f (x_1, x_2) to be perceived as a continuous function within a two-dimensional space, where x_1 and x_2 denote coordinates (Ouyang et al., 2014). The beamlet transform Tf of the function f is outlined as follows equation 1:

$$T_f(b) = \int_b f\big(x(l)\big)dl, b \in B_E \qquad (1)$$

Here, B_E represents the total collection of beamlets.

In the context of digital images, the beamlet transform evaluates the line integral within the discrete domain. As depicted in Figure 2, the depiction of the beamlet transform for all points along beamlet b is articulated in the following equation 2 manner: (Ouyang et al., 2014)

$$f(x_1, x_2) = \sum_{i_1,i_2} f_{i_1,i_2} \Phi_{i_1,i_2}(x_1, x_2) \qquad (2)$$

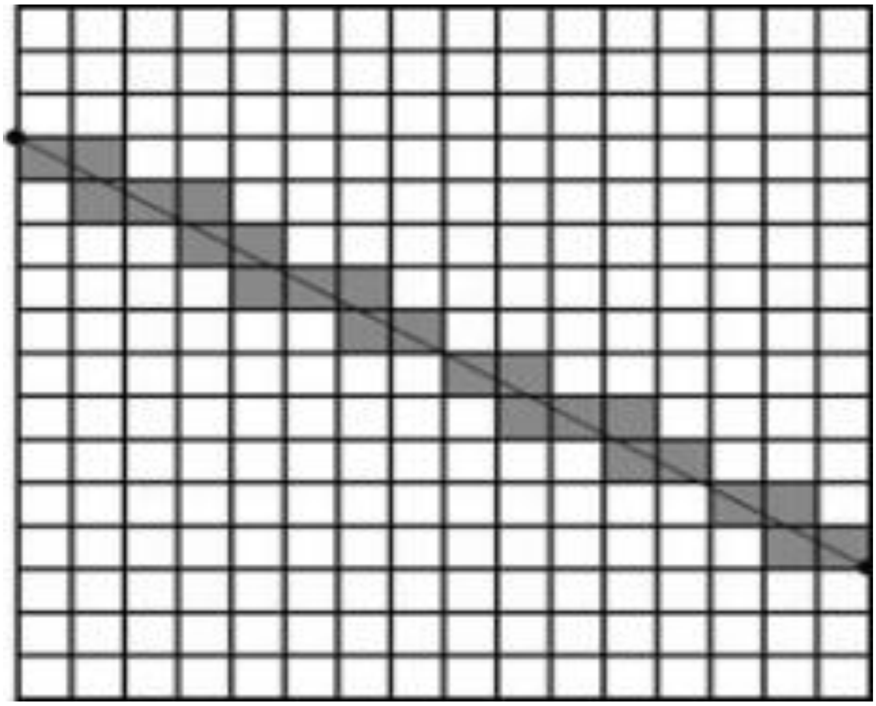

Figure 2. A weighted sum of pixel values along the lines' direction represents the beamlet transform.

Where f_{i_1,i_2} refers to the gray level value of the pixel located at (i_1, i_2) and $\Phi_{i_1,i_2}(x_1,x_2)$ stands for the pixel's related weight function. Multiple options are available for the selection of. $\Phi_{i_1,i_2}(x_1,x_2)$, and In this study, the average interpolation function is the one we choose. (Ouyang et al., 2014)

If $p(x_1, x_2)$ represent $[i_1/n, (i_1 + 1)/n] \times [i_2/n, (i_2 + 1)/n]$, choose function Φ_{i_1,i_2} fulfill the equation 3:

$$n^2 \int_{P(x_1,x_2)} \Phi_{i_1,i_2}(x_1,x_2) dx_1 dx_2 = \delta_{i_1,i_2} \qquad (3)$$

Methods

The data-set of the images used in the current study were procured from asphalt concrete pavement roads which is available at the https://github.com/cuilimeng/CrackForest-dataset. A total of 1000 images for four different types of cracks as presented in Table 1 were used in the testing processes.

Table 1. Four main types of cracks

Crack Types	Number of images	**Crack angle Ω**	Branches
Block	250	$\Omega \geq 60°$	NO
Longitudinal	250	$\Omega \leq 30°$	NO
Transverse	250	$60° > \Omega > 30°$	NO
Alligator	250	-	YES

Generally, images of pavement cracks display linear attributes and are often discontinuous due to considerable environmental interference, making it challenging for traditional pixel-based methods to effectively detect and categorize these cracks. On the other hand, the Beamlet algorithm as utilized in the current study proves robust in its line detection capabilities, making it suitable for asphalt pavement crack detection and classification tasks. The outline of the procedures followed for developing the crack detection and classification models by using beamlet algorithm was illustrated in Figure 3.

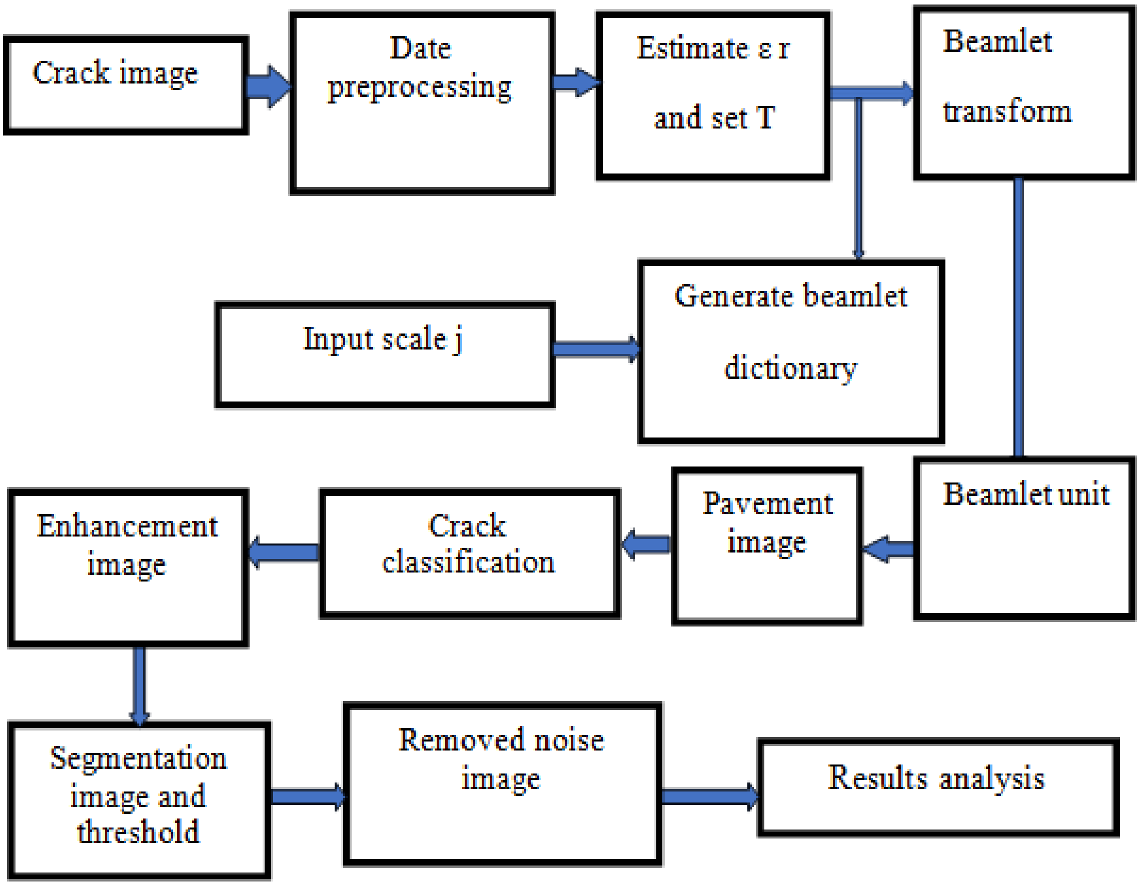

Figure 3. Processing steps Beamlet Transform Algorithm flowchart

Result and Discussion

Asphalt pavement crack detection was performed by using the steps outlined in Figure 1. Primarily the original images were converted to grey scale and then an image enhancement technique was utilized in order to enhance the crack visibility. Image segmentation by using a thresholding technique, and denoising were further applied in order to improve crack visuals and highlight crack features in the images. These procedures were conducted for all 1000 images which included longitudinal, transverse, alligator and block cracking features. Figures 4-7 illustrated the procedures followed during the crack detection and classification for each type of crack; longitudinal, transverse, alligator and block cracking respectively.

A single longitudinal crack was initially detected in Figure 4. The longitudinal crack was classified with a length of 0.7504 m and a crack angle of 66°. Figure 5 contained both transverse and lengthy cracks. Segmentation with a threshold value of 0.85m isolated the transverse crack. The transverse crack was classified with a length of 0.98556m and a crack angle of 11° using the classification of asphalt pavement crack detection based on Beamlet transform algorithm. The first crack image shown in Figure 6 displayed an alligator crack with four branches. Segmentation with a threshold value of 0.93 m isolated the alligator crack. The alligator crack was classified with a length of 0.53137 m and a crack angle of 14°. Finally, the block crack as shown in Figure 7 was detected with a threshold value of 0.84m and crack area of 0.72035m2.

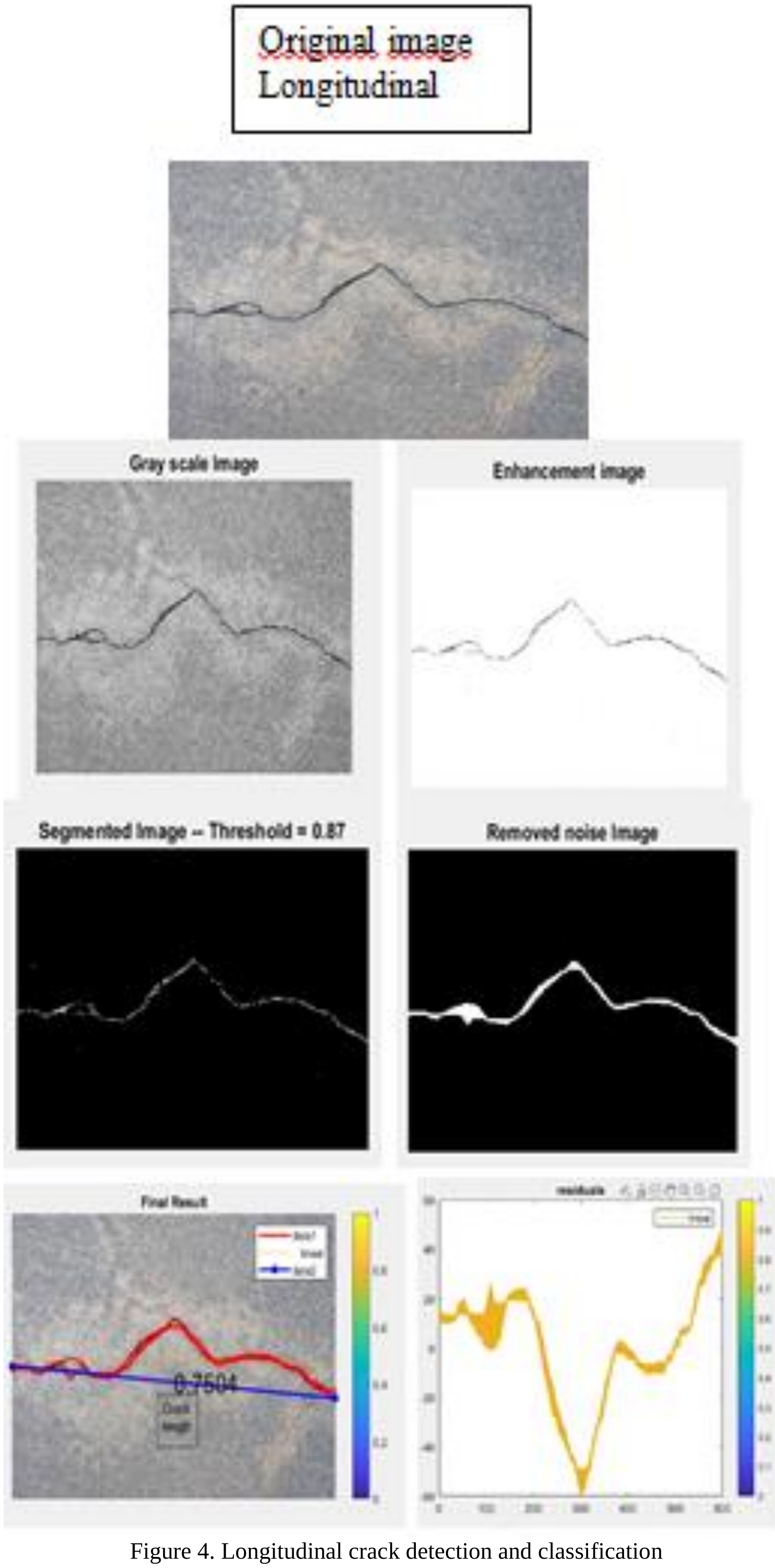

Figure 4. Longitudinal crack detection and classification

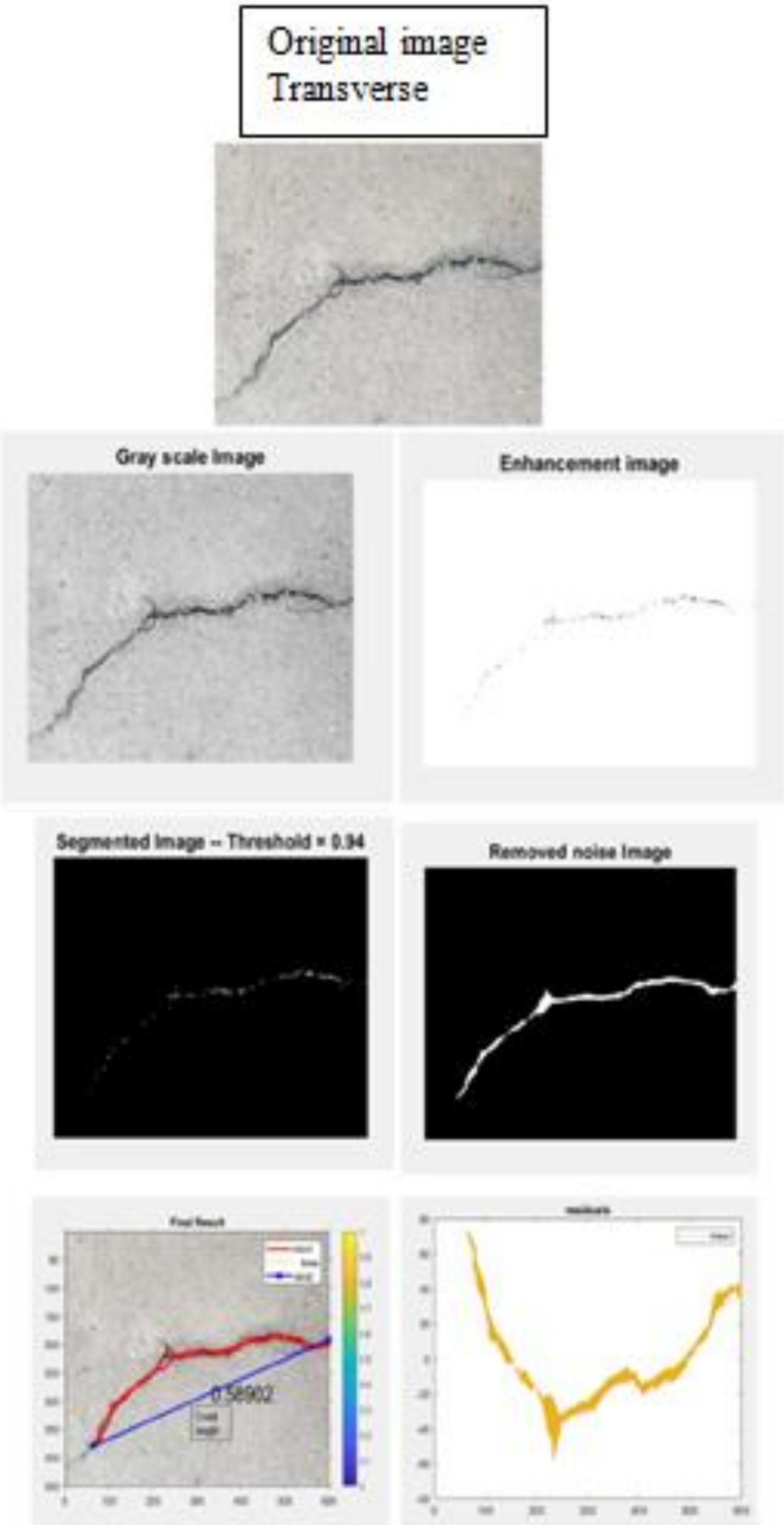

Figure 5. Transverse crack detection and classificatio

The outcomes of the complete analysis were summarized by using the crack angle, crack length, branches and threshold values and the analysis results were tabulated in Table 2

Table 2. Pavement crack detection and classification results

Crack angle **Ω**	Crack length	Branches	Threshold	Crack types
11°	0.98556 m	YES	0.85 m	Transverse
66°	0.7504 m	YES	0.87 m	Longitudinal
14°	0.53137 m	YES	0.93 m	Alligator
-	Area= 0.72035 m^2	YES	0.84 m	Block

The results showed that the Beamlet algorithm can accurately identify pavement crack images into longitudinal, Transverse block, and Alligator. As in table 3 the result of success rate percentage was identified by Using the percentage change formula: dividing the success rate number by the total crack tested number and then multiplying by 100.

Table 3. The classification of success rate

Types of Cracks	Number	Longitudinal	Transverse	Alligator	Block
Alligator	250		5	226	6
Block	250			2	234
Longitudinal	250	238			
Transverse	250	8	243	13	
Success rate		95.2%	97.2%	90.4%	93.6%

Conclusion

In this research, an improved model for detecting and classifying asphalt pavement cracks was developed by utilizing the beamlet transform algorithm. The suggested model showed a high degree of accuracy in accurately identifying and classifying various types of pavement cracks. These included block cracks, alligator cracks, transverse cracks, and longitudinal cracks. The models were able to observe crack information, enhance crack visibility, and provide precise crack measurements by utilizing the beamlet transform algorithm. The abilities of beamlet transform algorithm to efficiently detect and classify asphalt concrete pavement 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, further research is required.

Recommendations

The recommended that the use of the Beamlet Transform Algorithm for detecting and classifying pavement cracks. To make it really useful, also, need to test it on a wider range of real-world crack situations and see how well it works with noisy conditions and different road situations. The algorithm has done well in classifying cracks, even when there is noise, but we can make it even better. try different ways of processing images, and test it with different datasets. This will make it more accurate and useful for taking care of roads and making them safer. Also, recommended to make the width of the crack.

Scientific Ethics Declaration

The authors declare that the scientific ethical and legal responsibility of this article published in EPSTEM journal belongs to the authors.

Acknowledgements or Notes

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