European Transport \ Trasporti Europei (2026) Issue 107, Paper n° 6, ISSN 1825-3997

Adaptive Road Crack Detection Using Fuzzy-based Segmentation with HHO-Otsu's Thresholding, Maximum Entropy Methods

Pallav Kumar [1*], Shivangi Mishra[2]

[1]*Assistant Professor, Department of Civil Engineering, MIT Muzaffarpur, Muzaffarpur, Bihar, India, Email id:* pallav318@gmail.com

[2]*Urban Development and Housing Department, Patna, India, Email id:* shivangicivil0038@gmail.com

Abstract : Accurate and efficient road crack detection is crucial for maintaining road infrastructure and ensuring transportation safety. This paper presents a robust road crack detection model that leverages advanced preprocessing and segmentation techniques to achieve state-of-the-art results across multiple datasets. The methodology begins with contrast enhancement using histogram equalization and min-max normalization, which enhance feature visibility by improving the image quality. For segmentation, a fuzzy-fused approach combines HHO-Optimized Otsu's thresholding and maximum entropy-based segmentation, effectively leveraging their strengths while mitigating individual limitations to achieve precise crack identification. The proposed model was rigorously evaluated on five benchmark datasets – Crack Forest, Crack Tree, Deep Crack, Gaps, and a manually extracted dataset. It demonstrated outstanding performance, achieving the highest accuracy of 98.60% on the Gaps dataset, significantly surpassing state-of-the-art methods such as DeepCrack (87.00%), CrackSeg (91.00%), ConCrack (92.00%), and U-HDN (97.27%). This highlights the model's robustness and ability to adapt to diverse and complex environments.

Keywords: Fuzzy Logic, U-HDN, Otsu, Crack Detection, Image Segmentation, Infrastructure Maintenance

1. Introduction

Crack detection in images plays a crucial role in the maintenance and safety of infrastructure, including roads, bridges, and buildings. Accurate detection and classification of cracks help identify potential structural issues early, enabling timely interventions that prevent accidents or costly repairs. Over the years, researchers have proposed diverse approaches to tackle this challenge. These can be broadly categorized into traditional image processing and machine learning techniques, and modern deep learning-based detection networks.

Traditional methods for identifying cracks in images typically depend on manual feature extraction and rule-based algorithms. These methods often perform well in controlled environments with high-resolution images where cracks are distinct and

[*] Corresponding author: Name Family Name (mail@mail.mail)

isolated. For instance, Oliveira et al. employed a sample-based learning approach to classify image blocks as cracked or non-cracked, while the authors of [1] utilized Gabor filters for detecting transverse and longitudinal cracks. Similarly, the authors of [2] developed CrackTree, which combines geodesic shadow removal and tensor voting for crack mapping. The authors of [3] refined detection using a hybrid approach of histogram thresholding, mathematical morphology, and snake modeling. Despite their success in straightforward scenarios, these techniques struggle with real-world challenges such as complex textures, variable lighting conditions, and environmental noise.

Road crack detection involves inspecting and identifying cracks on road surfaces to evaluate conditions and plan maintenance effectively. This process can be performed either manually by human experts or automatically through machine vision techniques. While manual inspection relies heavily on expertise and is inherently time-consuming, automated methods aim to accelerate processing and surpass human performance in accuracy and efficiency. Despite decades of research, road crack detection remains a challenging area in computer vision and image processing.

This paper introduces a sophisticated machine learning approach for automated road crack detection and segmentation, facilitating precise assessments of road conditions. A key aspect of evaluating road cracks is calculating the cracking index, which requires precise measurements of crack length and width through pixel-level segmentation. Although certain aspects of cracking index computation remain subjective and not fully automatable, this study focuses on achieving accurate segmentation to support broader automation efforts.

The objectives of this research are:

- To develop a unified segmentation system that incorporates complementary thresholding algorithms (Otsu and maximum entropy) to enhance the quality of crack detection at different noise levels and common lighting circumstances.
- To optimize Otsu thresholding with the Harris Hawks Optimization (HHO) algorithm to faster and more reliable multi-level segmentation.
- To develop a fuzzy-based fusion rule to enable adaptive fusion between the methods thresholds, to improve the performance over complicated textures and weakly visible cracks.
- To test the proposed model on various benchmark datasets and to compare its performances with state-of-the-art methods.

Existing methods often prioritize either region-level detection or pixel-level segmentation, optimizing one at the expense of the other. This narrow focus limits overall performance, particularly when handling challenging data, such as noisy images with faint cracks or imbalanced datasets. To address these limitations, this study proposes a unified framework that integrates detection and segmentation to deliver superior results compared to existing methods.

Traditional approaches to crack detection and segmentation employ digital image processing techniques like the Canny edge detector and Gabor filters, which detect edges based on pixel intensity changes. While these methods can identify cracks as edge features, they are highly sensitive to noise and fine details, often struggling to reject noise effectively. Moreover, determining optimal parameters for noise removal and crack preservation is challenging, as these parameters can vary significantly across images.

To address the shortcomings of traditional methods, automatic crack detection systems have been developed to provide fast and reliable pavement defect analysis. These systems replace slower, subjective manual methods, improving the safety of surveying practices, particularly on high-speed roads such as highways. Additionally, such systems can integrate with intelligent transportation systems to monitor traffic conditions and identify roads requiring frequent maintenance.

Modern road crack detection techniques utilize advanced approaches such as neural networks, Markov random fields, edge detection algorithms, and morphological operators to effectively analyze and identify surface defects. For example, a two-step unsupervised pattern recognition process can identify image blocks containing crack pixels. This system utilizes a 2D feature space based on simple local statistics—such as the mean and standard deviation of gray levels within non-overlapping blocks—for crack detection. Various clustering techniques are compared to determine their suitability for this purpose. Subsequently, crack type characterization is performed by analyzing the spatial distribution of detected crack blocks using an additional 2D feature space. A novel severity assignment procedure is also introduced, which calculates the average width of each crack to evaluate its impact.

This integrated approach enhances the accuracy and efficiency of road crack detection, paving the way for more effective road condition evaluations and maintenance planning.

2. Literature Review

Crack detection in road and pavement images is vital for infrastructure maintenance. Techniques for this task are generally classified into traditional image processing and machine learning methods, and modern deep learning-based detection networks.

Traditional methods often involve feature extraction paired with simple classifiers. For example, the authors of [4] applied a sample-based unsupervised learning paradigm to classify image blocks into crack and non-crack categories. The authors of [5] used Gabor filters to detect transverse and longitudinal cracks from images captured by vehicles equipped with inertial profilers, GPS, and webcams. Similarly, the CrackTree approach by the authors of [2] utilized geodesic shadow removal and tensor voting to generate crack probability maps, identifying crack seeds through a minimum spanning tree algorithm. The authors of [3] introduced a hybrid method combining histogram thresholding, mathematical morphology, and snake modeling to refine crack contours.

Another approach introduced by the authors of [6] includes a dynamic programming technique for tracing the minimum path along cracks and the use of histograms of gradients (HoG) to compute edge intensities and orientations in grayscale images [7]. These methods generally perform well on high-quality images with clearly defined crack patterns but struggle in complex or noisy environments where pavement textures obscure cracks.

Deep learning methods have revolutionized crack detection, offering improved accuracy and adaptability by leveraging large labeled datasets and deep neural networks. The authors of [8] proposed an encoding-decoding network with a residual feature extractor, enhanced by transfer learning from black box camera data. The authors of [20] combined a deep convolutional neural network with adaptive thresholding and bilateral filtering to detect cracks and smooth image outputs. Nguyen et al. developed a two-stage CNN, isolating crack regions in the first stage and identifying background details in the second for precise delineation.

Other notable contributions include the use of Fast R-CNN for crack detection [9] and the application of scale-invariant feature transformation (SIFT) and graph convolutional networks, optimized for better performance [10]. The authors of [11] introduced MSK-UNet, an extended U-Net architecture with selective kernel (SK) units and an image pyramid for multi-scale input, which preserves background information critical in noisy or complex environments. However, many deep learning methods rely on close-range images with distinct cracks, making them less effective for UAV-captured images, where cracks are smaller and affected by environmental noise.

Crack classification methods aim to categorize cracks by type, orientation, and complexity. The authors of [12] utilized multiclass support vector machines (SVMs) to decompose classification into binary problems. The authors of [13] proposed graphical features for robust classification, while the authors of [14] applied decision tree heuristics. Song et al. used the orientation of enclosing rectangular boxes and the number of branches to classify cracks.

In deep learning, the authors of [15] employed multiple CNNs with varying perceptual field sizes, improving classification by integrating CNNs with K-means clustering in an unsupervised manner. The authors of [16] used local binary pattern (LBP) features with support vector machines, combined with principal component analysis (PCA) for dimensionality reduction. While effective for clean, isolated cracks, these methods often falter on datasets with overlapping or multiple cracks, particularly in noisy environments, where accuracy and processing speed are compromised. Scalability issues also limit the application of these methods for real-time analysis of large datasets.

Traditional methods are best suited for simple and well-defined conditions, whereas deep learning techniques excel in complex scenarios. However, UAV-captured data introduces unique challenges, as cracks are smaller, less distinct, and surrounded by noise. Addressing these issues requires enhanced methods capable of handling multi-scale data and robust noise reduction. Future advancements in crack detection and classification will likely focus on improving scalability, real-time processing, and adaptability across diverse datasets and imaging conditions.

3. Proposed Methodology

Figure 1 shows the proposed block diagram for the road crack detection.

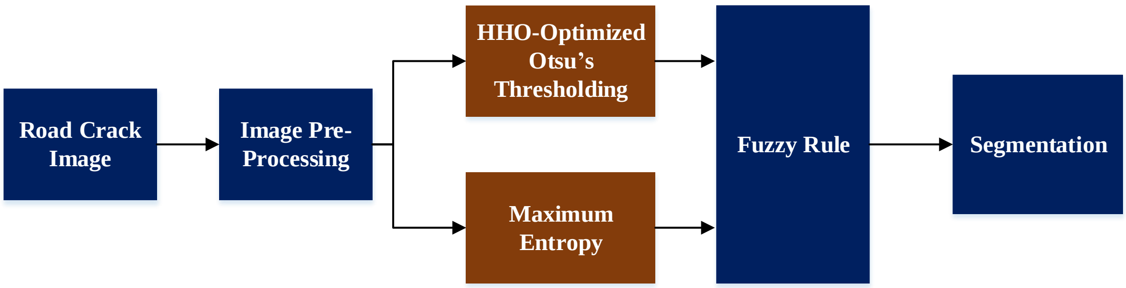


Figure 1: Proposed block diagram for road crack detection

3.1 Contrast Enhancement Using Histogram Equalization

Histogram equalization enhances image contrast by redistributing intensity values. For a grayscale image I with N pixels and L intensity levels (typically $L = 256$), let $h(r_k)$ be the histogram, where r_k is the k^{th} intensity level. The probability density function (PDF) is:

$$p(r_k) = \frac{h(r_k)}{N} \tag{1}$$

The cumulative distribution function (CDF) is:

$$c(r_k) = \sum_{j=0}^{k} p(r_j) \tag{2}$$

Each original intensity r_k is mapped to a new intensity s_k:

$$s_k = (L-1) \cdot c(r_k) \tag{3}$$

The equalized image $I_{equalized}$ is obtained by replacing each pixel's intensity with the corresponding s_k.

Normalization adjusts pixel values to a common scale using min-max normalization:

$$I_{normalized}(x, y) = \frac{I(x,y) - I_{\min}}{I_{\max} - I_{\min}} \tag{4}$$

3.2 HHO-Optimized Otsu's Thresholding

Otsu's method finds the optimal threshold that minimizes the intra-class variance (or equivalently maximizes the between-class variance), assuming a bimodal histogram. After computing the normalized histogram, the method evaluates all possible thresholds and selects the one that best separates foreground and background. In this work, we use the Harris Hawks Optimization (HHO) to efficiently find the optimal thresholds for multi-level segmentation $(k > 1)$.

HHO-Otsu's Thresholding: Otsu's method determines the optimal thresholds $\{T_1, T_2, \dots \dots T_k\}$ for segmenting an image into $k+1$ classes. The goal is to maximize the between-class variance σ_B^2 to separate the pixel intensities effectively.

Objective Function: Between-Class Variance

For an image histogram with L intensity levels $(0,1, \dots \dots \dots \dots . L)$:

- Class probabilities:

$$w_i = \sum_{j=T_{i-1}}^{T_i} P_j \;\; for\ i = 1,2, \dots \dots \dots \dots, k+1 \tag{5}$$

  Where P_j is the normalized histogram of intensity level j, and $T_0 = 0, T_{k+1} = L-1$

- Class Means:

$$\mu_i = \frac{\sum_{J=T_{i+1}}^{T_i} j.P_j}{w_i} \;\; for\ i = 1,2, \dots \dots, k+1 \tag{6}$$

- Global Mean:

$$\mu_T = \sum_{j=0}^{L-1} j.P_j \tag{7}$$

- Between-Class Variance:

$$\sigma_B^2 = \sum_{i=1}^{K+1} w_i(\mu_i - \mu_T)^2 \tag{8}$$

The goal is to find thresholds $\{T_1, T_2, \dots \dots \dots \dots \dots . T_k\}$ that maximize σ_B^2.

Harris Hawk Optimization (HHO): HHO is a nature-inspired metaheuristic algorithm that simulates the cooperative hunting strategy of Harris hawks. It has two primary phases: exploration and exploitation.

Key Components of HHO

- **Population Initialization:** Each hawk represents a potential solution $T = \{T_1, T_2, \dots\dots\dots\dots . T_k\}$, where $T_i \in |0, L-1|$The population of hawks is initialized randomly:$T_i = \{T_{i1,}T_{i2,\dots\dots}T_i\}, T_{ij} \sim Uniform(0, L-1)$
- **Escape Energy (E):** The prey's energy decreases as iterations progress, defined as:

$$E = 2E_0\left(1 - \frac{t}{T_{max}}\right) \tag{9}$$

Where E_0 is a random number in $[-1,1]$, t is the current iteration, and T_{max} is the maximum number of iterations. The value of E determines the transitions between exploration ($|E| < 1$).

- **Exploration Phase ($|E| > 1$):** Hawks search for prey in a wide area by randomly updating their positions:

$$T_i^{t+1} = T_i' + r.\left(T_j' - T_k'\right) \tag{10}$$

Where:

  - T_j', T_k are randomly selected hawks
  - $r \sim Uniform(0,1)$ is a random factor

- **Exploitation Phase ($|E| < 1$):** Hawks converge toward the prey (best solution) based on prey's escape behaviour:
  - Soft besiege with fast movement:

$$T_i^{t+1} = \Delta T - E.|\Delta T| \tag{11}$$

  - Hard besiege with fast movement (r<0.5):
- **Fitness Evaluation:** The fitness of each hawk is calculated using Otsu's between-class variance σ_B^2 :

$$f(T) = \sigma_B^2(T) \tag{12}$$

- **Best Solution Update:** The hawk with the maximum fitness is identified as the prey T_{prey}.
- **Termination:** The algorithm stops when the maximum number of iterations is reached or the improvement in fitness becomes negligible.

3.3 Maximum Entropy Thresholding Algorithm

We use a simulated annealing-based optimization to determine the threshold which maximizes the sum of foreground and background entropy. This algorithm follows as follows:

- Set the energy threshold E_t and acceptance probability P.
- Take a random threshold value and calculate the energy E.
- For a fixed number of iterations:
  - Create an adjacent threshold and calculate an energy difference ΔE.
  - Accept the new threshold in case $\Delta E \le E_t - E$ (Metropolis criterion).
  - When the new state is better and accepted than the best state previously found, then update the best state.

- Gradually reduce the energy threshold: $E_t = \alpha E_t$ with $\alpha < 1$.
- Return the best threshold encountered.

The optimal threshold T is determined as:

$$T = \arg\max_{T}\left[H_f(\tau) + H_b(\tau)\right] \tag{13}$$

$$H_f(\tau) = \sum_{i=0}^{\tau} P(i) log P(i) : Entropy\ of\ the\ foreground \tag{14}$$

$$H_b(\tau) = \sum_{i=\tau+1}^{L-1} P(i) \log P(i) : Entropy\ of\ the\ background \tag{15}$$

$$P(i): probability\ of\ intensity\ i \tag{16}$$

Step 1: Inputs as Fuzzy Sets

The thresholds T_1, T_2 obtained from the two methods (HHO-Otsu and maximum entropy) are treated as inputs to the fuzzy logic system. These inputs are converted into fuzzy sets using membership functions (μ).

- Membership Function: Membership functions map each threshold value to a degree of membership in the range [0, 1]. A common form is the triangular membership function:

$$\mu(T) = \begin{cases} 0 \\ \frac{T-a}{b-a} \\ \frac{c-T}{c-b} \end{cases} \quad T \leq a\ or\ T \geq c, a < T < b, b < T < c \tag{17}$$

Where a, b, c: Parameters defining the triangle.

3.4 Fuzzy Fusion Rule for Threshold

The two methods are combined through a fuzzified fusion rule, enhancing the segmentation process by considering the contribution of each method in a weighted manner. Let T_1, T_2 represent the thresholds from Otsu, maximum entropy, respectively. The fused threshold T_f is calculated as:

$$T_f = w_1 T_1 + w_2 T_2 \tag{18}$$

Where:

- $w_1 . w_2$ are weights derived from the fuzzy membership functions μ_1, μ_2, such that $w_1 + w_2$ =1.

$$\mu_i = \frac{contribution\ of\ method\ i}{total\ contribution\ from\ all\ methods} \tag{19}$$

3.5 Benefits of Fuzzy-Fused Approach

- Adaptive Segmentation: Combines the global thresholding strength of Otsu's method, the information maximization of entropy-based segmentation.
- Robustness to Noise: Fuzzified fusion balances the influence of each method, ensuring stability in noisy and complex environments.
- Enhanced Accuracy: By leveraging multiple methods, the fused approach achieves better segmentation accuracy than any single method.

This methodology ensures that the strengths of two techniques are synergistically used, making it particularly effective for road crack segmentation in challenging scenarios.

The proposed fuzzy-fused segmentation combines HHO-optimized Otsu thresholding and maximum entropy-based segmentation using a fuzzified rule for improved road crack segmentation.

4. Results and Analysis

4.1 Dataset: Manual Dataset

High-resolution images of pavement cracks were collected from Muzaffarpur, Bihar, India, using a Nikon D5600 camera (Figure 2). This camera boasts a 24.2 MP DX-format CMOS sensor, delivering a resolution of 6000×4000 pixels. It features an ISO range of 100-25600, allowing for excellent performance in low-light conditions, and includes EXPEED 4 image processing for fast and accurate image capture. The D5600 is equipped with a 39-point autofocus system and 5 fps continuous shooting, enhancing its capability to capture clear and detailed images even in dynamic environments. Additionally, the camera's built-in image stabilization and vari-angle touchscreen make it versatile for various shooting angles and conditions. These images were processed using Otsu thresholding, which effectively distinguishes cracks from the background and produces clear binary images (Figure 3). These segmented images are crucial for subsequent analysis, serving as the foundation for feature extraction and classification tasks, ultimately aiding in the automation of pavement crack detection and maintenance strategies. Additional samples from the manual dataset, along with their histograms and segmented images, are shown in Table 1.

Figure 2: Input image-2 from the dataset

4.2 Results

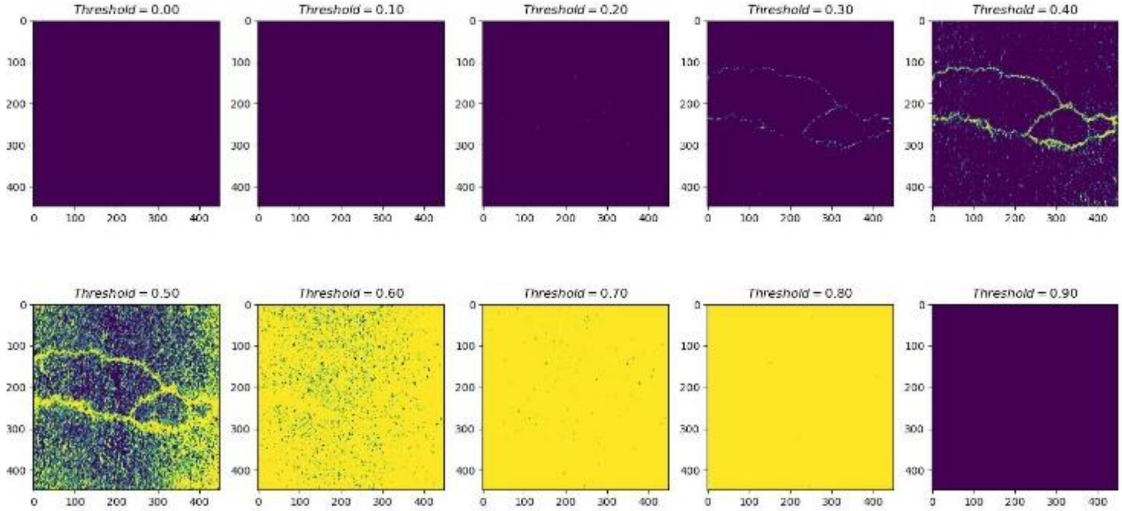
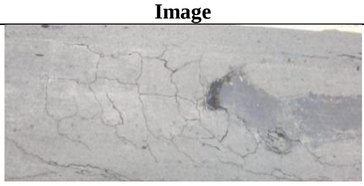
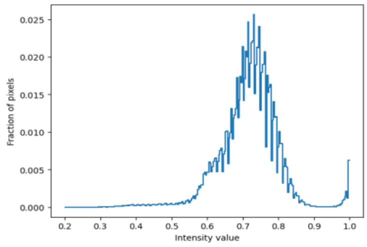
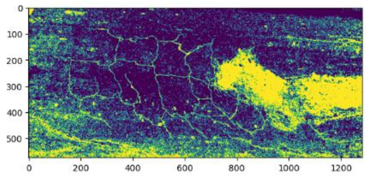
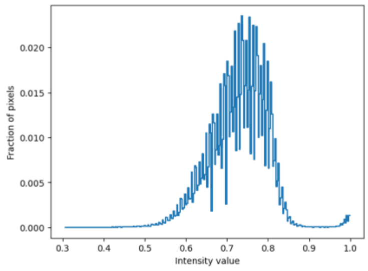
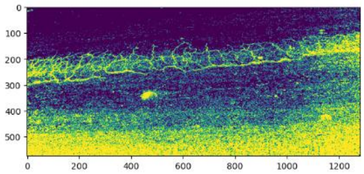
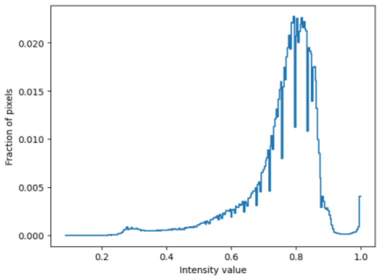
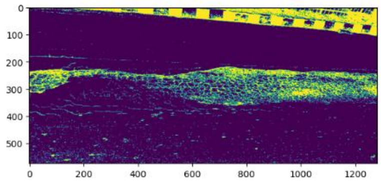
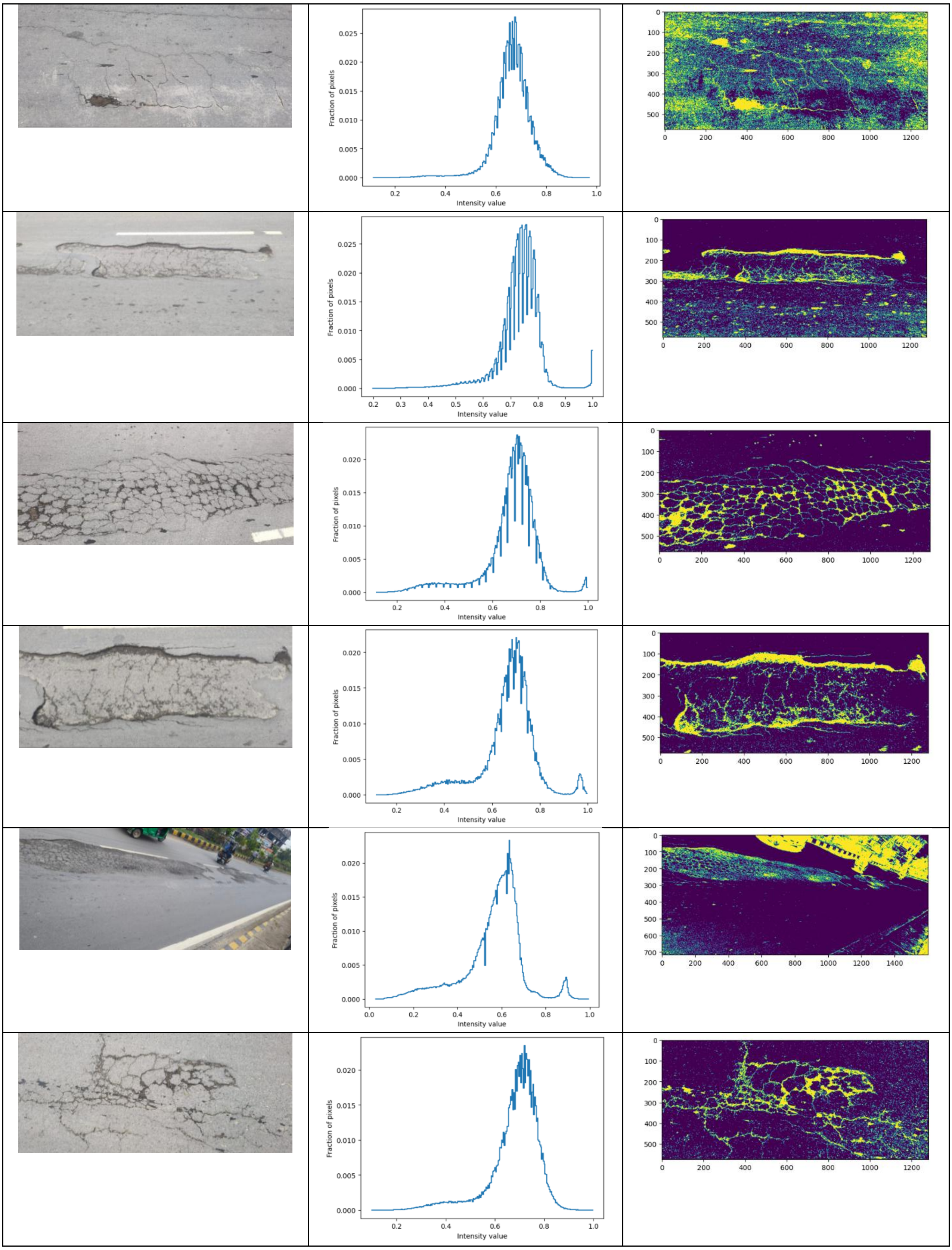


Figure 3: Segmentation at various threshold Segmentation results for various input images from the manual dataset

Table 1: Performance evaluation of the Proposed Approach using Manual Dataset

Image	Histogram	Segmented Image
		
		
		


Fraction of pixels
Intensity value

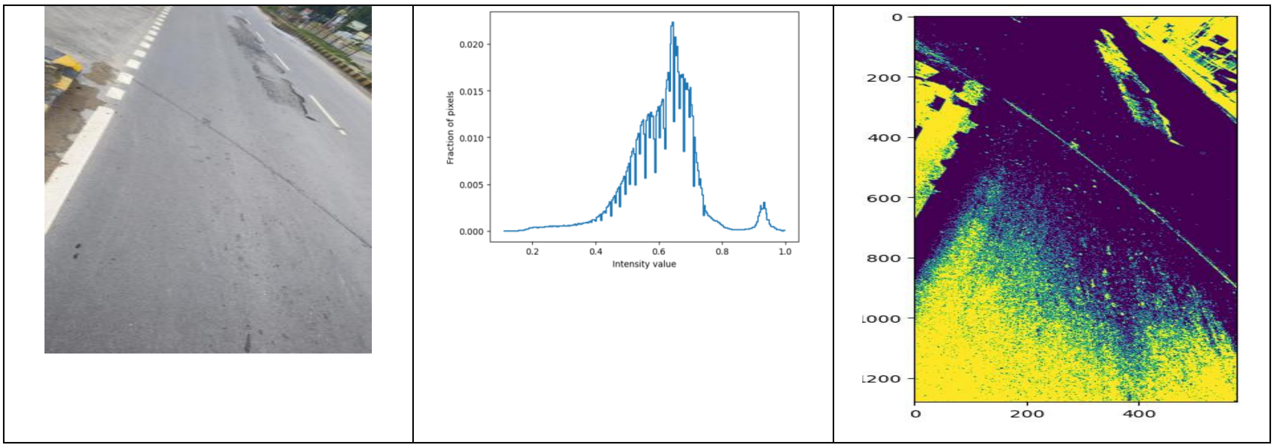


Figure 4 and Figure 5 show the confusion matrices for Deep Crack dataset and Gaps dataset.

Figure 4: Confusion matrix plot of proposed road crack detection for deep crack dataset

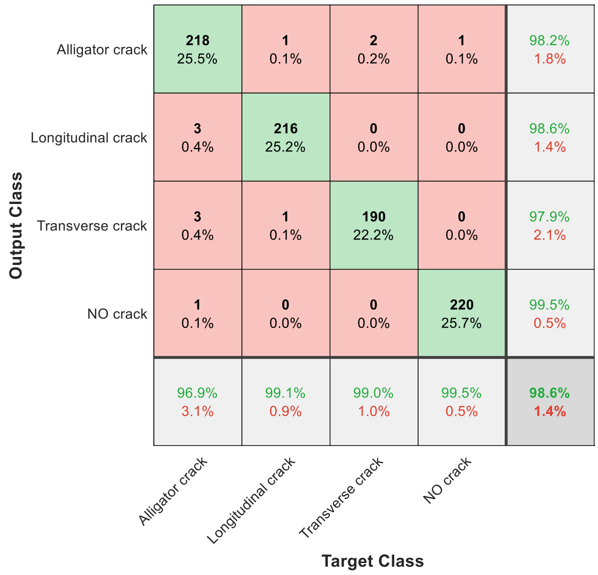


Figure 5: Confusion matrix plot of proposed road crack detection for Gaps dataset

The performance analysis of the road crack detection model across five datasets shows consistently high accuracy, ranging from 95.37% on the Crack Forest Dataset to 98.60% on the Gaps Dataset, as shown in Table 3. Sensitivity and specificity values indicate robust detection capabilities, with sensitivity peaking at 98.62% and specificity reaching up to 99.53%. Precision and F1 scores are also high, demonstrating the model's ability to balance true positive detection and accuracy, while low error rates (as low as 1.40%) and false positive rates (as low as 0.47%) highlight its reliability. The Matthews Correlation Coefficient (up to 98.13%) and Kappa statistics (up to 96.26%) further confirm the model’s strong agreement and predictive performance. Furthermore, the accuracy of the proposed model was compared with other models reported in the literature., as shown in Table 4. Table 4 compares the proposed method's accuracy (98.60%) with previous research, demonstrating superior performance over DeepCrack (87.00%), CrackSeg (91.00%), ConCrack (92.00%), and U-HDN (97.27%), highlighting its effectiveness in road crack detection.

Table 3 Comparative Performance Analysis Of Road Crack Detection Model Across Different Datasets

Metric	**Crack Forest Dataset**	**Manual Dataset**	**Crack Tree Dataset**	**Deep Crack Dataset**	**Gaps Dataset**
Accuracy	95.37%	95.71%	97.42%	98.39%	98.60%
Error	4.63%	4.29%	2.58%	1.61%	1.40%
Sensitivity	95.38%	95.70%	97.47%	98.42%	98.62%
Specificity	98.46%	98.57%	99.14%	99.46%	99.53%
Precision	95.46%	95.75%	97.44%	98.41%	98.58%
FPR	1.54%	1.43%	0.86%	0.54%	0.47%
F1 Score	95.39%	95.71%	97.45%	98.41%	98.60%
Matthews Correlation Coefficient	93.87%	94.29%	96.59%	97.87%	98.13%
Kappa	87.64%	88.56%	93.13%	95.71%	96.26%

Table 4: Comparative analysis of proposed work with previous research works

Method	Accuracy
DeepCrack [17]	87.00%
CrackSeg [18]	91.00%
ConCrack [19]	92.00%
U-HDN [20]	97.27%
Proposed Method	**98.60%**

5. Conclusion

This study introduces a novel and effective road crack detection model that combines advanced segmentation techniques, feature extraction, and optimized classification to achieve superior performance. The proposed fuzzy-fused segmentation approach, which integrates Otsu's thresholding and maximum entropy methods, ensures precise and noise-resistant crack detection. Experimental validation on multiple benchmark datasets demonstrates the robustness and adaptability of the model, with an outstanding accuracy of 98.60% on the Gaps Dataset, surpassing state-of-the-art methods such as DeepCrack, CrackSeg, ConCrack, and U-HDN. This research establishes a new benchmark for road crack detection, offering a highly accurate and reliable solution that can be applied across diverse datasets and challenging environments. The HHO optimization significantly accelerates threshold selection, and the fuzzy fusion rule adaptively balances the two methods, leading to consistent gains across all datasets. The findings highlight the potential of the proposed approach to improve road infrastructure maintenance and safety. Future work could explore real-time implementation, scalability for large-scale applications, and adaptation to varying road conditions, further enhancing the practical utility of this methodology.

References

Sulistyaningrum, D.R., Setiyono, B., Anita, J.N. and Muheimin, M.R., (2021). "Measurement of crack damage dimensions on asphalt road using Gabor filter". Journal of Physics: Conference Series, 1752(1), p.012086.

Zou, Q., Cao, Y., Li, Q., Mao, Q. and Wang, S., (2022). "CrackTree: Automatic crack detection from pavement images". Pattern Recognition Letters, 33(3), pp.227-238.

Tang, J. and Gu, Y., (2022). "Automatic crack detection and segmentation using a hybrid algorithm for road distress analysis". In: 2022 IEEE International Conference on Systems, Man, and Cybernetics, 2022. IEEE, pp.3026-3030.

Oliveira, H. and Correia, P.L., (2022). "Automatic road crack detection and characterization". IEEE Transactions on Intelligent Transportation Systems, 14(1), pp.155-168.

Zalama, E., Gómez-García-Bernejo, J., Medina, R. and Llamas, J., (2023). "Road crack detection using visual features extracted by Gabor filters". Computer-Aided Civil and Infrastructure Engineering, 29(5), pp.342-358.

Avila, M., Begot, S., Duculty, F. and Nguyen, T.S., (2014). "2D image-based road pavement crack detection by calculating minimal paths and dynamic programming". In: 2014 IEEE International Conference on Image Processing (ICIP), 2014. IEEE, pp.783-787.

Sun, Z., Caetano, E., Pereira, S. and Moutinho, C., (2023). "Employing histogram of oriented gradient to enhance concrete crack detection performance with classification algorithm and Bayesian optimization". Engineering Failure Analysis, 150, p.107351.

Bang, S., Park, S., Kim, H. and Kim, H., (2019). "Encoder-decoder network for pixel-level road crack detection in black-box images". Computer-Aided Civil and Infrastructure Engineering, 34(8), pp.713-727.

Hacıefendioğlu, K. and Başağa, H.B., (2022). "Concrete road crack detection using deep learning-based faster R-CNN method". Iranian Journal of Science and Technology, Transactions of Civil Engineering, 46(2), pp.1621-1633.

Djenouri, Y., Belhadi, A., Houssein, E.H., Srivastava, G. and Lin, J.C.W., (2022). "Intelligent graph convolutional neural network for road crack detection". IEEE Transactions on Intelligent Transportation Systems, 24(8), pp.8475-8482.

Jiang, X., Jiang, J., Yu, J., Wang, J. and Wang, B., (2023). "MSK-Unet: A modified U-Net architecture based on selective kernel with multi-scale input for pavement crack detection". Journal of Circuits, Systems and Computers, 32(1), p.2350006.

Gavilán, M., Balcones, D., Marcos, O., Llorca, D.F., Sotelo, M.A., Parra, I., Ocaña, M., Aliseda, P., Yarza, P. and Amírola, A., (2021). "Adaptive road crack detection system by pavement classification". Sensors, 11(10), pp.9628-9657.

Fernandes, K. and Ciobanu, L., (2023). "Pavement pathologies classification using graph-based features". In: 2023 IEEE International Conference on Image Processing (ICIP), 2023. IEEE, pp.793-797.

Cubero-Fernández, A., Rodriguez-Lozano, F.J., Villatoro, R., Olivares, J. and Palomares, J.M., (2022). "Efficient pavement crack detection and classification". EURASIP Journal on Image and Video Processing, 2022, pp.1-11.

Li, W., Huyan, J., Gao, R., Hao, X., Hu, Y. and Zhang, Y., (2021). "Unsupervised deep learning for road crack classification by fusing convolutional neural network and K-means clustering". Journal of Transportation Engineering, Part B: Pavements, 147(4), p.04021066.

Chen, C., Seo, H., Jun, C.H. and Zhao, Y., (2022). "Pavement crack detection and classification based on fusion feature of LBP and PCA with SVM". International Journal of Pavement Engineering, 23(9), pp.3274-3283.

Zou, Q., Zhang, Z., Li, Q., Qi, X., Wang, Q. and Wang, S., (2021). "DeepCrack: Learning hierarchical convolutional features for crack detection". IEEE Transactions on Image Processing, 28(3), pp.1498-1512.

Wang, X., Wang, Y., Yu, L. and Li, Q., (2023). "Automated pavement crack detection based on multiscale fully convolutional network". The Journal of Engineering, 2023(10), p.e12317.

Mei, Q. and Gül, M., (2020). "A cost-effective solution for pavement crack inspection using cameras and deep neural networks". Construction and Building Materials, 256, p.119397.

Fan, Z., Li, C., Chen, Y., Wei, J., Loprencipe, G., Chen, X. and Di Mascio, P., (2020). "Automatic crack detection on road pavements using encoder-decoder architecture". Materials, 13(13), p.2960.