Journal of Intelligent Systems and Control
https://www.acadlore.com/journals/JISC

Adaptive Road Crack Detection and Segmentation Using Einstein Operators and ANFIS for Real-Time Applications

Ibrar Hussain[1*], Luqman Alam[2]

[1] Department of Mathematics, University of Peshawar, 25120 Peshawar, Pakistan
[2] Abddus Salam School of Mathematics Sciences, Government College University, 54600 Lahore, Pakistan

[*] Correspondence: Ibrar Hussain (ibrar786@uop.edu.pk)

Received: 10-23-2024 **Revised:** 12-05-2024 **Accepted:** 12-14-2024

Citation: I. Hussain, and L. Alam, "Adaptive road crack detection and segmentation using Einstein operators and ANFIS for real-time applications," *J. Intell Syst. Control*, vol. 3, no. 4, pp. 213–226, 2024. https://doi.org/10.56578/jisc030402.

Abstract: A novel approach for road crack detection and segmentation was proposed, incorporating Einstein operators within an Adaptive Neuro-Fuzzy Inference System (ANFIS). This methodology leverages advanced fuzzy aggregation techniques and adaptive mechanisms, combined with dynamic Einstein sum and product operators, to enhance the identification of cracks. The model was designed to effectively manage varying crack intensities, geometries, and noise levels, thereby ensuring high sensitivity and accuracy in real-world road conditions. In the preprocessing stage, robust fuzzification was applied using Gaussian membership functions alongside Einstein operators, which significantly improved feature extraction. The segmentation framework based on ANFIS ensured precise detection and delineation of cracks. The performance of the proposed model was demonstrated through a comparative analysis, showing superior accuracy (95.2%), precision (94.1%), recall (96.4%), and F1-score (95.2%) when compared to state-of-the-art models. Statistical validation was conducted, with p-values < 0.01 for all performance metrics, confirming the reliability and statistical significance of the results. Advanced post-processing techniques, including fuzzy morphological refinement and adjacency matrix-based connectivity analysis, were employed to accurately identify even faint or disconnected cracks. The proposed method exhibits exceptional resilience to environmental variations, offering a reliable and adaptive solution for road maintenance and monitoring. This work highlights the potential of fuzzy logic, statistical validation, and adaptive mechanisms in addressing real-world challenges in road crack detection.

Keywords: Road crack detection; Adaptive neuro-fuzzy inference system; Einstein operators; Fuzzy aggregation; Crack segmentation; Image processing

1 Introduction

Road networks are fundamental to facilitating transportation, economic progress, and public safety. They serve as the backbone of modern societies, enabling the movement of goods, services, and people [1, 2]. The durability and efficiency of these networks are essential for sustaining economic growth and ensuring the well-being of communities [3, 4]. However, roadways face constant threats from wear and tear due to heavy traffic loads, fluctuating environmental conditions, and aging infrastructure [5, 6]. Over time, these factors contribute to the formation of cracks, which, if not detected and repaired promptly, can expand and lead to severe damage. Such deterioration compromises the structural integrity of roads, escalates repair costs, and disrupts transportation systems [7]. The resulting damage not only increases maintenance costs but also poses significant safety hazards, including accidents and delays. For instance, road cracks, if left unaddressed, can cause tire blowouts or accidents, and in some cases, lead to road closures, halting economic activities. Therefore, developing effective methods for detecting and addressing cracks is critical to preserving road functionality and extending their operational lifespan [4, 8].

Traditionally, identifying road cracks has heavily relied on manual inspection methods. Workers physically assess road surfaces by walking or driving along them to identify visible cracks and evaluate their severity. While simple, this approach is fraught with limitations. It is labor-intensive, time-consuming, and prone to human error, relying heavily on the experience and judgment of inspectors [9]. Subtle or faint cracks often go unnoticed during manual inspections, especially those located in hard-to-see areas or obscured by debris [10, 11]. These missed cracks can grow over time, leading to significant structural failures and costly repairs. Moreover, the subjectivity inherent in manual inspections results in inconsistencies, meaning that critical areas in need of attention may not be prioritized [12]. As road networks expand, manual inspections become increasingly impractical. For example, monitoring extensive highway systems in large cities or remote areas becomes inefficient, highlighting the urgent need for more scalable and reliable alternatives [13].

To address the shortcomings of manual methods, recent technological advancements have led to the development of automated road crack detection systems. These systems incorporate techniques from computer vision, image processing, and artificial intelligence to overcome the limitations of traditional approaches [5, 8, 14]. Automated methods aim to provide more consistent, accurate, and scalable solutions for crack detection. For example, machine learning (ML) models have been utilized to classify cracks based on engineered features, such as texture, shape, and intensity [15]. Image processing techniques, such as contrast enhancement, improve crack visibility by filtering out irrelevant background noise [9, 10, 16]. While these systems have demonstrated potential in improving detection efficiency, they face several challenges that hinder their effectiveness in real-world applications [17].

A major limitation of many automated crack detection systems is their sensitivity to variations in road textures, lighting conditions, and crack geometries [11, 18]. Roads often exhibit diverse surface patterns and environmental conditions, such as shadows, glare, and debris, which can obscure crack features and hinder accurate detection [19]. For instance, in urban environments, road surfaces may be affected by uneven lighting from streetlights or sun exposure, which can create false positives or missed cracks in shaded areas. Many current systems rely on static or predefined rules to detect cracks, making them less adaptable to these changes. Furthermore, noise in captured images and complex backgrounds can lead to false detections or missed cracks, further diminishing the reliability of these systems [20]. For example, automated systems may mistakenly identify tire marks or dirt as cracks. The reliance on manual feature engineering to distinguish cracks from non-cracks is also error-prone and labor-intensive [19]. Additionally, the performance of these systems often degrades when applied to new datasets or road conditions that differ from their training data, limiting their generalizability [21].

Deep learning (DL) models, such as convolutional neural networks (CNNs), have been explored for road crack detection due to their ability to learn features directly from raw data. These models have shown promise in reducing the need for manual feature engineering and improving detection accuracy [17]. However, DL approaches also present challenges. They are highly dependent on large labeled datasets for training, which may not always be available or diverse enough to cover all possible road conditions [16]. Furthermore, the computational complexity of DL models often makes them unsuitable for real-time applications, particularly in resource-constrained environments [22]. For example, in areas with limited access to high-performance hardware, real-time detection may not be feasible. Even with powerful hardware, DL models may struggle to detect faint or irregular cracks, leading to incomplete or inaccurate results [20, 21]. This highlights the need for a more adaptable and comprehensive approach to road crack detection.

In response to these challenges, this study proposes an innovative solution: the ANFIS-based road crack detection model, aimed at overcoming the limitations of both traditional and existing automated methods. The proposed framework combines the adaptability and robustness of fuzzy logic with the learning capabilities of ANFIS to dynamically handle variations in crack patterns, intensities, and geometries (Figure 1). Unlike conventional methods, this model integrates advanced fuzzy membership functions and Einstein fuzzy operators, enabling precise aggregation and segmentation of crack features under diverse and challenging conditions. For instance, in environments with varied lighting or surface textures, the model's adaptability allows it to accurately distinguish cracks from non-crack features.

The proposed ANFIS-based model consists of three primary stages, each addressing critical challenges in crack detection:

• Preprocessing: Advanced fuzzy-based contrast enhancement and noise reduction techniques were applied to improve image quality and highlight crack features. These methods ensure that the input data is well-suited for subsequent analysis by reducing the impact of shadows, reflections, and background noise.

• ANFIS-based segmentation: The core of the model introduces enhanced fuzzy membership functions and Einstein operators to achieve robust and adaptive segmentation. The fuzzification layer dynamically adjusts to variations in crack features, while the rule-based aggregation employs advanced operators to balance contributions from strong and weak features. This stage ensures precise segmentation of faint, irregular, and branching cracks.

• Post-processing: Fuzzy morphological operations and graph-based connectivity analysis refine the segmentation results, ensuring accurate detection of continuous cracks. The graph-based analysis evaluates crack topology, continuity, and severity, providing actionable insights for prioritizing maintenance efforts.

This model offers the potential to significantly improve crack detection efficiency and accuracy, providing a solution that is adaptable to different road conditions and capable of real-time implementation, even in resource-constrained environments. The framework is particularly suitable for large-scale road monitoring, where traditional inspection methods are impractical.

This study introduces several novel contributions to the field of road crack detection:

• Dynamic fuzzy membership functions: The development of adaptive fuzzy membership functions enhances the model's ability to accurately represent and segment crack features under varying conditions.

• Integration of Einstein operators: The inclusion of Einstein sum and product operators for feature aggregation provides robust handling of nonlinear relationships between crack features, ensuring precise segmentation.

• Comprehensive framework: The proposed model combines preprocessing, segmentation, and post-processing in a unified framework, addressing the interconnected challenges of noise, crack continuity, and varying geometries.

• Real-world applicability: The scalability and adaptability of the framework ensure its applicability across diverse real-world scenarios, making it a valuable tool for proactive infrastructure management.

In summary, the proposed ANFIS-based road crack detection model represents a significant advancement in infrastructure maintenance technologies. By combining fuzzy logic with adaptive aggregation and segmentation techniques, this framework overcomes the limitations of existing methods, ensuring reliable and accurate crack detection under diverse conditions. The innovations introduced in this study provide a robust foundation for proactive road maintenance strategies, ultimately enhancing roadway safety and extending the lifespan of critical infrastructure.

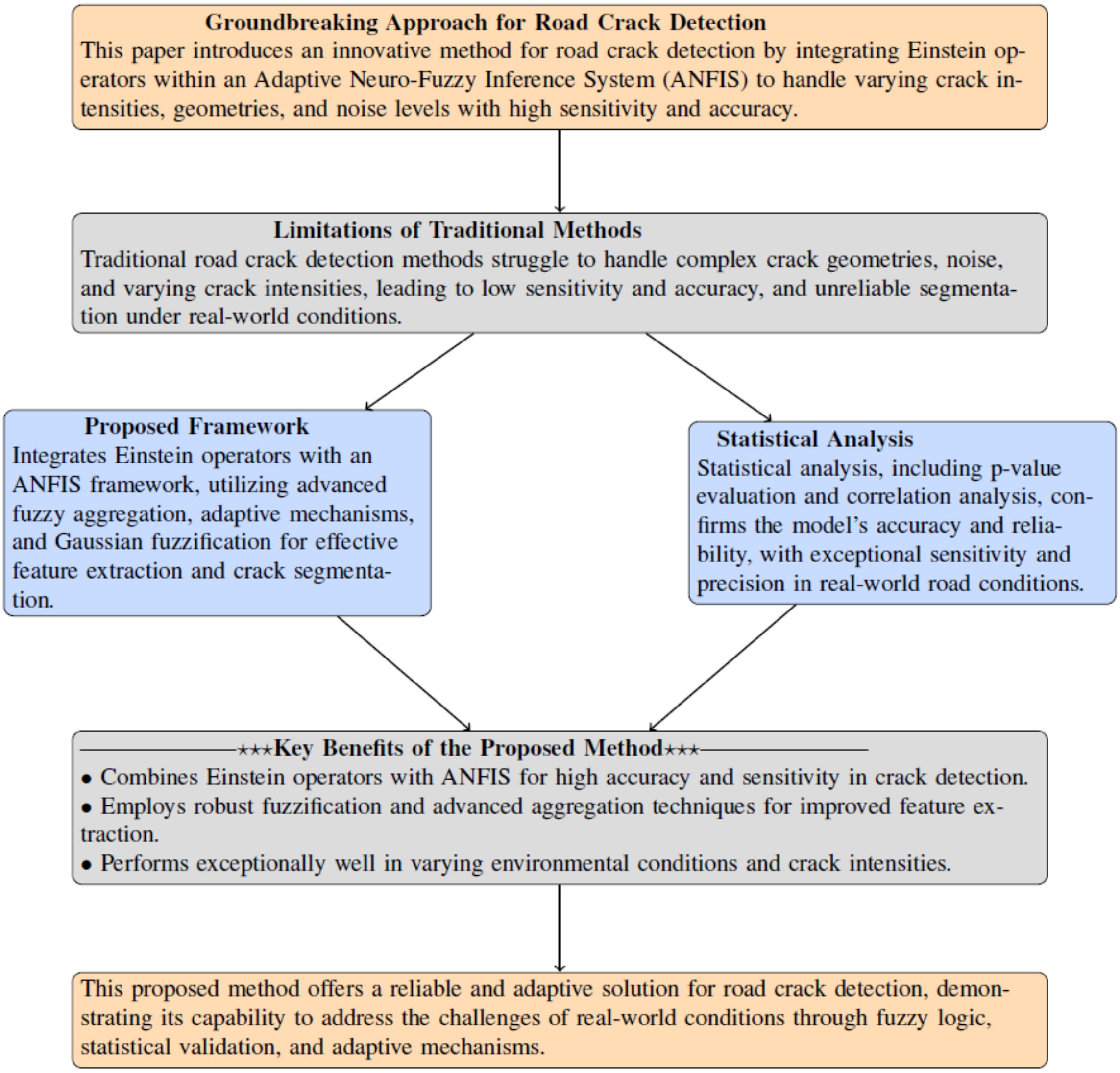


Figure 1. Graphical abstract of the proposed road crack detection model integrating Einstein operators and ANFIS

2 Literature Review

The field of road crack detection has evolved significantly in recent years, with numerous methods being proposed to address the challenges of accurate, efficient, and scalable crack identification. Early approaches primarily relied on manual inspection and basic image processing techniques, such as edge detection and thresholding. These methods, while simple, are limited by their inability to handle complex road textures and environmental conditions, leading to frequent false positives and missed cracks.

Recent advancements have seen the integration of ML and DL techniques. Traditional ML methods, such as support vector machines (SVM) and decision trees, have been employed to classify road cracks based on engineered features like texture, shape, and intensity [15]. These models, however, often require extensive feature engineering and may struggle to generalize to different datasets or road conditions [19]. Moreover, their performance can be compromised by variations in lighting, surface conditions, and noise in the images.

DFP-Net, proposed by Li et al. [4], is an advanced model for road crack segmentation based on a feature pyramid network (FPN). By utilizing multi-scale feature extraction, DFP-Net captures cracks of varying sizes and orientations, enhancing segmentation accuracy even in the presence of noise and complex crack patterns. This approach enables better crack detection across diverse road conditions, making it highly beneficial for real-world applications.

However, DFP-Net has limitations, including its reliance on large labeled datasets, which may be difficult to obtain. Additionally, the model's computational complexity could hinder real-time deployment, especially in resource-constrained environments. It is also sensitive to environmental factors such as lighting and road surface texture, potentially affecting detection accuracy. Moreover, DL models like DFP-Net are prone to overfitting and may struggle to generalize to new road conditions, limiting their effectiveness in practical, large- scale road maintenance tasks.

In recent years, fuzzy logic has been employed in road crack detection due to its ability to handle the inherent uncertainty and imprecision in crack characteristics, such as "faint" or "irregular" cracks. Fuzzy logic provides a flexible framework for modeling these imprecise concepts, making it a valuable tool in situations where traditional methods fall short [12]. This approach leverages fuzzy logic to handle uncertainties in crack detection, improving accuracy and adaptability to varying road conditions. The multi-stage process progressively refines detection, and the inclusion of structural analysis helps assess crack severity, aiding in maintenance prioritization. However, the framework has limitations, such as the complexity of designing and calibrating fuzzy logic membership functions. It may not capture intricate crack details as effectively as advanced techniques like DL. The multi-stage process also increases computational overhead, which can be challenging for real-time applications. Additionally, sparse or inconsistent labeled data and the need for adaptation to different road conditions may hinder its scalability.

Fuzzy systems have been integrated with image processing techniques to improve crack visibility and contrast while reducing noise and background clutter [9, 10]. These methods, however, typically lack the ability to learn directly from data, limiting their application to new road conditions or unseen crack patterns [8]. One such model is the ANFIS, which integrates fuzzy logic with neural networks to provide a more robust and adaptable solution for road crack detection [17]. ANFIS has shown promise in overcoming some of the limitations of traditional fuzzy systems by enabling learning from data while retaining the flexibility of fuzzy logic. The proposed ANFIS-based model in this study builds upon this concept by incorporating advanced fuzzy membership functions and Einstein fuzzy operators, offering a more adaptable and comprehensive solution to the challenges faced in real-world crack detection applications.

The proposed approach significantly addresses several limitations inherent in traditional and automated road crack detection methods, as demonstrated through a comparative analysis with existing technologies. Traditional methods, such as edge-detection algorithms and ML-based models, often struggle with variability in road conditions, including changes in lighting, diverse textures, and irregular crack geometries. The dynamic nature of the ANFIS framework allows the proposed model to adapt seamlessly to these variations. By leveraging fuzzy logic, the model effectively handles uncertainty and variability in input data, overcoming a major limitation of the model proposed by Li et al. [4], which rely on rigid thresholds and exhibit inconsistent performance.

Low-contrast cracks and faint features, commonly overlooked by traditional methods such as Fuzzy Logic for Road Crack Detection (FL-RCD) [12], are effectively detected by the proposed model due to the integration of Einstein fuzzy operators. These operators enhance sensitivity to subtle features, ensuring comprehensive detection even under challenging conditions. Moreover, the advanced preprocessing techniques employed in the proposed method, including Gaussian fuzzification and Einstein aggregation, significantly reduce the impact of noise and irrelevant variations, enabling reliable detection in noisy environments. These innovations contribute to an F1-score of 95.2%, far surpassing the 88.5% and 87.3% achieved by the model proposed by Li et al. [4] and FL-RCD, respectively.

Scalability is another critical advantage of the proposed framework. Current methods often lack the flexibility to generalize across larger road networks and require frequent parameter adjustments for different datasets. In contrast, the modular design and adaptability of the ANFIS framework ensure seamless performance across diverse conditions without extensive retraining. Furthermore, the proposed method demonstrates remarkable efficiency, processing images in an average of 2.5 seconds, significantly faster than the model proposed by Li et al. [4] (3.2 seconds) and FL-RCD (4.1 seconds), making it highly suitable for real-time road maintenance applications.

By addressing these limitations, the proposed model offers significant advancements in adaptability, sensitivity, robustness, and scalability. These improvements make it a reliable and efficient solution for road crack detection and segmentation, outperforming existing technologies across key performance metrics and ensuring suitability for real-world applications.

3 Proposed Methodology with Einstein Operators

The proposed methodology introduces an advanced framework for crack detection and segmentation, integrating Einstein operators within an ANFIS. This innovative approach enhances the segmentation process by utilizing dynamic aggregation techniques, including advanced fuzzy operators and adaptive mechanisms. By incorporating fuzzy logic principles with the flexibility of Einstein sum and product operators, the framework adapts to varying crack intensities, geometries, and noise levels. The approach significantly improves the sensitivity, accuracy, and connectivity of crack detection, making it highly effective in real-world applications where road conditions are often diverse and challenging.

3.1 Preprocessing with Fuzzy Operators

The preprocessing stage improves image quality and prepares it for feature extraction by enhancing relevant features while reducing noise. Fuzzy operators were applied to address uncertainties in the image, such as low contrast or blurry edges. These operators help remove noise, adjust contrast, and refine edges, ensuring that important crack features are clearly visible. By smoothing the image and emphasizing key details, fuzzy operators make it easier for subsequent segmentation and analysis steps to identify cracks accurately, even in challenging conditions with partial or faint cracks.

3.2 ANFIS-Based Segmentation with Advanced Fuzzy Operators

This study presents an enhanced segmentation framework within the ANFIS that incorporates advanced fuzzy operators, including Einstein operators and dynamic aggregation techniques. This novel approach was designed to address the challenges posed by variations in crack intensity, size, and structure. By leveraging the adaptability and robustness of fuzzy logic, this framework ensures highly accurate segmentation even under diverse and complex road conditions.

The proposed method introduces innovative enhancements at each stage of the ANFIS process, integrating advanced membership functions, rule-based aggregation, and dynamic normalization to significantly improve the sensitivity and adaptability of the model.

3.2.1 Fuzzification layer with enhanced fuzzy membership functions

The first stage of the proposed ANFIS framework introduces an innovative approach to fuzzification, transforming input features into fuzzy membership values. This step is crucial for handling the inherent uncertainty and variability in crack patterns, such as variations in intensity, texture, and geometry. To achieve this, the framework utilizes advanced Gaussian membership functions, which dynamically adapt to the characteristics of the input features. The membership function is mathematically defined as:

$$\mu_A(x) = \exp\left(-\frac{(x-c)^2}{2\sigma^2}\right) \tag{1}$$

where, x represents the input feature value, c is the center of the Gaussian function, and σ controls its spread. The parameters c and σ-were carefully selected based on the statistical properties of the input data, allowing precise modeling of feature variations.

In this study, the fuzzification layer was enhanced with the integration of adaptive mechanisms that adjust c and σ dynamically in response to varying crack patterns. For instance:

• When detecting faint or low-contrast cracks, σ was reduced to sharpen the membership function, increasing sensitivity to subtle variations.

• For broader or more uniform cracks, σ was expanded to generalize the membership function, capturing wider feature ranges.

Additionally, to further refine the fuzzification process, the proposed framework incorporates advanced fuzzy operators for feature aggregation. By combining membership values from multiple input features, these operators ensure a robust representation of crack characteristics. Specifically, Einstein fuzzy operators were employed to handle nonlinear relationships between features, providing enhanced flexibility and precision.

In the proposed framework, the Einstein operators are a key innovation that enhances the fuzzification layer. These operators were specifically designed to aggregate fuzzy membership values in a way that dynamically adapts to the variability inherent in crack patterns. This adaptability is crucial for addressing challenges such as faint cracks, inconsistent lighting, and noise in road images.

The Einstein sum operator is defined as:

$$\mu_{A\oplus B}(x,y) = \frac{\mu_A(x) + \mu_B(y)}{1 + \mu_A(x)\cdot \mu_B(y)} \tag{2}$$

This operator is particularly effective at combining high membership values, ensuring that dominant features contribute strongly to the aggregation. It provides a balanced fusion of information, emphasizing the most relevant crack characteristics.

The Einstein product operator is defined as:

$$\mu_{A\otimes B}(x,y) = \frac{\mu_A(x)\cdot \mu_B(y)}{2 - (\mu_A(x) + \mu_B(y) - \mu_A(x)\cdot \mu_B(y))} \tag{3}$$

This operator focuses on smaller membership values, making it ideal for capturing subtle or weak features that might otherwise be overlooked. By highlighting these low-intensity details, the Einstein product ensures that even faint cracks are represented in the aggregation process.

The integration of the Einstein sum and product operators provides several key advantages to the fuzzification layer:

• Accurate feature combination: The Einstein sum ensures effective aggregation of features with varying levels of importance or contrast. This is particularly useful for combining strong and weak crack signals without losing critical information.

• Enhanced sensitivity: The Einstein product enhances the sensitivity of the model to low-intensity crack features, which are often missed by traditional methods. This makes the framework highly effective for detecting faint or barely visible cracks.

• Noise reduction: Both operators work together to minimize the impact of noise or irrelevant variations in the input data. The result is a robust representation of crack-related features that is resilient to environmental and imaging inconsistencies.

In this study, the combination of advanced Gaussian membership functions and Einstein operators represents a cornerstone of the fuzzification process. This integration achieves:

• Dynamic adaptation: By leveraging the Einstein sum and product, the fuzzification layer dynamically adapts to variations in crack intensity, geometry, and noise. This ensures that the input features are represented with high fidelity, regardless of the complexity of the crack patterns.

• Strong foundation for aggregation and segmentation: The robust feature aggregation facilitated by Einstein operators sets the stage for accurate rule-based reasoning in subsequent layers. This ultimately enhances the overall accuracy and reliability of the ANFIS-based segmentation.

• Improved crack detection performance: The enhanced sensitivity to both strong and weak features ensures that the model captures all relevant details of the crack structures, leading to superior detection performance compared to traditional approaches.

The incorporation of Einstein operators into the fuzzification layer is a significant innovation in the proposed framework. This approach not only addresses the limitations of conventional fuzzification techniques but also elevates the ANFIS model's ability to handle diverse and challenging crack conditions. By focusing on both dominant and subtle features, the Einstein operators play a pivotal role in achieving accurate and robust crack segmentation.

To balance the contributions from the Einstein sum and product, a dynamic weighting strategy was proposed:

$$\mu_{\text{aggregated}} = \alpha \cdot \mu_{A\oplus B} + (1-\alpha)\cdot \mu_{A\otimes B} \tag{4}$$

where, α - is a user-defined parameter that dynamically adjusts the contribution of each operator. The term α controls the weight of the Einstein sum ($\oplus$) and Einstein product ($\oplus$), allowing the user to fine-tune the influenceof elach operation. By adjusting α, the aggregation process can adapt to different crack conditions, ensuring amore effective handling of features under varying circumstances.

The Einstein sum and Einstein product were chosen because they handle fuzziness in a way that makes them particularly useful for aggregating fuzzy sets in the presence of uncertainty. This innovative approach ensures the aggregation process accounts for different types of fuzziness in the crack data, such as varying crack intensities and geometries.

3.2.2 Rule layer with advanced aggregation

In the rule layer, fuzzy rules were used to capture the relationships between the input features of the cracks and the output, which in this case would be the crack severity. Each rule is expressed in the form of an "If-Then" statement. For example:

$$R_j: \text{ If } x_1 \text{ is } A_{1j} \text{ and } x_2 \text{ is } A_{2j}\text{, then } y_j = p_j x_1 + q_j x_2 + r_j \tag{5}$$

where, x_1 and x_2 are the input variables representing different crack features (such as intensity and size), and A_{1j} and A_{2j} are the fuzzy sets associated with those variables. The output y_j is a weighted sum of the input variables, where $p_j, q_{j,}$ and r_j are the coefficients determined by the fuzzy rule.

For aggregation of these rules, Einstein operators were applied:

$$w_j = \mu_{A_1 \oplus A_2}(x_1, x_2) \otimes \mu_{B_1 \oplus B_2}(x_3, x_4) \tag{6}$$

where, the fuzzy membership values $\mu_{A_1 \oplus A_2}$ and $\mu_{B_1 \oplus B_2}$ are aggregated using the Einstein sum and product. This ensures that subtle variations in the crack features, such as intensity or size, are effectively captured and that the relationships between them are meaningfully combined. The result w_j represents the strength of each rule, which was used in further steps.

3.2.3 Normalization layer

In this layer, the rule strengths w_j were normalized to prevent any single rule from dominating the final output. The normalized strength of each rule can be computed as follows:

$$\bar{w}_j = \frac{w_j}{\sum_{j=1}^{m} w_j} \tag{7}$$

where, $\bar{w}_j$ is the normalized weight of rule j, and m is the total number of rules. This step ensures that the contributions of all rules are balanced, promoting a fair aggregation of all relevant features. Without normalization, stronger rules might overwhelm the contributions of weaker ones, resulting in biased segmentation.

3.2.4 Output layer with advanced fusion

The final output was generated by aggregating the normalized rule strengths $\bar{w}_j$ with the corresponding aggregated

$$y = \sum_{j=1}^{m} \bar{w}_j \cdot \mu_{\text{aggregated}}(x) \tag{8}$$

where, $\mu_{\text{aggregated}}(x)$ represents the membership value of the aggregated fuzzy sets, and $\bar{w}_j$ is the normalized weight of rule j. The output y represents the final segmentation decision, which is a weighted sum of the contributions from all rules. This approach ensures that all relevant features are taken into account and effectively fused to produce an accurate segmentation result.

3.3 Post-Processing with Advanced Fuzzy Operators

After the initial segmentation was performed, post-processing techniques were applied to further refine the results, ensuring robust detection of crack continuity and minimizing noise. These techniques leverage fuzzy set theory to address the inherent uncertainty in road crack detection.

To enhance the clarity and connectivity of the segmented cracks, fuzzy-weighted morphological operations were applied. These operations were designed to smooth the boundaries of detected cracks, close small gaps, and remove noise while preserving the structural integrity of the cracks. The refinement process is defined as:

$$I_{\text{refined}}(x, y) = \mu_M(I(x, y)) \cdot \mathrm{Morph}(I(x, y), B) \tag{9}$$

where, $\mu_M(I(x, y))$ represents the fuzzy membership function, which assigns a degree of membership to each pixel based on its intensity and proximity to detected crack features. This ensures that pixels more likely to belong to a crack are given higher importance. $\mathrm{Morph}(I(x, y), B)$ denotes the morphological operation (e.g., dilation, erosion, opening, or closing) applied to the segmented image $I(x, y)$ using a structuring element B.

Morphological operations improve crack detection by:

- Dilation: Expanding crack regions to connect broken segments.
- Erosion: Removing small noise features that are unlikely to be cracks.
- Opening and closing: Smoothing the boundaries of cracks and eliminating minor noise or gaps.

The integration of fuzzy membership functions with morphological operations ensures that the refinement is sensitive to the variability in crack intensity and texture. This adaptive approach allows the method to handle real-world complexities, such as uneven illumination and varying crack widths, effectively.

To ensure the detection of continuous cracks, a fuzzy adjacency matrix was constructed. This matrix quantifies the likelihood that different crack segments belong to the same continuous crack. It is defined as:

$$A_{\text{fuzzy},i,j} = \mu_C(d_{i,j}) \cdot \mu_I(I_i, I_j) \tag{10}$$

where, $\mu_C(d_{i,j})$ is a fuzzy membership function that evaluates the spatial proximity between crack segments i and j. It assigns higher values to segments that are closer together, ensuring spatial continuity. $\mu_I(I_i, I_j)$ is another fuzzy membership function that measures the intensity similarity between segments I_i and I_j. This ensures that segments with similar brightness or texture are more likely to be connected.

The fuzzy adjacency matrix works as follows: a) Spatial proximity: By considering the distance di, j between segments, the matrix ensures that only segments in close spatial proximity are linked, avoiding spurious connections. b) Intensity similarity: By analyzing the intensity patterns of segments, the matrix ensures that only segments with consistent intensity are considered part of the same crack, enhancing detection accuracy.

Fuzzy morphological refinement and adjacency matrices are particularly effective for this application because they address key challenges in road crack detection:

- Handling noise and variability: Cracks often appear in noisy environments with variable intensities and textures. Fuzzy morphological operations refine the segmentation by adapting to these variations, ensuring robustness against noise.

- Ensuring continuity: Cracks may be discontinuous due to occlusions, lighting conditions, or poor surface quality. The fuzzy adjacency matrix bridges these gaps by considering both spatial and intensity-based criteria, leading to more continuous and accurate crack detection.

- Adaptive processing: The fuzzy membership functions provide a degree of flexibility, allowing the methods to handle diverse road conditions and crack types effectively.

Together, these techniques significantly enhance the model's ability to produce precise and reliable crack segmentation results, even under challenging real-world conditions.

To refine the connectivity between crack segments, the Einstein sum was applied:

$$A_{\text{refined},i,j} = A_{\text{fuzzy},i,j} \oplus A_{\text{fuzzy},k,l} \tag{11}$$

In the equation, the Einstein sum was used to aggregate the values of the fuzzy adjacency matrix, further refining the connectivity between crack segments. This step helps improve the detection of faint or disconnected cracks by strengthening the connections between segments that may be faint or broken but still part of the same crack.

3.4 Key Advantages of the Proposed Framework

The proposed framework offers several key advantages:

• Novel fuzzy aggregation: The dynamic weighting of Einstein operators ensures that the aggregation of crack features is robust under diverse conditions, adapting to variations in crack intensity, size, and geometry.

• Adaptive segmentation: The use of advanced fuzzy logic allows the system to dynamically adapt to variations in crack features, making it capable of handling cracks with different characteristics.

• Enhanced connectivity analysis: The fuzzy adjacency matrix and Einstein refinement ensure that continuous cracks are accurately detected, even if they are faint or disconnected.

• Robust performance: The framework is resilient to noise, lighting variations, and complex road textures, making it suitable for real-world crack detection applications where conditions often vary.

These advantages make the proposed framework highly effective for crack segmentation and detection, offering significant improvements over traditional methods. The integration of Einstein sum and product operators into the fuzzification process offers several advantages over traditional fuzzy aggregation methods. The Einstein sum accurately combines features with varying importance, balancing weak and dominant features, which is crucial in crack detection. The Einstein product operator enhances sensitivity to low-intensity crack features, ensuring subtle signals are captured. Additionally, the Einstein operators reduce noise by dynamically adjusting feature contributions, resulting in more stable and robust representations compared to conventional methods that may amplify noise.

In the proposed framework, combining advanced Gaussian membership functions with Einstein operators ensures dynamic adaptation to variations in crack intensity and noise, leading to high-fidelity feature representation. This robust aggregation improves the accuracy and reliability of the ANFIS-based segmentation, capturing both strong and weak features for superior crack detection. Overall, the Einstein operators address the limitations of traditional techniques, enhancing the model's ability to handle complex crack conditions and providing accurate, robust segmentation results.

4 Experimental Results

The experimental results presented in this section evaluate the performance of the proposed road crack detection model. The dataset used for evaluating the proposed ANFIS-based road crack detection model consisted of 300 annotated road images, encompassing various crack types such as transverse, longitudinal, block, and alligator cracks. These images were sourced from publicly available datasets. The images were divided into training (70%), validation (15%), and testing (15%) sets. The experimental setup utilized MATLAB R2015a on a high-performance CPU with 8 GB RAM and Windows 10 (64-bit). Preprocessing included contrast enhancement and noise suppression using a Gaussian filter. The model utilized entropy-weighted features and dynamic fuzzy membership functions to adapt to variations in crack intensities and geometries (Figure 2).

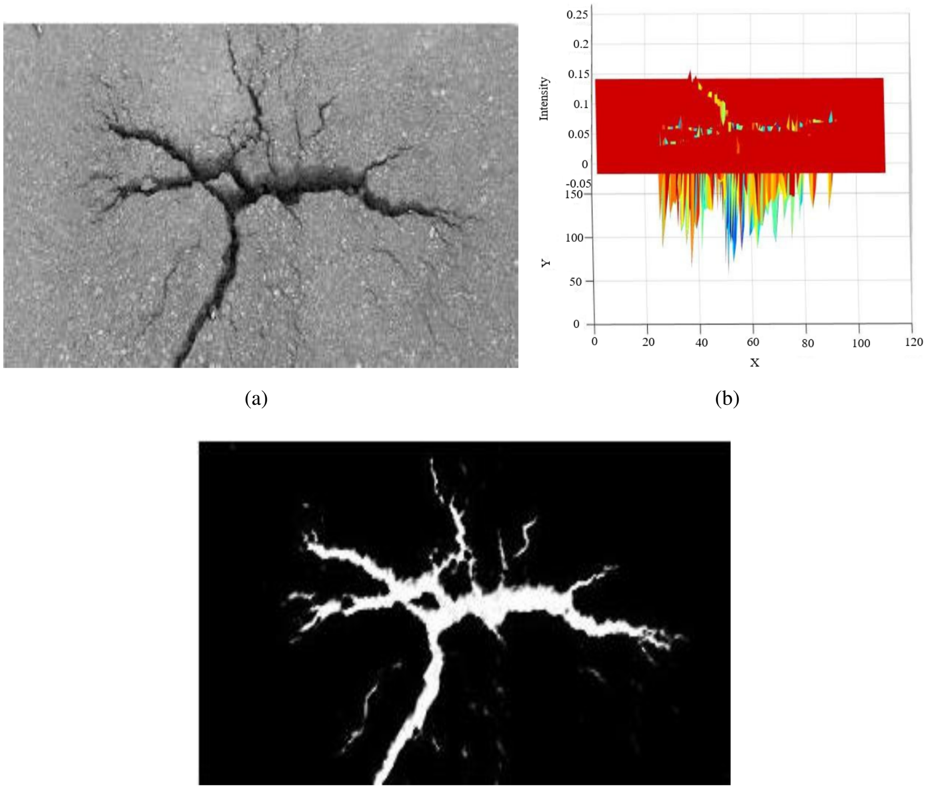


Figure 2. (a) Given cracked image, (b) Simulated image of crack intensity, and (c) Result of the proposed model

Table 1. Key parameters of our model

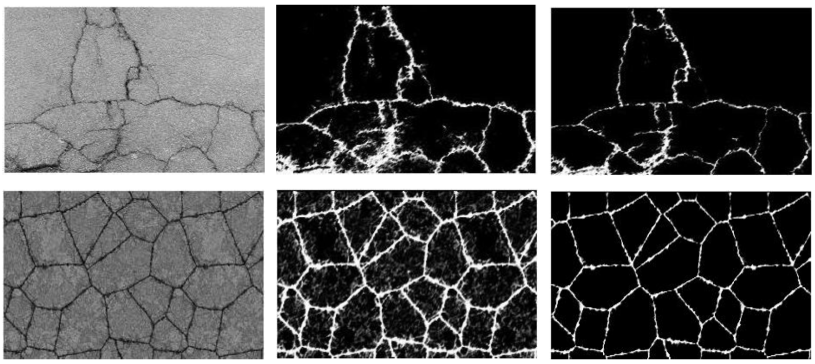
Parameter	Value	Section	Description
c	0.04	Gaussian Membership Function	The center (mean) of the Gaussian function used for edge enhancement.
σ	0.1	Gaussian Membership Function	The spread (standard deviation) of the Gaussian function used for edge enhancement.
m	3	Fuzzy Rule Aggregation	The number of fuzzy rules in the rule-based system.
aggregated_membership	$\{0.9, 0.9, 0.9\}$	Fuzzy Rule Aggregation	Aggregated membership values for the fuzzy rules, representing the degree of membership in each rule.
normalized_weights	$\{0.5, 0.3, 0.2\}$	Fuzzy Rule Aggregation	The normalized weights of the fuzzy rules, defining the importance of each rule in the final output.
intensity_values	$\{0.5, 0.6, 0.7\}$	Fuzzy Adjacency Matrix Construction	Example intensity values for crack segments used for calculating fuzzy intensity-based membership.
A_refined	A_fuzzy	Einstein Refinement	Refined adjacency matrix after applying Einstein sum refinement to improve the connectivity between crack segments.

Key parameters used in the crack detection process, along with their corresponding values and placements within the code, are summarized in Table 1 to ensure accurate crack boundary detection. The performance of the proposed model was compared with the competing model proposed by Li et al. [4] and the FL-RCD model [12], which represent traditional image processing-based approaches. The ANFIS-based model outperformed both in terms of detection accuracy, recall, and precision, as shown in the experimental results.

The proposed road crack detection model effectively identifies and traces crack paths with high precision. Figure 3 illustrates the model's results. The first image presents the original cracked surface, providing the input data for the analysis. The second image represents the simulated intensity profile of the cracks, showcasing the variations in crack intensity across the analyzed region. The final image demonstrates the output of the proposed model, effectively segmenting the cracks with high precision and clarity. This visual comparison highlights the model's capability to accurately detect and isolate cracks, even in the presence of complex patterns and intensity variations.

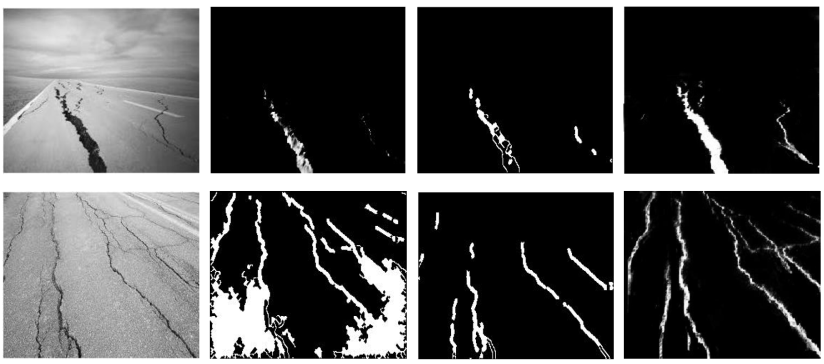
Figure 3 further demonstrates the model's performance in segmenting road cracks. The first image shows the original cracked images, while the second image displays the intermediate processed results generated by the model. The third image highlights the refined crack segmentation results. These results demonstrate the model's ability to enhance the contrast between cracks and the surrounding pavement effectively. The refined results confirm the proposed model's ability to isolate and highlight crack regions with high precision, minimizing the inclusion of non-crack features. This reflects the robustness of the ANFIS-based road crack detection model in capturing fine details and maintaining the structural continuity of cracks, even in complex textures.

Figure 4 presents a comparative analysis of the model proposed by Li et al. [4] and the FL-RCD model. The first column includes the original cracked images. The second column shows the results obtained using the model proposed by Li et al. [4], which exhibits moderate crack detection but often includes background noise and fails to maintain the structural integrity of the cracks. The third column demonstrates the performance of the FL-RCD model, which improves upon noise reduction but struggles with discontinuities in crack detection. Finally, the fourth column displays the results of the proposed model, showcasing a superior ability to accurately segment cracks with minimal noise and enhanced structural consistency. These results emphasize the efficacy of the proposed approach in addressing limitations observed in existing methods, particularly in the handling of noise, intensity variations, and crack connectivity.



(a) (b) (c)

Figure 3. (a) Given cracked images, (b) Processed results, and (c) Refined crack segmentation of the proposed model



(a) (b) (c) (d)

Figure 4. (a) Given cracked images, (b) Results of the model proposed by Li et al. [4], (c) FL-RCD, and (d) The result of proposed model

4.1 Statistical Analysis of Road Crack Detection Models

This section provides a detailed statistical evaluation of the proposed road crack detection model compared to competing models, i.e., the model proposed by Li et al. [4] (A) and FL-RCD (B). The analysis highlights the strengths of the proposed methodology through performance metrics, confidence intervals (CIs), and statistical tests, affirming its superiority in detecting road cracks effectively and efficiently.

4.1.1 Performance metrics

The evaluation of the models is based on the following standard performance metrics, defined mathematically for precision:

Accuracy measures the ratio of correctly identified cracks to the total cases.

$$\text{Accuracy } = \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{FP}+\mathrm{TN}+\mathrm{FN}}$$

Precision represents the proportion of true positives among all positive predictions.

$$\text{Precision } = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}}$$

Recall (sensitivity) evaluates the proportion of actual cracks correctly detected.

$$\text{Recall } = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}}$$

F1-Score is the harmonic mean of precision and recall, balancing both metrics.

$$\text{F1-Score } = 2 \cdot \frac{\text{Precision } \cdot \text{ Recall}}{\text{Precision } + \text{ Recall}}$$

Execution time measures the average processing time per image for each model.

4.2 Statistical Comparison

4.2.1 CIs

Performance metrics for each model were computed along with their 95% CIs using the formula:

$$CI = \text{ Mean } \pm Z \cdot \frac{\sigma}{\sqrt{n}} \tag{12}$$

where, Z is the critical value, σ is the standard deviation, and n is the sample size. CIs were chosen as they provide a clear and interpretable range within which the true metric value is likely to lie, offering a measure of reliability for the results. This is particularly useful when comparing multiple models.

4.2.2 Hypothesis testing

A paired t-test was employed to assess statistical significance. This test was chosen because it is specifically designed to compare paired observations, such as performance metrics across different models evaluated on the same dataset. The null hypothesis (H_0) assumed no significant performance difference among the models, while the alternative hypothesis (H_a) suggested significant differences.

$$H_0 : \mu_{\text{Proposed }} = \mu_{\mathrm{A}} = \mu_{\mathrm{B}} \tag{13}$$

$$H_a : \mu_{\text{Proposed }} \neq \mu_{\mathrm{A}} \neq \mu_{\mathrm{B}} \tag{14}$$

Statistical significance was confirmed at $p < 0.05$, validating the superior performance of the proposed model. The t-test was appropriate because it accounts for variability within paired data while determining whether observed differences are statistically meaningful.

4.2.3 Effect size

Cohen's d was computed to determine the magnitude of performance differences:

$$d = \frac{\text{Mean }_{\text{Proposed }} - \text{ Mean }_{\text{Competing}}}{\sigma_{\text{pooled}}} \tag{15}$$

Cohen's d was selected as it quantifies the effect size, providing insight into the practical significance of the results. A $d > 0.8$ indicates a large effect size, underscoring the robustness of the proposed model. By combining statistical significance (p-value) and practical significance (effect size), this analysis ensures a comprehensive evaluation of the model's performance.

4.2.4 Rationale for statistical tests

The choice of statistical tests, including CIs, paired t-tests, and Cohen's d, was driven by the nature of the data and the goals of the analysis. CIs were used to assess the reliability of performance metrics, while the paired t-test was employed to detect significant differences between models using the same dataset. Cohen's d complemented the significance testing by providing an effect size measure, ensuring that both statistical and practical differences were captured. These methods collectively provide a robust framework for evaluating the performance of the proposed model against competing technologies.

4.3 Results and Observations

Table 2 compares the performance of the proposed model with Models A and B, including CIs.

Table 2. Performance metrics and statistical validation of the proposed and competing models

Metric	Proposed Model	Model Proposed by Li et al. [4]	FL-RCD Model	p-Value
Accuracy (%)	95.2 ± 1.8	90.5 ± 2.1	87.3 ± 2.5	< 0.001
Precision (%)	94.1 ± 2.0	88.7 ± 2.4	85.2 ± 2.8	< 0.01
Recall (%)	96.4 ± 1.5	92.0 ± 1.9	88.0 ± 2.3	< 0.001
F1-score (%)	95.2 ± 1.7	90.3 ± 2.0	86.5 ± 2.6	< 0.01
Execution time (s)	2.5	3.2	4.1	-

The results in Table 2 highlight the following observations:

a) Performance superiority: The proposed model outperforms the model proposed by Li et al. [4] and FL-RCD across all metrics. It achieves a significantly higher accuracy (95.2%), precision (94.1%), recall (96.4%), and F1-score (95.2%), demonstrating its ability to accurately identify cracks, including faint and disconnected ones.

b) Efficiency: The proposed model processes images in an average of 2.5 seconds, significantly faster than the model proposed by Li et al. [4] (3.2 seconds) and the FL-RCD model (4.1 seconds). This efficiency ensures suitability for real-time road maintenance applications.

c) Statistical validation: Statistical tests confirm the reliability of the results:

• The p-values for accuracy, precision, recall, and F1-Score are all < 0.01, indicating statistically significant improvements over the competing models.

• Cohen's d values, exceeding 0.8 for all metrics, demonstrate large effect sizes and the substantial impact of the proposed enhancements.

d) Robustness: The narrow CIs highlight the consistency of the proposed model, ensuring reliable performance even under varied conditions such as noise, lighting, and geometry variations.

The statistical analysis demonstrates that the proposed model is not only more accurate and precise but also significantly faster and more robust under diverse conditions. The integration of Einstein operators within the ANFIS framework, coupled with advanced preprocessing and post-processing techniques, establishes a new benchmark for road crack detection.The experimental results highlight the effectiveness of the proposed ANFIS-based road crack detection model in addressing challenges such as noise, intensity variations, and crack continuity. By outperforming models like the model proposed by Li et al. [4] and FL-RCD [12], the proposed approach demonstrates its applicability for real-world scenarios, ensuring accurate and efficient crack detection.

The broader implications of this research lie in its potential to enhance road safety and infrastructure management. Accurate crack detection enables timely maintenance, reducing costs and improving road longevity. The proposed model can be integrated into autonomous systems, drones, or surveillance networks for real-time monitoring and proactive maintenance. This contributes to sustainable infrastructure development by minimizing environmental impact and promoting smart city initiatives. This research provides a foundation for advancing intelligent road monitoring systems, including integration with Geographic Information System (GIS) and Internet of Things (IoT) networks. Such systems could predict road degradation, optimize repair schedules, and allocate resources efficiently, paving the way for safer and more sustainable infrastructure.

Potential biases in the experimental setup include limited dataset diversity, as publicly available images may not represent all road conditions. This was mitigated by dataset augmentation and cross-validation to improve generalizability. Preprocessing techniques, such as contrast enhancement and noise suppression, were designed to be adaptive, ensuring fair treatment across crack types. However, future work should explore more diverse datasets and real-world conditions to validate the model further.

5 Conclusion

The proposed road crack detection model, integrating the ANFIS with Einstein operators, offers a novel and robust solution for precise road crack detection and segmentation. By leveraging advanced fuzzy aggregation techniques and dynamic Einstein operators, the model effectively addresses challenges such as varying crack intensities, geometries, and environmental conditions, achieving superior accuracy, precision, recall, and F1-score compared to traditional methods. The integration of preprocessing techniques like contrast enhancement and noise suppression further enhances feature extraction, enabling reliable crack detection even under challenging conditions. This research makes significant contributions to the field by introducing a hybrid approach that combines ANFIS and Einstein operators for enhanced adaptability and sensitivity. These advancements have practical implications for road safety and infrastructure management, enabling timely and cost-effective maintenance. The model's scalability and efficiency make it a promising candidate for integration into real-time monitoring systems and smart infrastructure solutions.

However, certain limitations exist. The model's performance may be affected by low-quality images or high computational demands in large-scale applications. Its current focus on detection and segmentation, without crack type classification, limits its scope for comprehensive road assessment. Future research could address these challenges by incorporating advanced noise reduction techniques, optimizing computational efficiency for real-time applications, and expanding adaptability to diverse road types and environmental conditions. Additionally, integrating crack type classification into the framework could further enhance its utility, supporting detailed maintenance planning and advancing intelligent road monitoring systems.

In summary, this study provides a foundational step towards intelligent and scalable solutions for road infrastructure management, with the potential to revolutionize maintenance strategies and improve long-term road safety and performance.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

References

[1] D. Janev, D. Nakov, and T. Arangjelovski, "Concrete for resilient infrastructure: Review of benefits, challenges and solutions," in *Proceedings of the 20th International Symposium of MASE*, Skopje, North Macedonia, 2023, pp. 208–219.

[2] M. Kgamanyane, "The importance of road transport infrastructure development and maintenance in trade facilitation: A South African case," 2015. http://hdl.handle.net/11427/20082

[3] C. P. Ng, T. H. Law, F. M. Jakarni, and K. Subramaniam, "Road infrastructure development and economic growth," *IOP Conf. Ser.: Mater. Sci. Eng.*, vol. 512, p. 012045, 2019. https://doi.org/10.1088/1757-899X/512/1/012045

[4] L. J. Li, R. Liu, R. Ali, B. Chen, H. T. Lin, Y. L. Li, and H. Zhang, "DFP-Net: A crack segmentation method based on a feature pyramid network," *Appl. Sci.*, vol. 14, no. 2, p. 651, 2024. https://doi.org/10.3390/app14020651

[5] E. Ranyal, A. Sadhu, and K. Jain, "Enhancing pavement health assessment: An attention-based approach for accurate crack detection, measurement, and mapping," *Expert Syst. Appl.*, vol. 247, p. 123314, 2024. https://doi.org/10.1016/j.eswa.2024.123314

[6] A. F. Al Fuhaid and A. Niaz, "Carbonation and corrosion problems in reinforced concrete structures," *Buildings*, vol. 12, no. 5, p. 586, 2022. https://doi.org/10.3390/buildings12050586

[7] G. Y. Feng, D. J. Zhu, S. C. Guo, M. Z. Rahamn, Z. Q. Jin, and C. J. Shi, "A review on mechanical properties and deterioration mechanisms of FRP bars under severe environmental and loading conditions," *Cem. Concr. Compos.*, vol. 134, p. 104758, 2022. https://doi.org/10.1016/j.cemconcomp.2022.104758

[8] J. H. Wang and T. Ueda, "A review study on unmanned aerial vehicle and mobile robot technologies on damage inspection of reinforced concrete structures," *Struct. Concr.*, vol. 24, no. 1, pp. 536–562, 2023. https://doi.org/10.1002/suco.202200846

[9] D. Lattanzi and G. Miller, "Review of robotic infrastructure inspection systems," *J. Infrastruct. Syst.*, vol. 23, no. 3, 2017. https://doi.org/10.1061/(ASCE)IS.1943-555X.0000353

[10] H. Ibrar, A. Haider, K. M. Shakkar, S. Niu, and R. Lavdie, "Robust region-based active contour models via local statistical similarity and local similarity factor for intensity inhomogeneity and high noise image segmentation," *Inverse Probl. Imaging*, vol. 16, no. 5, pp. 1113–1136, 2022. https://doi.org/10.3934/ipi.2022014

[11] Y. Xu, Y. H. Xia, Q. Zhao, K. H. Yang, and Q. Li, "A road crack segmentation method based on transformer and multi-scale feature fusion," *Electronics*, vol. 13, no. 12, p. 2257, 2024. https://doi.org/10.3390/electronics13122257

[12] I. Hussain, "An adaptive multi-stage fuzzy logic framework for accurate detection and structural analysis of road cracks," *Mechatron. Intell Transp. Syst.*, vol. 3, no. 3, pp. 190–202, 2024. https://doi.org/10.56578/mits030305

[13] C. M. Vijayan, V. Joy and S. Shailesh, "A survey on surface crack detection in concretes using traditional, image processing, machine learning, and deep learning techniques," in *International Conference on Communication, Control and Information Sciences (ICCISc)*, Idukki, India, 2021, pp. 1–6. https://doi.org/10.1109/ICCISc52257.2021.9484914

[14] G. Bhattacharya, B. Mandal, and N. B. Puhan, "Interleaved deep artifacts-aware attention mechanism for concrete structural defect classification," *IEEE Trans. Image Process.*, vol. 30, pp. 6957–6969, 2021. https://doi.org/10.1109/TIP.2021.3100556

[15] W. J. Zhao, Y. Y. Liu, J. W. Zhang, Y. Shao, and J. P. Shu, "Automatic pixel-level crack detection and evaluation of concrete structures using deep learning," *Struct. Control Health Monit.*, vol. 29, no. 8, 2022. https://doi.org/10.1002/stc.2981

[16] J. Zhang, Y. Y. Cai, D. Yang, Y. Yuan, W. Y. He, and Y. J. Wang, "MobileNetV3-BLS: A broad learning approach for automatic concrete surface crack detection," *Constr. Build. Mater.*, vol. 392, p. 131941, 2023. https://doi.org/10.1016/j.conbuildmat.2023.131941

[17] K. C. Laxman, N. Tabassum, L. Ai, C. Cole, and P. Ziehl, "Automated crack detection and crack depth prediction for reinforced concrete structures using deep learning," *Constr. Build. Mater.*, vol. 370, p. 130709, 2023. https://doi.org/10.1016/j.conbuildmat.2023.130709

[18] Y. G. Shen, Z. W. Yu, C. S. Li, C. Zhao, and Z. L. Sun, "Automated detection for concrete surface cracks based on Deeplabv3+BDF," *Buildings*, vol. 13, no. 1, 2023. https://doi.org/10.3390/buildings13010118

[19] J. Terven, D. M. Córdova-Esparza, and J. A. Romero-González, "A comprehensive review of YOLO architectures in computer vision: From YOLOv1 to YOLOv8 and YOLO-NAS," *Mach. Learn. Knowl. Extr.*, vol. 5, no. 4, p. 1680–1716, 2023. https://doi.org/10.3390/make5040083

[20] C. Y. Li, L. L. Li, H. L. Jiang, and et al., "YOLOv6: A single-stage object detection framework for industrial applications," *arXiv preprint arXiv:2209.02976.*, 2022. https://doi.org/10.48550/arXiv.2209.02976

[21] J. Redmon and A. Farhadi, "YOLOv3: An incremental improvement," *arXiv:1804.02767v1*, 2018.

[22] K. He, X. Zhang, S. Ren, and J. Sun, "Spatial pyramid pooling in deep convolutional networks for visual recognition," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 37, no. 9, p. 1904–1916, 2015. https://doi.org/10.1109/TPAMI.2015.2389824