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Prediction of Road Safety Risks through Crack Detection and Structural Deterioration Assessment

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Abstract: Road surface cracks are a major contributor to vehicular accidents, particularly in high-speed and high-traffic environments. Conventional crack detection techniques that rely on grayscale imaging often fail to maintain accuracy under varying lighting conditions and in the presence of noise. To address these challenges, a robust detection methodology is proposed, based on a Gradient-based Crack Enhancement, Color Consistency, and Smoothness Regularization Model (GCSM). This model leverages Gaussian smoothing to reduce noise, gradient-based enhancement to accentuate crack features, and color consistency to effectively differentiate cracks from surrounding textures. Smoothness regularization ensures the continuity of crack patterns and minimizes false positives, enhancing the accuracy of detection. The resulting crack maps form the foundation for advanced risk analysis, directly linking crack detection to safety evaluation. The integration of crack detection with accident prediction is achieved by a hybrid model that estimates the likelihood of accidents induced by road surface deterioration. This hybrid model combines logistic regression to assess variables such as crack density, width, traffic volume, vehicle speed, and pavement condition, with a fuzzy inference system (FIS) to handle the imprecision inherent in road condition assessments. The final accident risk score is computed as a weighted combination of these components, offering enhanced prediction accuracy. Experimental results on datasets from Peshawar, Khyber Pakhtunkhwa, demonstrate that GCSM outperforms existing methods in terms of Intersection over Union (IoU), Precision, Recall, and Structural Similarity Index Measure (SSIM), with statistical significance ($p < 0.01$) confirmed via ANOVA. The hybrid prediction model achieves an accuracy of 88.23% and a mean squared error (MSE) of 0.042, highlighting its efficiency and robustness. This framework facilitates automated crack visualization and accident risk classification, providing valuable insights for engineers and urban planners. Future work will focus on real-time deployment and system adaptability to various road conditions, supporting intelligent transportation systems and proactive road safety management.

Keywords: Image segmentation; Road crack detection; Gradient-based enhancement; Color consistency; Smoothness regularization; Automated pavement inspection

1 Introduction

Detecting cracks on road surfaces is crucial for timely maintenance and ensuring road safety. Various data-driven methodologies, such as statistical analysis, spatial assessments, and regulatory measures, have been employed to enhance traffic safety. Predictive models play a significant role in identifying accident-prone locations, understanding contributing factors, and implementing preventive strategies. Additionally, sustainable safety initiatives focus on long-term infrastructure planning and risk mitigation to lower the rate of traffic-related fatalities and injuries. The integration of these strategies enables a proactive and comprehensive approach to managing road hazards [1–4].

Maintaining well-structured road networks is essential, as surface deterioration can lead to unsafe driving conditions, vehicle damage, and increased repair costs. Detecting road cracks at an early stage is vital for infrastructure preservation and accident prevention. Manual inspection methods, while traditional, are often time-consuming and inefficient, necessitating the adoption of automated approaches. Recent advancements in road crack detection incorporate deep learning, computer vision, and remote sensing techniques, significantly improving accuracy and efficiency [5–7]. Modern detection frame- works leverage adaptive classification, hybrid methodologies, and machine learning algorithms [8, 9] to enhance performance. Adaptive systems first categorize pavement types before applying specialized detection techniques, ensuring robustness across diverse road surfaces. Hybrid models combine edge detection with region-based segmentation for improved precision, while deep learning-based classifiers enable automated and highly accurate crack identification. These technological advancements facilitate efficient road maintenance by reducing reliance on manual inspections and ensuring timely interventions [10–12].

Recent advancements in road crack detection have leveraged deep convolutional neural networks (CNNs), enhanced YOLO-based architectures, and UAV-assisted imaging systems to improve crack identification and classification under diverse road conditions and environmental settings [13–16]. These approaches utilize high-resolution image processing, sophisticated edge detection techniques, and advanced feature extraction methods to enhance the robustness of detection models. Challenges such as image noise, variations in lighting, and inconsistencies in pavement surfaces are addressed by integrating hybrid models that blend traditional image processing with artificial intelligence-based learning techniques. This fusion has significantly improved detection accuracy while minimizing computational overhead. The continuous refinement of these methodologies has led to more effective road maintenance strategies, enabling timely repairs, reducing infrastructure costs, and promoting overall road safety.

Detecting cracks in road surfaces presents various challenges, including fluctuating lighting conditions, differences in pavement textures, and environmental interference, all of which can contribute to false positives, misclassifications, and reduced reliability in practical applications. Conventional detection methods often struggle with these complexities, leading researchers to explore more advanced and adaptable techniques. One such approach involves fuzzy C-means clustering, which enhances crack segmentation by refining edge features and differentiating cracks from background noise. This method has demonstrated superior performance compared to conventional thresholding techniques by improving crack localization and minimizing false detections [17]. However, its effectiveness is influenced by pre-defined membership functions and sensitivity to parameter tuning, which can limit its adaptability to diverse datasets with varying crack patterns.

To address these limitations, Ashraf et al. [18] introduced a road pavement crack detection model utilizing multi-scale feature aggregation and transformer-based attention mechanisms (MFA-TAM). Their approach effectively captures fine-grained crack patterns across varying scales, enhancing the accuracy of detection and segmentation. However, the reliance on deep learning models presents certain limitations, particularly concerning computational efficiency and model interpretability. Transformer-based architectures demand substantial computational power, making them less feasible for real-time applications on edge devices or in low-resource environments. Additionally, the model's performance is heavily reliant on the quality and diversity of the training data. Road pavement surfaces exhibit significant variations due to lighting conditions, material properties, and environmental factors, which may lead to inconsistent performance in real-world deployment. Furthermore, deep learning methods often function as black-box models, making it challenging to interpret the decision-making process, which is critical for practical infrastructure maintenance applications.

Das et al. [19] proposed a fuzzy logic-based crack detection (FLBCD) method for cantilever-laminated composite beams, leveraging frequency response analysis. While this approach benefits from the interpretability and adaptability of fuzzy logic, it may not be directly applicable to complex road pavement surfaces, which exhibit more intricate and non-uniform crack patterns. The use of frequency response as a primary detection metric may not effectively generalize to irregular cracks or variable pavement compositions. Moreover, the model's reliance on predefined fuzzy rules and membership functions limits its adaptability to diverse road conditions without extensive tuning. Unlike deep learning models that can learn features automatically, fuzzy logic-based methods require expert-defined rules, which can introduce subjectivity and affect detection accuracy. Additionally, integrating fuzzy logic with spatially aware image-processing techniques could enhance its effectiveness in road crack detection, making it a viable alternative to deep learning-based approaches while maintaining interpretability. Another emerging technique involves the integration of multi-criteria decision-making (MCDM) frameworks to optimize road maintenance strategies by evaluating multiple factors contributing to pavement degradation. This approach considers elements such as crack severity, traffic load, and environmental impact to prioritize repair work efficiently [20]. However, MCDM's effectiveness depends heavily on selecting appropriate criteria and assigning accurate weightings, which may introduce subjectivity and require expert analysis to ensure reliable decision-making.

Despite significant advancements in road crack detection, existing models still face critical limitations. Deep learning-based approaches, such as CNNs and transformer-based architectures, require extensive labeled datasets and high computational resources, making real-time deployment challenging. Additionally, conventional clustering methods, including fuzzy C-means, struggle with parameter sensitivity and are less effective in distinguishing micro-cracks from complex pavement textures. Hybrid techniques that integrate traditional image processing with artificial intelligence improve accuracy but often introduce computational overhead, limiting their scalability for large-scale road inspections. These challenges highlight the need for a more adaptable, efficient, and robust segmentation model.

To address the confusion between the two main components, we first clarify that this study comprises two interconnected yet distinct modules: (1) an accident risk prediction model that estimates the probability of accidents based on road surface conditions and traffic parameters, and (2) a road crack detection model that provides the structural input required for accurate risk estimation.

The proposed framework begins by analyzing road surface cracks using an advanced detection model, the Gradient and Color-based Smoothness Model (GCSM). The output of this model—quantified crack severity and density—serves as an input feature for the subsequent accident risk prediction model.

1) Accident Risk Prediction Model: A novel hybrid framework is developed to estimate the probability of road accidents influenced by surface cracks, lighting conditions, and traffic parameters. This hybrid model integrates logistic regression with an FIS, where the regression component captures statistical relationships, and the FIS models uncertainty using linguistic rules. The approach enables adaptive prediction even under incomplete or imprecise data conditions.

2) Road Crack Detection Model (GCSM): The proposed road crack detection model integrates gradient-based crack enhancement, color-based regional consistency, and smoothness regularization into a unified energy functional. The process begins with Gaussian smoothing applied separately to each color channel to reduce noise while preserving edge details. Crack boundaries are enhanced using RGB gradient magnitude, while an edge-preserving exponential function suppresses non-crack features. Additionally, a color-based regional consistency term differentiates cracks from road textures, and Laplacian-based smoothness regularization ensures continuity. The resulting energy functional optimally combines these components, improving segmentation accuracy and robustness.

Novelty and Key Contributions

The novelty and key contributions of the proposed accident risk prediction and road crack detection framework are as follows:

• **Hybrid Accident Risk Prediction Model**: A novel framework combining logistic regression and fuzzy inference to estimate accident probability due to road surface degradation. This model integrates both statistical patterns and expert-defined fuzzy rules, effectively handling uncertainty in traffic and environmental parameters.

• **RGB-Based Gradient Enhancement**: Unlike traditional grayscale methods, the GCSM utilizes RGB gradient information to enhance crack boundaries while preserving color variations, ensuring robustness under varying illumination and pavement textures.

• **Edge-Preserving Exponential Function**: A novel edge-suppression function refines crack detection by minimizing the influence of non-crack high-gradient features such as lane markings, shadows, and surface roughness.

• **Color-Based Regional Consistency**: The model incorporates a regional consistency measure that differentiates cracks from surrounding textures by analyzing local intensity variations, reducing false positives and improving segmentation accuracy.

• **Smoothness Regularization**: A Laplacian-based smoothness constraint maintains structural continuity, preventing crack fragmentation and ensuring coherent segmentation of detected cracks.

• **Unified Energy Functional**: Integration of gradient-based enhancement, color-based consistency, and smoothness regularization into a single energy formulation enables robust crack detection, adaptable to diverse road conditions.

• **Real-World Validation**: The framework is validated using real-world data from Peshawar, Khyber Pakhtunkhwa, incorporating image-based crack analysis, traffic parameters, and historical accident records, confirming its effectiveness in both detection and risk estimation tasks.

2 Proposed Methodology

Our approach consists of four key steps: preprocessing with Gaussian smoothing, gradient-based crack enhancement, color-based regional consistency enforcement, and smoothness regularization. Each of these steps is carefully designed to address specific challenges in crack detection, including noise suppression, edge preservation, and maintaining structural continuity. The integration of these components into a unified energy minimization framework ensures a robust and reliable method for crack segmentation. All the parameters and symbols used in the proposed model are listed in Table 1.

2.1 Preprocessing with Gaussian Smoothing

To eliminate noise while preserving essential crack edges, Gaussian smoothing is applied separately to each color channel. The smoothed image for each channel c (where $c \in \{R, G, B\}$) is computed as:

$$I_s^{(c)}(x, y) = I^{(c)}(x, y) * G_\sigma(x, y), \tag{1}$$

where, $G_\sigma(x, y)$ is the Gaussian kernel defined as:

$$G_\sigma(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{2}$$

The Gaussian kernel smooths the image by reducing high-frequency noise while preserving significant structural details. Since road surfaces often have texture variations and small imperfections, applying Gaussian smoothing helps suppress unwanted artifacts that could interfere with crack detection. Additionally, the separate processing of each RGB channel ensures that fine details in different color bands are preserved, which is particularly important for detecting cracks in roads with varying pavement colors and illumination conditions. By controlling the parameter σ, we can balance the level of smoothing applied to the image, ensuring that cracks remain detectable without excessive blurring.

Table 1. List of symbols, parameters, and their meanings in the proposed model

Symbol	Parameter Name	Meaning
$G_\sigma(x, y)$	Gaussian Kernel	Kernel used for noise reduction in preprocessing
∇I_{RGB}	RGB Gradient Magnitude	Edge response from all three color channels
λ	Edge Suppression Parameter	Controls the strength of edge suppression
I_m	Local Mean Intensity	Average intensity of a local region Ω
$F_g(I, C)$	Gradient-Based Enhancement	Function enhancing crack edges
$F_r(I, C)$	Regional Consistency Function	Measures deviation from local mean color intensity
$F_s(C)$	Smoothness Regularization	Ensures continuity of detected crack structures
$\nabla^2 C$	Laplacian Operator	Measures the second-order derivative for smoothness
$E(C)$	Energy Functional	Total energy integrating all components

2.2 Gradient-Based Crack Enhancement

Cracks typically exhibit high contrast against the road surface, making gradient-based enhancement essential. The RGB gradient magnitude is computed as:

$$\nabla I_{RGB} = \sqrt{(\nabla I_R)^2 + (\nabla I_G)^2 + (\nabla I_B)^2}. \tag{3}$$

This equation combines the gradients of the red, green, and blue channels to form a comprehensive edge response. Since cracks often appear as thin, elongated structures with significant contrast differences, computing the RGB gradient helps in detecting these structures while minimizing false detections from non-crack features. Unlike grayscale-based methods that rely on a single intensity gradient, our RGB gradient approach ensures that color variations are accounted for, which improves the robustness of crack detection under varying lighting conditions and surface textures.

However, to further enhance crack boundaries while suppressing weaker edges, we introduce an edge-preserving exponential function:

$$F_g(I, C) = |\nabla I_{RGB}| \, e^{-\lambda|\nabla C|}, \tag{4}$$

where, λ is a tuning parameter controlling edge strength suppression. This function reduces the influence of non-crack edges, focusing detection on crack-specific structures. Since road surfaces often contain other high-gradient regions such as lane markings, shadows, or surface roughness, the exponential term $e^{-\lambda|\nabla C|}$ ensures that only the most prominent crack features are preserved while reducing interference from irrelevant details. By carefully selecting λ, we can adapt the model to different road conditions, ensuring optimal crack segmentation.

2.3 Color-Based Regional Consistency Enforcement

Cracks often exhibit distinct intensity differences compared to their local surroundings. To measure the deviation from local mean color intensity, we define the regional consistency function:

$$F_r(I, C) = \frac{|I_{RGB} - I_m|}{1 + |I_{RGB} - I_m|} \tag{5}$$

where, I_m is the local mean color intensity, calculated as:

$$I_m = \frac{1}{N} \sum_{(x', y') \in \Omega} I_{RGB}(x', y') \tag{6}$$

This formulation normalizes intensity variations and ensures that regions with minimal contrast changes are suppressed, improving the segmentation of crack-like patterns. By incorporating local color information, we can differentiate cracks from road textures and environmental noise. The denominator $1 + |I_{RGB} - I_m|$ Im ensures stability in the computation and prevents division by zero errors, making the function robust to varying lighting conditions and color variations on the road surface.

2.4 Smoothness Regularization

To maintain crack structure continuity and prevent fragmented detections, smoothness regularization is introduced using the Laplacian operator:

$$F_s(C) = \left(\nabla^2 C - \frac{\partial C}{\partial n}\right)^2 \tag{7}$$

where, the Laplacian is defined as:

$$\nabla^2 C = \frac{\partial^2 C}{\partial x^2} + \frac{\partial^2 C}{\partial y^2} \tag{8}$$

This regularization ensures that detected cracks maintain continuity and do not appear overly fragmented or noisy. Since real-world cracks often exhibit a continuous structure rather than isolated pixel clusters, enforcing smoothness ensures that detected cracks retain their natural shape. The term $\frac{\partial C}{\partial n}$ counts for boundary smoothness, preventing abrupt changes that may arise due to noise or discontinuities in the detection process.

2.5 Proposed Energy Functional

The proposed energy functional integrates gradient-based crack enhancement, color-based regional consistency, and smoothness regularization. Each component is controlled by a weighting coefficient to balance its relative contribution to the overall energy. It is formulated as follows:

$$E(C) = \int_\Omega \left(\alpha \left|\nabla I_{RGB}\right| e^{-\lambda|\nabla C|} + \beta \frac{|I_{RGB} - I_m|}{1 + |I_{RGB} - I_m|} + \gamma \left(\nabla^2 C - \frac{\partial C}{\partial n}\right)^2\right) d\Omega \tag{9}$$

Here, α, β, and γ are weighting coefficients that regulate the influence of each term. Specifically, α controls the strength of the gradient-based crack enhancement, ensuring that significant edge structures are emphasized while suppressing weaker gradients. β adjusts the contribution of the color consistency term, maintaining regional homogeneity across RGB channels under varying illumination. γ governs the smoothness regularization, promoting structural continuity of cracks and suppressing spurious noise.

To achieve optimal balance among these components, the coefficients were empirically tuned through cross-validation, with final values set to α = 0.5, β = 0.3, and γ = 0.2, which yielded the best trade-off between crack continuity and false detection suppression.

In above equation, each term plays a crucial role in detecting and refining the segmentation of road cracks. The first term,

$$\left|\nabla I_{RGB}\right| e^{-\lambda|\nabla C|} \tag{10}$$

enhances crack boundaries by utilizing the gradient magnitude of the RGB image. The exponential factor $e^{-\lambda|\nabla C|}$ suppresses weak edges, allowing significant crack structures to be preserved while reducing noise interference. The parameter λ controls the attenuation of weak gradients, ensuring that only prominent cracks are emphasized. The second term,

$$\frac{|I_{RGB} - I_m|}{1 + |I_{RGB} - I_m|} \tag{11}$$

ensures segmentation consistency by penalizing large intensity differences between local regions. Here, I_m represents the mean color intensity of the local neighborhood. This formulation helps in distinguishing cracks from normal road textures by considering the intensity contrast and avoiding over-segmentation caused by small texture variations. The third term,

$$\left(\nabla^2 C - \frac{\partial C}{\partial n}\right)^2 \tag{12}$$

imposes a smoothness constraint on the detected cracks. The Laplacian $\nabla^2 C$ ensures continuity in crack structures, while the boundary condition prevents abrupt segmentation discontinuities. This term is essential for maintaining the coherence of detected cracks and minimizing the risk of fragmented detections.

3 Accident Risk Modeling Based on Road Surface Conditions

The proposed model aims to estimate the probability of road accidents caused by surface cracks using a hybrid approach that combines logistic regression with fuzzy inference. This integration allows for both precise statistical analysis and the handling of uncertainty and linguistic assessments inherent in road condition evaluation.

To establish the statistical foundation of the framework, we first describe the logistic regression component before introducing the complementary fuzzy module.

The input feature set consists of five variables: crack density (x_1), average crack width (x_2), vehicle speed (x_3), traffic volume (x_4), and pavement condition index (x_5). The output variable, y, represents the probability of an accident occurring due to road surface degradation. The logistic regression component provides a probabilistic foundation based on historical accident data and is defined as follows:

$$P(y=1) = \frac{1}{1 + \exp^{-(\beta_0+\beta_1 x_1+\beta_2 x_2+\beta_3 x_3+\beta_4 x_4+\beta_5 x_5)}}$$

here, β_0,..., β_5 are regression coefficients learned from empirical datasets comprising past accident records and corresponding road condition parameters.

While logistic regression captures data-driven statistical dependencies, it cannot effectively handle subjective or uncertain aspects of road safety. Therefore, we next introduce a fuzzy logic module to complement this limitation.

To complement this statistical prediction, a fuzzy logic module is incorporated to handle subjective and uncertain aspects of road safety, such as how severe a crack appears or how deteriorated the pavement condition feels. This module defines fuzzy sets for each input variable. For instance, crack density is categorized into fuzzy sets such as Low, $Medium$, and $High$, while crack width may be described as $Narrow$, $Moderate$, or $Wide$. Vehicle speed is linguistically represented as Low, $Moderate$, or $High$, and the pavement condition index is labeled as $Poor$, $Fair$, or $Good$.

Once both modules are formulated, their outputs are integrated to yield a single interpretable accident risk measure.

The FIS uses a set of expert-defined rules. For example, a rule might state: "IF crack density is High AND crack width is Wide AND speed is High THEN risk is Very High." Another rule might specify: "IF crack density is Low AND pavement condition is Good THEN risk is Low." Based on these rules, the system computes a fuzzy risk score R_f in the interval [0, 1], which is then defuzzified using the centroid or weighted average method to produce a crisp value.

The final accident risk score, denoted as R, is obtained by linearly combining the outputs of the logistic and fuzzy modules:

$$R = \alpha \cdot R_f + (1-\alpha) \cdot P(y=1) \tag{13}$$

Here, the parameter α [0, 1] controls the influence of the fuzzy system relative to the logistic regression model. A higher α gives more weight to the fuzzy-based interpretation, while a lower α emphasizes the statistical evidence.

This combined formulation provides a natural balance between quantitative data and qualitative expert knowledge, paving the way for a practical, real-world accident prediction framework.

This hybrid model benefits from the interpretability and domain knowledge embedded in fuzzy logic while retaining the rigorous predictive capability of logistic regression. It is particularly suitable for real-world deployment in intelligent transportation systems, where both empirical data and heuristic assessments contribute to decision-making.

To ensure the methodological integrity of the approach, the following subsection details the dataset, training protocol, and validation process used in developing the hybrid model.

To ensure the reproducibility and fairness of model training, a dataset comprising 2,500 labeled samples was used, collected from various road segments within Peshawar city. The dataset was divided into training (70%), validation (15%), and testing (15%) subsets to evaluate model generalization. A 5-fold cross-validation procedure was implemented to fine-tune the logistic coefficients and the fuzzy membership parameters. This process minimized overfitting and improved the robustness of the hybrid model across diverse traffic and surface conditions.

3.1 Risk Categorization

After computing the continuous accident risk score, it is essential to interpret these results in a way that supports actionable decision-making.

To translate the continuous accident risk score R into actionable safety classifications, we define discrete risk categories. These categories assist transportation authorities, engineers, and decision-makers in interpreting the model's output and implementing appropriate mitigation strategies. The risk score R, computed from the fuzzy model Eq. (13), lies in the interval [0, 1], with higher values indicating a greater likelihood of accidents due to road surface cracks.

Based on domain knowledge and safety thresholds from road safety standards, we define three primary risk levels: Safe, Moderate Risk, and High Accident Risk. Table 2 provides a summary of these categories. **Safe** ($R <$ 0.3):

In this range, the road surface conditions and traffic parameters indicate minimal risk. Cracks are either minor or absent, the pavement condition is generally good, and vehicle speeds do not exacerbate the risk. Routine monitoring is sufficient, and no immediate intervention is required. **Moderate Risk** ($0.3 \leq R < 0.6$): This interval indicates a medium level of concern. Road cracks may be present at a moderate level, and vehicle speed or traffic volume may elevate the accident probability. Preventive maintenance, warning signs, or speed regulation may be considered to reduce potential hazards. **High Accident Risk** ($R \geq 0.6$): A score in this range signifies a dangerous situation where the combination of surface degradation, traffic intensity, and speed significantly increases the likelihood of accidents. Immediate remedial measures such as resurfacing, crack filling, speed reduction enforcement, or traffic rerouting are recommended to ensure road user safety. This categorization enables practical implementation of the model in real-world road safety systems by offering clear thresholds for response and policy actions. These categories provide a practical interface between the model's quantitative outputs and field-level safety interventions.

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Having defined the interpretation of the model's output, the next step involves validating its predictive performance using real-world data from Peshawar.

Table 2. Risk score interpretation

Risk Score R	**Interpretation**
$R < 0.3$	Safe
$0.3 \leq R < 0.6$	Moderate Risk
$R \geq 0.6$	High Accident Risk

3.2 Implementation and Validation

3.2.1 Data collection

To validate the proposed hybrid fuzzy-statistical model for predicting road accidents due to surface cracks, a dataset was compiled from real-world sources within Peshawar, a major urban center in the Khyber Pakhtunkhwa (KPK) province of Pakistan. The region presents a diverse range of traffic conditions, road surface qualities, and environmental influences, making it a suitable case study for model testing.

The dataset integrates visual, statistical, and historical data components, ensuring that both surface-level and contextual variables are represented.

The model's training and testing were performed on the same dataset under consistent preprocessing and feature normalization procedures. Validation was conducted using unseen test data to assess prediction accuracy and generalization performance, ensuring that results were statistically reliable and reproducible.

3.2.2 Model implementation

Following data preparation, the implementation phase involves model training, optimization, and hybrid integration.

The logistic regression model was trained on the collected dataset using the maximum likelihood estimation technique. Input variables were normalized before training to ensure stable convergence. A total of 2,500 samples were used, with a 70%-15%-15% train-validation-test split to ensure reliable generalization. A 5-fold cross-validation approach was employed to fine-tune the model parameters and assess consistency across different data partitions.

Once the statistical model was optimized, the fuzzy inference module was developed and integrated to generate the final hybrid predictions.

For the fuzzy logic module, fuzzy membership functions were manually defined using expert input from civil engineers and traffic safety officers. The FIS was implemented using MATLAB's Fuzzy Logic Toolbox, while the hybrid integration was coded using a custom MATLAB script that linearly combines the fuzzy and logistic outputs as:

$$R = \alpha \cdot R_f + (1 - \alpha) \cdot P(y = 1)$$

The weighting factor α was optimized through cross-validation, with the best performance achieved at $\alpha = 0.6$, providing an optimal balance between the statistical and fuzzy components. All experiments were conducted on the same hardware configuration (Intel i7 CPU, 8 GB RAM) to ensure consistency in computational results.

The next subsection presents the evaluation metrics used to assess the overall predictive strength and classification accuracy of the proposed model.

3.2.3 Evaluation metrics

To quantitatively assess the performance of the proposed hybrid model, we employed a set of widely accepted evaluation metrics that measure both classification quality and prediction accuracy. Validation was carried out using the held-out test subset to ensure unbiased performance estimation, and the results were averaged across all cross-validation folds.

Collectively, these quantitative metrics confirm the effectiveness of the proposed hybrid model and demonstrate its consistent performance across multiple testing folds, providing strong evidence of its reliability in real-world applications.

4 Experimental Setup

In this section, we evaluate the performance of the proposed model through extensive experiments conducted on road crack images under diverse environmental conditions. The implementation is carried out in MATLAB R2015a, leveraging its image processing and optimization capabilities. The dataset comprises real-world road images affected by varying levels of noise, illumination, and surface textures to ensure a comprehensive assessment of the model's robustness. The experiments are designed to analyze the effectiveness of each component, including Gaussian smoothing for noise suppression, gradient-based crack enhancement, color-based regional consistency enforcement, and smoothness regularization. Quantitative and qualitative evaluations are performed using standard image quality metrics. Additionally, comparative analysis with state-of-the-art crack detection methods FLBCD [19] and MFA-TAM [18] is conducted to demonstrate the superiority of the proposed approach in terms of accuracy, robustness, and computational efficiency.

The effectiveness of the proposed crack detection model depends on the careful selection of parameters that control various aspects of image preprocessing, feature extraction, and segmentation. The Gaussian smoothing parameter σ determines the degree of noise suppression while preserving crack edges; typical values range from 1.0 to 2.5, depending on the noise level in the input road images. The gradient-based enhancement term is regulated by the parameter λ, which controls the suppression of weaker edges; values between 0.3 and 0.8 ensure that cracks remain prominent while reducing false detections from road textures and shadows. The local mean color intensity Im is computed over a neighborhood Ω with a size typically set to 5×5 pixels to capture regional variations while preventing over-smoothing. The smoothness regularization component is influenced by the weighting of the Laplacian term, ensuring that detected cracks maintain structural continuity. The energy functional is minimized using an iterative gradient descent approach, ensuring convergence to an optimal segmentation of crack regions. During implementation, parameter tuning is performed through cross-validation on a dataset of road images with diverse lighting conditions, surface textures, and crack types.

To ensure reproducibility and optimal performance, parameter tuning for Gaussian smoothing (σ), gradient control (λ), and neighborhood size (Ω) was conducted using a five-fold cross-validation strategy on the training dataset. During each fold, the model's performance was evaluated using IoU, Precision, and SSIM as key metrics. The parameter values that achieved the highest average scores across all folds were selected as the final configuration. These optimized parameters were then applied uniformly across all test images to maintain consistency and ensure fair comparison.

Figure 1 illustrates the step-by-step process of crack detection using the proposed model. The first image (a) represents the original road surface image, which contains visible cracks along with various surface textures and noise. In (b), a 3D visualization of the crack intensity distribution is shown, where the elevation represents the intensity variations in the grayscale image. This visualization helps in understanding the prominence of cracks compared to the surrounding road surface. In (c), the crack region is enhanced by applying the proposed gradient-based crack enhancement and color-based regional consistency enforcement techniques. The red-highlighted regions indicate the detected crack areas, demonstrating the effectiveness of the model in isolating crack structures while suppressing non-crack regions. Finally, (d) presents the binarized segmentation output, where the cracks are distinctly extracted from the background. This result is obtained after applying smoothness regularization to maintain the continuity of crack structures while minimizing false detections. The overall process highlights the robustness of the proposed model in accurately detecting cracks under varying road surface conditions and illumination levels.

Figure 2 presents a comparative evaluation of crack detection performance across three rows, each representing a different type of road crack: alligator cracks, longitudinal cracks, and transverse cracks. Each row consists of four columns: the original crack image, detection results from competing FLBCD [19], detection results from competing MFA-TAM [18], and the final segmentation obtained from the proposed model.

The first row illustrates alligator cracks, which appear as interconnected patterns resembling reptile scales, typically caused by structural fatigue in asphalt pavements. While FLBCD [19] and MFA-TAM [18] capture portions of the cracks, their segmentations include false positives and miss fine details. The proposed model, however, accurately delineates the crack network while effectively suppressing background noise, leading to more precise detection.

The second row displays longitudinal cracks, which extend parallel to the direction of traffic due to material fatigue or poor construction joints. The FLBCD model struggles with detecting the full extent of the cracks, often missing finer segments, whereas MFA-TAM [18] introduces excessive noise. In contrast, the proposed model successfully preserves crack continuity while minimizing false detections, demonstrating its robustness in handling elongated cracks.

The third row showcases transverse cracks, which run perpendicular to the pavement direction and usually result from temperature fluctuations or inadequate pavement support. FLBCD [19] and MFA-TAM [18] fail to capture the cracks comprehensively, either under-segmenting or introducing background artifacts. The proposed model, however, effectively distinguishes the crack region with clear boundaries, ensuring improved segmentation accuracy.

Overall, the figure highlights the effectiveness of the proposed model in detecting diverse crack patterns compared to competing approaches. While Model A and Model B exhibit segmentation inconsistencies, the proposed method consistently provides superior detection with better structural integrity and reduced noise interference.

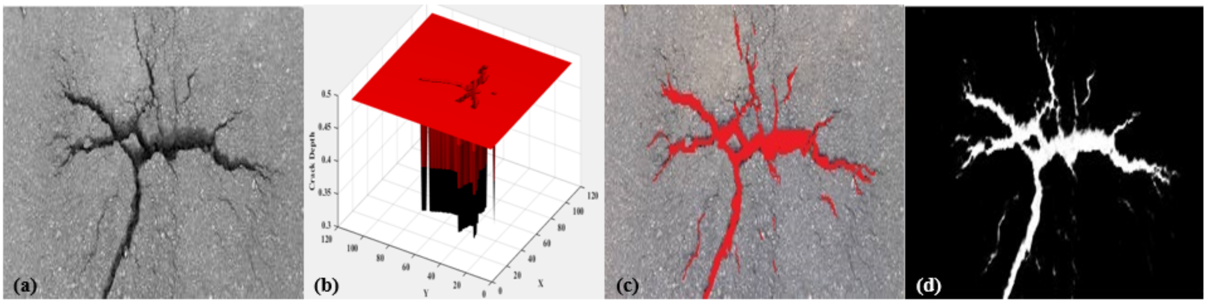

Figure 1. Illustration of the crack detection process using the proposed model: (a) Original road surface image; (b) 3D visualization of crack intensity distribution; (c) Crack region enhancement using gradient and color consistency enforcement; (d) Final binarized crack segmentation result

Figure 3 illustrates crack detection on asphalt roads under different lighting conditions, demonstrating the performance of FLBCD [19] and MFA-TAM [18], and the proposed model. The first row presents images of road cracks, followed by the corresponding detection outputs from the three models. Model FLBCD exhibits limitations in detecting fine crack structures, often failing to capture the full extent of the cracks. Model MFA-TAM improves upon this but still struggles with false positives, leading to over-segmentation in certain areas. The proposed model, however, effectively detects the cracks with greater accuracy, preserving the structural integrity of the cracks while minimizing unnecessary noise.

The second row showcases a similar analysis but with real-world asphalt road images under varying illumination. The detection outputs demonstrate how lighting conditions affect crack visibility. FLBCD and MFA-TAM struggle in certain regions due to contrast variations, leading to missed detections or excessive false positives. The proposed model, in contrast, maintains robust segmentation across different lighting intensities, accurately identifying the cracks while reducing misclassification. The results emphasize the effectiveness of the proposed model in handling complex road conditions, making it a more reliable approach for crack detection in real-world asphalt pavement scenarios.

4.1 Quantitative and Computational Performance Comparison of Road Crack Detection Models

Table 3 presents a quantitative and computational assessment of three road crack detection models: our proposed GCSM, MFA-TAM, and FLBCD. The comparison is based on several key performance metrics, including IoU, SSIM, Precision, Recall, ANOVA significance, processing speed, and memory usage. The results demonstrate the superiority of our GCSM model, making it the best-performing method across all evaluation criteria.

4.1.1 Quantitative performance metrics

- IoU: IoU measures the overlap between predicted cracks and ground truth annotations. Our GCSM model achieves 0.91 $\pm$ 0.02, significantly outperforming MFA-TAM (0.79 $\pm$ 0.03) and FLBCD (0.79 $\pm$ 0.04). A higher IoU indicates that GCSM provides more precise crack localization with minimal false detections.

- $SSIM$: SSIM evaluates the perceptual similarity between detected cracks and actual cracks. GCSM attains an SSIM of 0.92 $\pm$ 0.01, while MFA-TAM and FLBCD score 0.85 $\pm$ 0.02 and 0.81 $\pm$ 0.03, respectively. The superior SSIM score of GCSM confirms that it maintains better crack structure preservation without excessive distortions.

- $Precision$: Precision represents the accuracy of crack predictions by measuring the proportion of correctly identified cracks. Our proposed model achieves 0.91 $\pm$ 0.02, whereas MFA-TAM scores 0.82 $\pm$ 0.03 and FLBCD achieves 0.77 $\pm$ 0.04. A higher precision score indicates that GCSM effectively minimizes false positive detections.

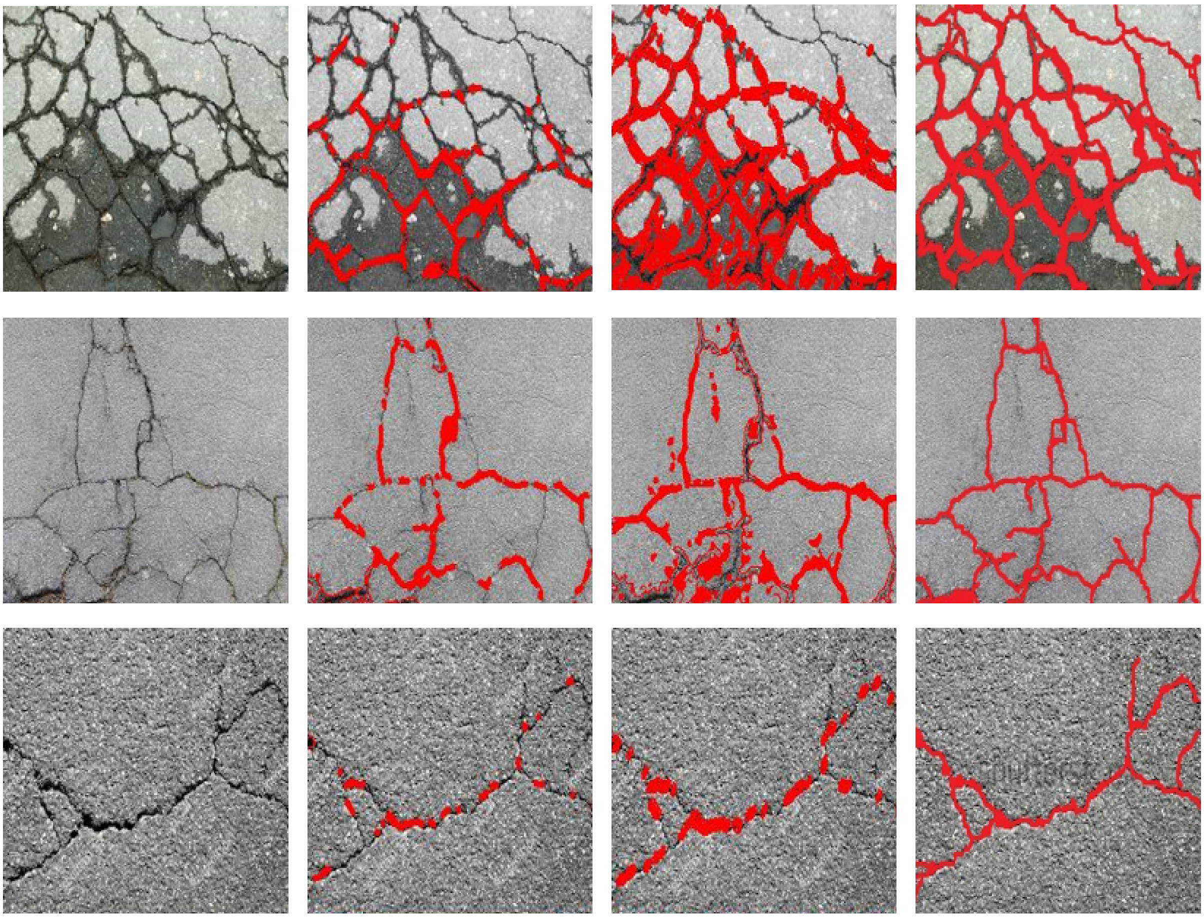

Figure 2. Crack detection results using competing models and the proposed model. The first column shows original images, while the second, third and fourth columns present results from FLBCD [19] and MFA-TAM [18], and the proposed model, respectively

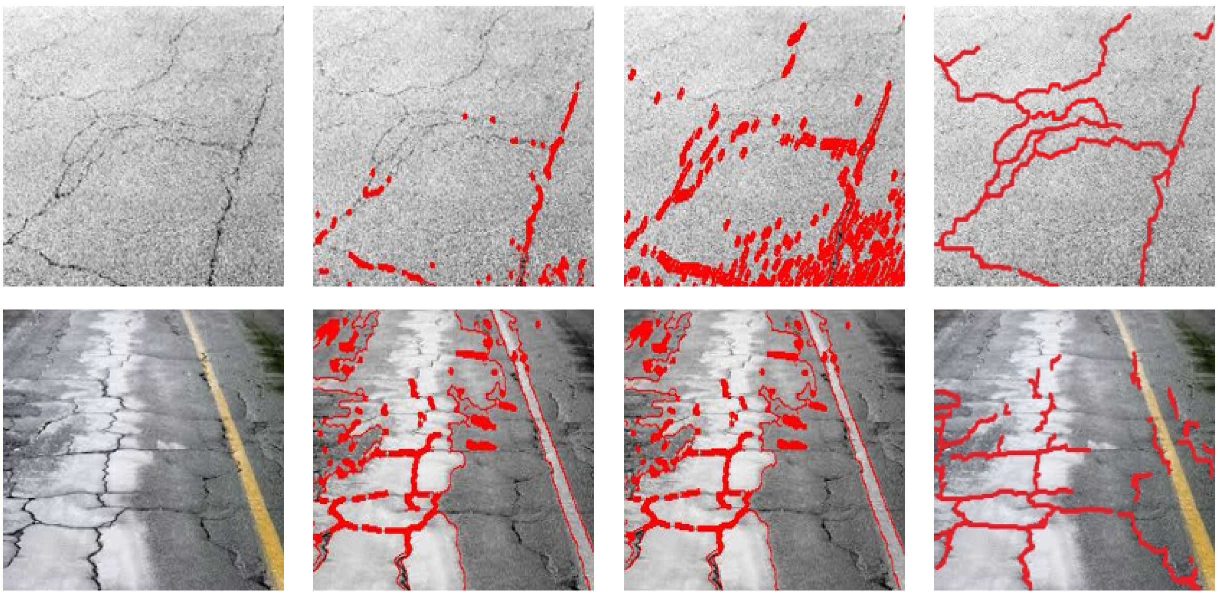

Figure 3. Crack detection under varying lighting conditions. The first row shows cracks, with detection results from FLBCD [19] and MFA-TAM [18], and the proposed model. The second row depicts road cracks where the proposed model achieves better segmentation

Table 3. Quantitative and computational assessment of road crack detection models

Metric	Our GCSM	MFA-TAM	FLBCD	Best Model
IoU ($\uparrow$)	0.91 ± 0.02	0.79 ± 0.03	0.79 ± 0.04	GCSM
SSIM ($\uparrow$)	0.92 ± 0.01	0.85 ± 0.02	0.81 ± 0.03	GCSM
Precision ($\uparrow$)	0.91 ± 0.02	0.82 ± 0.03	0.77 ± 0.04	GCSM
Recall ($\uparrow$)	0.89 ± 0.03	0.80 ± 0.03	0.75 ± 0.04	GCSM
ANOVA (p value)	$p < 0.01$	$p = 0.04$	$p = 0.08$	GCSM
Processing Speed (sec $\downarrow$)	0.92 sec	1.45 sec	1.87 sec	GCSM
Memory Usage (MB $\downarrow$)	220 MB	280 MB	310 MB	GCSM

- $Recall$: Recall quantifies the model's ability to detect actual cracks. GCSM achieves 0.89 $\pm$ 0.03, whereas MFA-TAM and FLBCD score 0.80 $\pm$ 0.03 and 0.75 $\pm$ 0.04, respectively. This result highlights that GCSM can capture a larger number of true cracks compared to existing models.

4.1.2 Statistical significance (ANOVA)

The ANOVA p value is used to test whether the performance differences among the models are statistically significant. Our GCSM model achieves $p < 0.01$, indicating a highly significant improvement over competing models. In contrast, MFA-TAM has $p = 0.04$, which is marginally significant, while FLBCD's $p = 0.08$ suggests no strong statistical difference in its performance. This confirms that GCSM's superior results are not due to random variations but are statistically valid.

4.1.3 Computational efficiency

- $Processing\ Speed$: Efficiency is crucial for real-time applications. GCSM processes an image in just 0.92 seconds, making it the fastest among the three models. In comparison, MFA-TAM takes 1.45 seconds, and FLBCD requires 1.87 seconds, making them significantly slower.

- $Memory\ Usage$: The computational efficiency of a model is also measured by the memory it consumes. GCSM only requires 220 MB of memory, whereas MFA-TAM consumes 280 MB and FLBCD uses 310 MB. The lower memory footprint of GCSM makes it more scalable and suitable for deployment on resource-limited systems.

The results in the table confirm that our proposed GCSM model significantly outperforms existing road crack detection approaches in terms of both accuracy and computational efficiency. It achieves the highest IoU, SSIM, precision, and recall, while also demonstrating statistically significant improvements through ANOVA testing. Additionally, GCSM is the fastest model with the lowest memory consumption, making it the most reliable and efficient solution for road crack detection applications.

5 Conclusion

This study presents an integrated framework for road crack detection and accident risk prediction, combining fuzzy logic and statistical modeling to enhance accuracy and interpretability. The proposed GCSM effectively detects road cracks under challenging illumination and noise conditions, while the hybrid fuzzy-logistic risk prediction component provides reliable estimation of accident probability based on critical parameters such as crack density, width, vehicle speed, and traffic volume. The key contributions of this research include: (1) improved robustness of crack detection through RGB-based enhancement and color consistency, (2) integration of fuzzy reasoning with statistical analysis for reliable accident risk prediction, and (3) validation on real-world road data from Peshawar, confirming both high detection accuracy and computational efficiency.

Despite its strong performance, the model has certain limitations, including sensitivity to complex surface textures and uneven illumination, which may introduce minor segmentation bias. Addressing these issues will further enhance the model's adaptability and reliability.

Future work will focus on real-time implementation and optimization for embedded systems, enabling deployment on mobile or drone-based platforms for autonomous road condition and risk assessment. Additionally, further research will explore adaptive parameter tuning to enhance robustness across diverse environmental conditions, such as wet roads, nighttime imagery, and varying pavement materials. Extending the model to incorporate deep learning-based feature extraction while maintaining computational efficiency will also be a potential avenue for improvement.

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.

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