International Journal of Science and Research (IJSR)
ISSN: 2319-7064
Impact Factor 2025: 7.089

BridgeGuard-Lite: A Low-Cost Image-Based Framework for Surface Crack Detection in Steel Structures

Manjunath Gunjikar[1], Seema Narain[2], Dhanashree Tulankar[3]

[1]M-Tech (Structures), Faculty of Civil Engineering, College of Military Engineering, Pune, Maharashtra, India

[2]Associate Professor, Faculty of Civil Engineering, College of Military Engineering, Pune, India

[3]Assistant Professor, Faculty of Civil Engineering, College of Military Engineering, Pune, India

Abstract: *Surface cracks in steel structures are critical indicators of structural degradation caused by fatigue, corrosion, and stress concentration. Early detection of such defects is essential for ensuring the safety and reliability of infrastructure systems. This paper proposes BridgeGuard-Lite, a simplified and cost-effective framework for detecting surface cracks in steel structures using basic image processing techniques. The proposed method utilises grayscale conversion, noise reduction, thresholding, and edge detection to identify crack patterns from steel surface images. A parameter adjustment step, including contrast enhancement, shape filtering, and minimum defect size constraints, is incorporated to improve detection performance under varying surface conditions. The effectiveness of the method is evaluated using object-based comparison and tuning-based analysis. The results demonstrate that the system successfully detects primary crack features and that parameter tuning significantly improves detection quality by reducing noise and enhancing crack continuity. The proposed framework provides a practical and low-cost solution for structural inspection and is suitable for preliminary condition assessment. Future enhancements may include integration of machine learning techniques and larger datasets to improve robustness and adaptability across diverse real-world conditions.*

Keywords: Steel Crack Detection, Image Processing, Structural Health Monitoring, Bridge Monitoring, Automated Defect Detection.

1. Introduction

Steel structures, particularly bridge components, are subjected to various forms of deterioration including fatigue, corrosion, and stress-induced cracking [8][9]. These defects can significantly reduce structural integrity and may lead to sudden failure if not detected at an early stage.

Conventional inspection methods primarily rely on manual visual assessment, which is time-consuming, subjective, and dependent on the experience of inspectors [9][10]. Advanced non-destructive testing techniques are available, but they often require specialised equipment and higher operational costs. With the advancement of digital imaging and computational tools, image-based crack detection has emerged as a promising alternative for structural inspection [8][13]. However, many existing approaches rely on complex machine learning models, which require large datasets and significant computational resources.

To address these limitations, this study proposes **BridgeGuard-Lite**, a lightweight and simplified crack detection framework for steel surfaces. The focus of this work is to develop an easily implementable method using basic image processing techniques that can be deployed in practical scenarios without requiring advanced computational infrastructure.

2. Types of Cracks in Steel Structures

Steel structures are prone to different types of cracks depending on loading conditions, environmental exposure, and material properties. Understanding these crack types is important for effective detection and structural assessment.

2.1 Fatigue Cracks

Fatigue cracks develop due to repeated cyclic loading over time. These cracks typically initiate at stress concentration points such as weld joints, bolt holes, or geometric discontinuities.

- Usually appear as fine, progressive cracks
- Grow gradually under repeated stress cycles
- Common in bridges and moving load structures

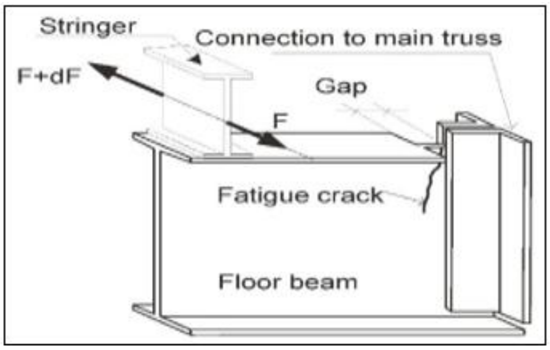

Figure 1: Fatigue based crack

2.2 Corrosion-Induced Cracks

Corrosion-induced cracks occur due to environmental exposure, especially in humid or marine conditions. Rust formation weakens the steel surface and leads to crack development.

- Associated with **rust and surface degradation**
- Often irregular in shape

Paper ID: SR26424231009 DOI: https://dx.doi.org/10.21275/SR26424231009

- Common in exposed steel structures

Figure 2: Corrosion induced crack

2.3 Stress Cracks

Stress cracks are caused by excessive loading or stress concentration in structural members. These cracks may appear suddenly when stress exceeds material strength.
- Typically straight or slightly curved
- Occur in high-load regions
- Can lead to sudden failure

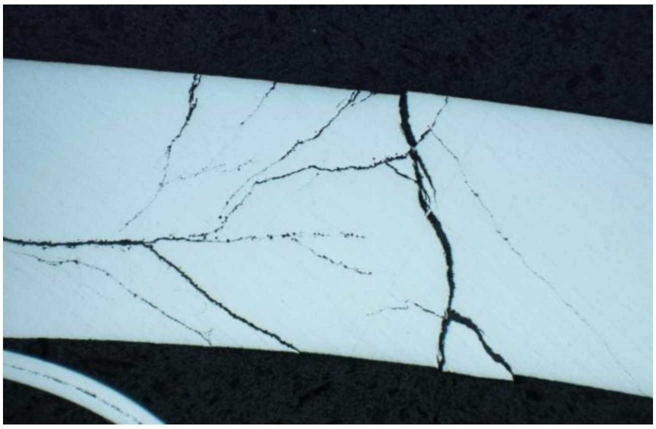

Figure 3: Stress crack in steel surface

2.4 Surface Cracks

Surface cracks are small cracks that appear on the outer layer of steel components. These may not be structurally critical initially but can propagate over time.
- Appear as hairline cracks
- Difficult to detect visually
- Early indicator of damage

Figure 4: Surface cracks

The proposed BridgeGuard-Lite framework is primarily designed to detect visible surface cracks, including fatigue and stress-related crack patterns. The ability to identify such crack types at an early stage can significantly improve maintenance and inspection strategies.

3. Methodology

3.1 Overview of the Proposed Framework

The proposed **BridgeGuard-Lite** framework is designed as a lightweight image-based crack detection system for steel structures. The methodology follows a sequential image processing pipeline consisting of preprocessing, segmentation, and feature extraction stages.

The primary objective of the framework is to detect visible surface cracks using computationally efficient techniques without relying on complex machine learning models. The workflow processes input images through a series of transformations to enhance crack features and suppress background noise.

3.2 Image Acquisition

Steel surface images containing visible crack patterns are collected from publicly available sources and online datasets. These images represent typical inspection scenarios, including variations in lighting conditions, surface texture, and crack orientation.

The input images are assumed to be in RGB format and are used as the initial input for further processing.

3.3 Preprocessing

3.3.1 Grayscale Conversion

The input RGB image is converted into a grayscale image to reduce computational complexity and focus on intensity variations [1]. This step simplifies the image representation while retaining essential structural features.

3.3.2 Noise Reduction

To minimise unwanted variations and enhance image quality, Gaussian filtering is applied to the grayscale image [1]. This smoothing operation reduces noise while preserving important edges associated with crack structures.

3.4 Segmentation Using Thresholding

Thresholding is used to separate crack regions from the background [3]. The grayscale image is converted into a binary image based on a selected threshold value.

$$I_{bin}(x,y) = \begin{cases} 1, & I(x,y) > T \\ 0, & I(x,y) \leq T \end{cases} \quad (1)$$

Where:
- $I(x,y)$ represents pixel intensity
- T is the threshold value

This process highlights potential crack regions while suppressing non-relevant areas.

3.5 Edge Detection

Edge detection is performed to extract the boundaries of crack structures from the processed image [4]. The edge

Paper ID: SR26424231009 DOI: https://dx.doi.org/10.21275/SR26424231009

detection algorithm identifies sharp intensity changes, which correspond to crack edges implemented through OpenCV [2][15]. The resulting edge map provides a clear representation of crack paths and structural discontinuities.

3.6 Parameter Adjustment

A simple parameter adjustment step is incorporated to improve detection performance under varying conditions. The following parameters are adjusted:

- Threshold value for segmentation
- Edge detection sensitivity
- Noise filtering intensity

These parameters are tuned using sample images to achieve an optimal balance between crack visibility and noise suppression. This step enhances the robustness of the system without increasing computational complexity.

3.7 Crack Visualisation

The detected crack regions are superimposed on the original image to provide a clear visual representation. This helps in identifying the exact location and orientation of cracks. The final output highlights crack paths, making it easier for engineers to interpret structural conditions.

3.8 Summary of Workflow

The overall methodology of the proposed system is illustrated in Figure 5.

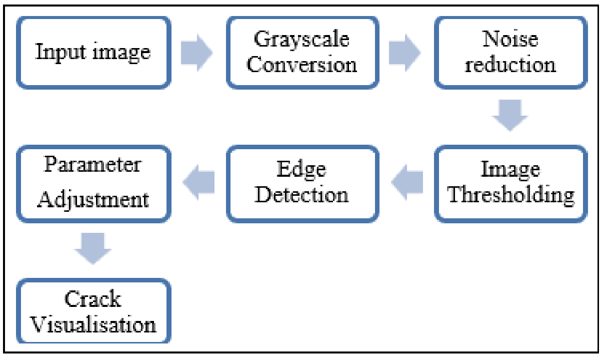

Figure 5: Workflow of the proposed BridgeGuard-Lite crack detection framework

4. Results and Analysis

The proposed BridgeGuard-Lite framework was evaluated using steel surface images containing visible crack patterns under varying surface conditions. The objective of the analysis was to assess the effectiveness of the image processing pipeline in identifying crack features while minimising background noise.

4.1 Visual Results

The processing stages demonstrate a progressive enhancement of crack features:

- **Original Image:** Displays the raw steel surface with visible crack patterns
- **Grayscale Image:** Reduces colour complexity and highlights intensity variations
- **Threshold Image:** Segments crack regions from the background
- **Edge Detection:** Extracts crack boundaries clearly
- **Final Output:** Highlights crack path on the original image

4.2 Observations

- Crack features appear as continuous linear structures
- Thresholding effectively isolates darker crack regions
- Edge detection enhances crack visibility
- The method performs well under uniform lighting conditions

However, variations in illumination and surface reflections may influence detection accuracy. The crack detection outputs for different test images are presented in Figures 6–8.

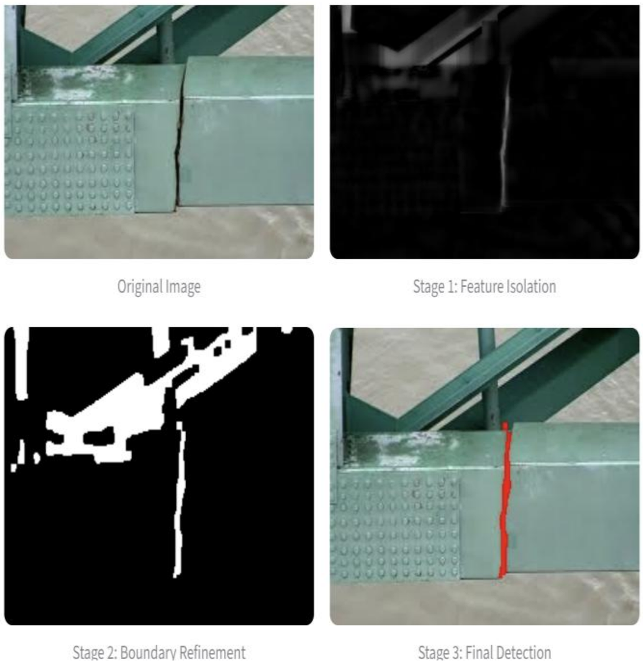

Figure 6: Crack detection result for steel surface (SC 01)

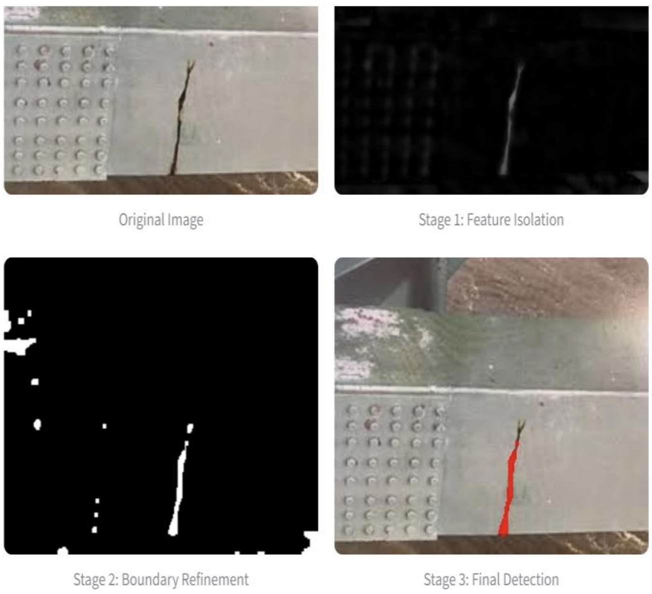

Figure 7: Crack detection result for steel surface (SC 02)

Paper ID: SR26424231009 DOI: https://dx.doi.org/10.21275/SR26424231009

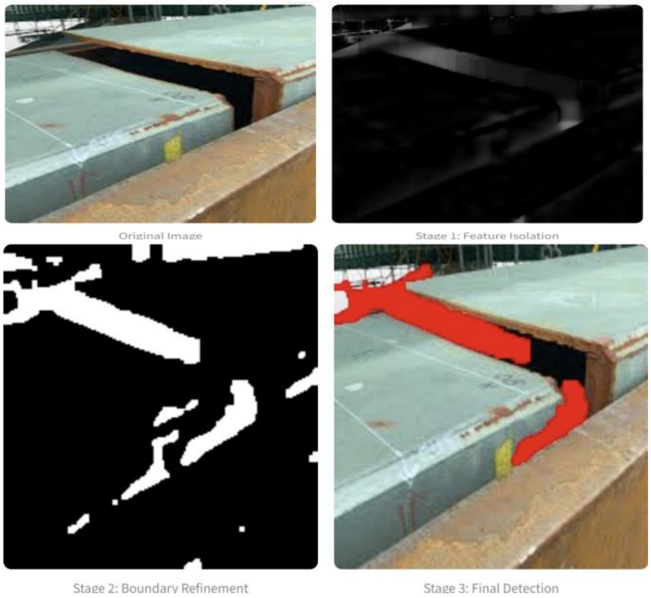

Figure 8: Crack detection result for steel surface (SC 03)

5. Performance Evaluation

The performance of the proposed method is evaluated using standard detection metrics based on visual comparison between original and processed images.

5.1 Evaluation Metrics

The performance of the proposed crack detection method is evaluated using standard classification metrics. In this context:

- True Positive (TP): Crack regions correctly detected
- False Positive (FP): Non-crack regions incorrectly detected as cracks
- False Negative (FN): Actual crack regions that were not detected

5.2 Performance Table

Table 1: Crack Detection Performance (Object-Based Evaluation)

Image	Actual Cracks	Detected Cracks	FP	FN	Result
SC 01	1	1	0	0	Correct
SC 02	1	1	0	0	Correct
SC 03	1	1	0	0	Correct

Table 2: Crack Detection Performance (Tuning Based)

Image	Stage	Detected Crack	Noise (FP)	Missed (FN)	Result
SC 01	Before	Partial	High	Yes	Poor
SC 01	After	Complete	Low	No	Good
SC 02	Before	Partial	Medium	Yes	Moderate
SC 02	After	Complete	Low	No	Good
SC 03	Before	Partial	High	Yes	Poor
SC 03	After	Complete	Medium	Slight	Improved

5.3 Interpretation

The results indicate that the proposed method successfully detects the primary crack in all test images. Since each image contains a single dominant crack, evaluation is performed at the object level. The results show that the system correctly identifies the crack in all cases after parameter adjustment.

Furthermore, the comparison between pre- and post-adjustment results demonstrates that parameter tuning significantly improves detection quality by reducing noise and enhancing crack continuity. The detection output becomes more refined and accurate after applying contrast enhancement, shape filtering, and minimum defect size constraints. These results validate the effectiveness of the proposed BridgeGuard-Lite framework for practical crack detection applications.

6. Discussion

The experimental results demonstrate that the BridgeGuard-Lite framework is capable of detecting visible cracks in steel surfaces using simple image processing techniques.

One of the major strengths of the proposed approach is its low computational requirement, making it suitable for real-time and field applications. The absence of complex training procedures further simplifies deployment. The parameter adjustment step plays an important role in improving detection performance by adapting the system to different surface conditions.

However, certain limitations were observed. The detection accuracy is influenced by lighting conditions [14] and surface reflections. Highly reflective steel surfaces may introduce noise, affecting the segmentation process. Despite these limitations, the proposed framework provides a practical and efficient solution for preliminary crack detection.

7. Advantages

The proposed BridgeGuard-Lite framework offers several advantages for practical structural inspection of steel components. One of the primary benefits of the system is its **low computational requirement**, as it relies on basic image processing techniques rather than complex machine learning models. This makes the approach highly suitable for deployment on standard computing devices such as laptops and mobile systems without the need for specialized hardware. Additionally, the framework is **cost-effective**, since it does not require expensive sensors or large annotated datasets for training.

Another significant advantage is the **simplicity and ease of implementation**. The step-by-step image processing pipeline allows engineers and practitioners with limited programming experience to understand and apply the method effectively. The inclusion of a **parameter adjustment step** further enhances the adaptability of the system by enabling users to fine-tune detection settings based on varying lighting conditions and surface characteristics.

The method also provides **real-time applicability**, as the processing steps are computationally lightweight and can be executed quickly. This makes the system suitable for field inspections and rapid preliminary assessments of structural

Paper ID: SR26424231009 DOI: https://dx.doi.org/10.21275/SR26424231009

conditions. Furthermore, the visual output generated by the framework is intuitive, allowing engineers to easily interpret crack locations and patterns without requiring advanced analytical tools.

8. Limitations

Despite its advantages, the proposed BridgeGuard-Lite framework has certain limitations that must be considered. One of the primary challenges is its **sensitivity to lighting conditions and surface reflections**, particularly in the case of steel structures, which often exhibit reflective properties. Variations in illumination can affect the accuracy of thresholding and edge detection, leading to potential inconsistencies in crack identification.

Another limitation is the system's **dependency on visible crack features**. The proposed method is primarily designed to detect surface-level cracks and may not be effective in identifying micro-cracks or subsurface defects that are not clearly visible in images. In such cases, advanced non-destructive testing techniques or deep learning-based methods may be required. Additionally, the detection accuracy is influenced by the **selection of parameter values** during the adjustment step. Improper parameter tuning may result in either excessive noise detection or missed crack regions. The method may also produce **false positives** in cases where surface textures, stains, or shadows resemble crack patterns.

Finally, the current approach does not incorporate automated classification or severity assessment of cracks. While it successfully highlights crack regions, further analysis is required to determine the structural significance of the detected defects. The present study uses a limited test dataset. Future work will validate the framework using larger and more diverse steel crack images.

9. Conclusion

This paper presented **BridgeGuard-Lite**, a simplified image-based crack detection framework for steel structures using basic image processing techniques. The proposed approach effectively identifies visible surface cracks while maintaining low computational requirements, making it suitable for cost-effective structural health monitoring applications.

The experimental results demonstrate that the system can reliably detect primary crack features, particularly after parameter adjustment techniques such as contrast enhancement and noise filtering. The framework is therefore well-suited for preliminary inspection tasks and rapid condition assessment of steel bridge components.

However, for large-scale deployment and improved robustness, the integration of advanced **machine learning techniques** can further enhance performance. In practical scenarios, image datasets collected from one side of a bridge often exhibit similar visual characteristics, whereas images from different sections may vary significantly due to lighting conditions, geometry, and surface properties. Incorporating learning-based models trained on diverse datasets (e.g., thousands of images) can improve generalization and enable more accurate detection across varying conditions.

Future work will focus on extending the proposed framework by integrating data-driven approaches and expanding the dataset to support more comprehensive and automated crack detection systems

References

[1] R. C. Gonzalez and R. E. Woods, "Digital Image Processing," 4th ed., Pearson Education, New York, 2018.
[2] G. Bradski, "The OpenCV Library," Dr. Dobb's Journal of Software Tools, pp. 120–125, 2000.
[3] N. Otsu, "A Threshold Selection Method from Gray-Level Histograms," IEEE Transactions on Systems, Man, and Cybernetics, vol. 9, no. 1, pp. 62–66, 1979.
[4] J. Canny, "A Computational Approach to Edge Detection," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 8, no. 6, pp. 679–698, 1986.
[5] S. Dorafshan, R. J. Thomas, and M. Maguire, "SDNET2018: An Annotated Image Dataset for Non-Contact Concrete Crack Detection Using Deep Convolutional Neural Networks," Data in Brief, vol. 21, pp. 1664–1668, 2018.
[6] S. Cha, O. Choi, and M. Büyüköztürk, "Deep Learning-Based Crack Damage Detection Using Convolutional Neural Networks," Computer-Aided Civil and Infrastructure Engineering, vol. 32, no. 5, pp. 361–378, 2017.
[7] Q. Zou, Z. Zhang, Q. Li, X. Qi, Q. Wang, and S. Wang, "DeepCrack: Learning Hierarchical Convolutional Features for Crack Detection," IEEE Transactions on Image Processing, vol. 28, no. 3, pp. 1498–1512, 2019.
[8] H. Li, D. Song, Y. Liu, and B. Li, "Computer Vision-Based Structural Damage Detection: A Review," Automation in Construction, vol. 94, pp. 278–289, 2018.
[9] C. Koch, K. Georgieva, V. Kasireddy, B. Akinci, and P. Fieguth, "A Review on Computer Vision Based Defect Detection and Condition Assessment of Civil Infrastructure," Advanced Engineering Informatics, vol. 29, no. 2, pp. 196–210, 2015.
[10] S. Dorafshan and M. Maguire, "Comparing Automated Image-Based Crack Detection Techniques in Civil Infrastructure," Automation in Construction, vol. 102, pp. 130–139, 2019.
[11] J. Serra, "Image Analysis and Mathematical Morphology," Academic Press, London, 1982.
[12] T. C. Hutchinson and Z. Chen, "Improved Image Analysis for Evaluating Concrete Damage," Journal of Computing in Civil Engineering, vol. 20, no. 3, pp. 210–216, 2006.
[13] B. F. Spencer Jr., V. Hoskere, and Y. Narazaki, "Advances in Computer Vision-Based Civil Infrastructure Inspection and Monitoring," Engineering, vol. 5, no. 2, pp. 199–222, 2019.
[14] A. Mohan and S. Poobal, "Crack Detection Using Image Processing: A Critical Review and Analysis,"

Paper ID: SR26424231009 DOI: https://dx.doi.org/10.21275/SR26424231009

Alexandria Engineering Journal, vol. 57, no. 2, pp. 787–798, 2018.

[15] OpenCV, "Open Source Computer Vision Library Documentation," [Online]. Available: https://opencv.org. [Accessed: 2026].

[16] Python Software Foundation, "Python Language Reference," [Online]. Available: https://www.python.org. [Accessed: 2026].