IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

Enhanced Artificial Intelligence System For Automated Crack Detection In Bridge Structures

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Abstract: This work presents a novel approach to automated bridge inspection focusing on robust crack detection using advanced computer vision techniques. The methodology integrates deep learning with image processing algorithms to analyze a comprehensive dataset of bridge images under varying conditions. Customized convolutional neural network (CNN) architecture is employed for accurate crack localization and classification, leveraging its ability to extract detailed features from bridge images. Additionally, a graph-based algorithm enhances detection reliability by validating and refining crack identifications. Experimental results demonstrate superior performance compared to traditional methods, highlighting the framework's potential for real-time deployment in enhancing infrastructure safety and efficiency.

Index Terms – SSD, CNN, Crack, AI, Intersection over Union (IOU), Horizontal Crack, Vertical Crack, Slanted Crack, Crossed Crack.

I. Introduction

Bridge structures play a crucial role in transportation infrastructure, but they are subject to deterioration over time due to environmental factors and traffic loads. Among the various types of defects that affect their structural integrity, cracks pose significant risks if undetected or untreated. Traditional methods of crack detection, reliant on manual inspection, are labor-intensive, time-consuming, and often unable to cover every part of a bridge comprehensively. In response to these challenges, automated crack detection systems have emerged as a promising alternative, leveraging advancements in artificial intelligence (AI) and computer vision. Automated crack detection systems offer several advantages over manual methods, including increased efficiency, broader coverage, and the ability to operate in hazardous or difficult-to-access locations. Various technologies such as ultrasonic testing and optical fiber sensors have been explored, but recent attention has shifted towards image-based approaches for their cost-effectiveness and scalability. In particular, the use of unmanned aerial vehicles (UAVs) equipped with high-resolution cameras allows for detailed inspection of bridge surfaces, capturing images that serve as the basis for crack detection algorithms. The evolution of deep learning, a subset of AI, has revolutionized image analysis tasks including crack detection. Deep learning models, such as convolutional neural networks (CNNs), have demonstrated remarkable capability in automatically identifying cracks from image data. Techniques like the Single Shot Multibox Detector (SSD) algorithm have been adapted to efficiently detect cracks in bridge images by leveraging multi-scale feature maps and prior knowledge about crack dimensions and shapes.

Despite these advancements, challenges persist in ensuring robust crack detection under varying environmental conditions, such as changing lighting and background textures. This paper proposes an enhanced AI system designed to address these challenges through a comprehensive two-stage approach. The first stage involves a sophisticated image classification process to distinguish between complex and simple images, optimizing subsequent processing steps. For images classified as complex, a preprocessing phase is applied to normalize lighting and enhance contrast, ensuring uniformity in image quality for accurate feature extraction. In the second stage, texture analysis-based features are extracted using a non-overlapping sliding window approach. These features capture detailed information about local image regions, which are then fed into a CNN classifier trained specifically for crack detection. The classifier utilizes deep learning techniques to differentiate between cracked and non-cracked regions with high accuracy and efficiency. The contributions of this research lie in the development of a robust AI system that integrates advanced image processing techniques with state-of-the-art deep learning models. Experimental validation on real-world bridge images demonstrates the system's effectiveness in detecting cracks under diverse conditions, thereby facilitating timely maintenance interventions and ensuring the continued safety and reliability of bridge infrastructure.

II. BACKGROUND AND RELATED WORK

Cai et al. [1] proposed a novel method for enhancing crack detection in concrete bridge structures using computer vision technologies and coordinate mapping. Their approach involved integrating a high magnification image acquisition system, a two-dimensional electric cradle head device, and a laser ranging system. This system utilized observation coordinates to map image coordinates of marking points. By assigning crack coordinates to nearly identical world coordinates as the marking points, they achieved independent geographical positioning of measured cracks, which proves valuable for identifying surface cracks in concrete bridge systems under varying test periods and instrument configurations. Experimental results demonstrated the effectiveness and practicality of their approach, achieving automatic detection of cracks within 16 seconds and measuring crack diameters with high accuracy (0.12 mm at a distance of 100 m).

Lin and Gao [2] conducted a study on longitudinal cracking in hollow-core slab bridges, focusing on typical issues observed in expressway structures. They numerically simulated the stress conditions and spatial deformations of a 13-meter hollow-core slab bridge to analyze the impact of overload and hinge failures on longitudinal cracks. Their findings revealed several key insights: (1) Following the tensioning of prestressed steel strands, the longitudinal normal stress at the bottom of the hollow-core slab beam remained under compression during construction and under vehicle loads. (2) Longitudinal cracking in the beam bottom did not occur below an overload factor of 0.96 times, but the risk increased between 0.96 and 1.5 times, with definite cracking observed above 1.5 times the overload factor. (3) Hinge joint failures did not significantly affect the transverse normal stress of the hollow slab.

Jia, Xiaoyu, Luo, and Wenguang [3] focus on detecting crack damage in bridges, a common issue affecting bridge integrity. Traditional crack detection methods often lack accuracy in classifying cracks and fail to measure crack parameters effectively. This paper introduces a modern approach using convolutional neural networks (CNNs) combined with optical image analysis to improve crack image recognition and parameter measurement. By optimizing the CNN configuration and introducing digital image processing as a specialized layer, the authors enhance image recognition accuracy. They also propose constructing a new image using a linear regression model based on extracted feature graphs, enabling precise measurement of crack length by pixel count. Experimental results demonstrate a crack classification accuracy of 95% and an error of less than 4% in calculating crack lengths using their proposed method.

Ye Li and Yong Liu [4] address the significant issue of crack detection in concrete bridges, highlighting cracks as a primary factor contributing to structural damage. Effective crack detection is critical for maintaining bridge safety and structural integrity. Recognizing the importance of precision in crack detection, their research introduces an advanced algorithm designed to achieve high accuracy at the sub-pixel level. This approach goes beyond traditional methods by enhancing the capability to detect cracks with greater detail and accuracy, ensuring early identification and remediation of potential structural weaknesses. By focusing on sub-pixel level detection, their methodology aims to improve the reliability and effectiveness of bridge inspection practices, ultimately contributing to safer and more durable infrastructure.

Elmer R. Magsino, John Robert B. Chua, Lawrence S. Chua, Carlo M. de Guzman, and Jan Vincent L. Gepaya [5] have developed an innovative approach using a quadrotor for efficient and safe inspection of concrete bridge columns for cracks. The quadrotor conducts vertical scans at regular height intervals, capturing structural images. These images are then transmitted wirelessly to an Android device equipped with a rapid screening algorithm specifically designed for crack detection. In their experiments, they analyzed 23 images from bridge structures, achieving an average accuracy rate of 95.65%. Precision was measured at 91.67% and recall at 83.33%.

Wang Xuejun and Zhang Yan [6] propose a system for digital and intelligent detection and recognition of bridge cracks using Deep Belief Network (DBN) technology. The detection and classification of bridge fractures are crucial due to their significant impact on safety. Their system integrates machine vision capabilities with a Deep Belief Network, leveraging a Raspberry Pi for image capture and pre-processing. Images are transmitted via GPRS, 3G, or wired networks and analyzed using high-level image servers. The approach involves selecting and optimizing processing algorithms tailored to bridge crack characteristics, ensuring accurate detection and recognition of real-world bridge fractures. Experimental results demonstrate that the DBN achieves a classification accuracy exceeding 90%, meeting engineering accuracy standards.

Gong XingQi, Li Quan, Zhou MeiLing, and Jiang HuiFeng [7] conducted an analysis and testing of concrete surface cracks on Railway Bridges using deep learning techniques. The rapid expansion of high-speed railways in China in recent years has underscored the critical need for effective bridge maintenance to ensure train service safety. This study investigates the characteristics of surface cracks on bridge structures under previous operational conditions. They employ the YoloV3 deep learning network to enhance crack detection, annotation, and age estimation, achieving high-precision results in identifying bridge surface cracks. The study also identifies certain limitations in the current approach and proposes updates for future phases.

Huai Yu, Wen Yang, Heng Zhang, and Wanjun He [8] have developed a novel UAV-based crack inspection system for monitoring concrete bridges, addressing the critical task of crack detection. Traditional human-based inspection methods are costly and pose safety risks. To overcome these challenges, their system utilizes unmanned aerial vehicles (UAVs) equipped with onboard cameras to inspect the lateral sides and underside of bridges. The UAVs employ obstacle avoidance modules to safely approach and capture high-resolution images of the bridge surfaces. To accurately locate cracks across large areas and overcome the limited field of view of single images, they developed a fast feature-based stitching algorithm. Additionally, an edge detection method using structured forests is applied to identify cracks on the stitched panoramas. Correcting image distortions further enhances the accuracy of crack detection. Experimental results confirm the effectiveness and efficiency of the UAV-based crack inspection system in real-world applications.

Hui Zhang, Jinwen Tan, Li Liu, Q. M. Jonathan Wu, Yaonan Wang, and Liu Jie [9] focus on automatic crack inspection for concrete bridge bottom surfaces using machine vision technology. Concrete is widely favored in construction due to its cost-effectiveness and high plasticity, but it is susceptible to cracking, necessitating regular inspections to prevent deterioration. To address this, they have developed a bridge inspection robot equipped with machine vision capabilities for accurate and reliable crack detection. The system gathers a variety of images, which are stitched together into high-quality panoramas to facilitate detailed crack analysis. Initially, they employ a fast and high-quality image stitching method based on the ORB algorithm. As a preprocessing step, they use the Local Directional Edge (LDE) approach to enhance crack structures in low-contrast images. Subsequently, crack-like defects in the panorama are segmented using morphological operations and the Tubularity Flow Area technique. Experimental results underscore the efficiency and high quality of the image stitching process, along with the effectiveness of the segmentation method in identifying and analyzing cracks.

Chen Ziqiang, Long Haihui, and Zhao Jiankang [10] have investigated an algorithm for calculating the length of bridge cracks using stereo vision technology. While cracks on bridge surfaces and bottoms are commonly inspected, those at intermediate support structures like piers are often overlooked. Additionally, errors can arise when the camera plane is not parallel to the bridge plane, resulting in inaccurate crack size calculations based solely on image projections. To address these challenges, their study proposes a bridge crack detection method based on stereo vision, which incorporates depth information to accurately measure crack lengths. Experimental results demonstrate that this method effectively detects and characterizes bridge cracks, offering superior performance compared to existing measurement techniques.

The traditional method for detecting bridge cracks relies heavily on manual inspection, typically conducted using bridge inspection vehicles or maintenance walkways, requiring close proximity to the bridge structure. This approach is known for being time-consuming, labor-intensive, and poses risks to inspectors' safety due to the need for physical proximity to potentially hazardous environments. In contrast, automatic detection methods offer nondestructive alternatives for crack detection. These methods encompass various technologies such as ultrasonic surface wave testing, impact-echo, acoustic emission, optical fiber sensor network monitoring, and machine vision. These technologies enable remote or automated inspection capabilities, reducing the need for human proximity to the structure and mitigating associated risks. Automatic detection methods also promise improvements in efficiency and accuracy compared to traditional manual methods, making them increasingly attractive for enhancing bridge inspection practices.

Summary of the review is automated bridge inspection and crack detection has advanced significantly through innovations such as deep learning networks and UAV-based systems. Challenges remain in adapting these technologies to diverse environmental conditions and complex bridge geometries. Improvements are needed in refining deep learning models for real-time adaptability and enhancing image processing techniques to mitigate distortion and improve crack segmentation accuracy. UAV-based systems require optimization in obstacle avoidance and imaging capabilities to capture comprehensive data from varying angles. Addressing these challenges will lead to more reliable and efficient automated systems for ensuring the structural integrity and safety of bridges.

III MATERIALS AND METHODS

The architecture of a Convolutional Neural Network (CNN) integrated with a Single Shot Multibox Detector (SSD) is tailored for efficient and precise object detection tasks. Initially, the network employs a pre-trained CNN, such as VGG16 or MobileNet, as its backbone. This base network extracts feature maps from input images, capturing both low-level details like edges and high-level features such as object shapes. Following the base network, additional convolutional layers are introduced to facilitate detection at multiple scales. These layers generate predictions across various spatial resolutions, enabling the network to accurately localize objects of different sizes within the image. Each feature layer outputs a set of default bounding boxes (or anchor boxes) associated with specific spatial locations on the feature map. These boxes serve as references for predicting object presence and adjusting bounding box coordinates based on learned feature representations. Ultimately, the SSD architecture's multi-scale approach and predictive layers enhance its capability to swiftly and effectively detect and classify objects, making it suitable for real-time applications demanding both speed and accuracy in object detection tasks.

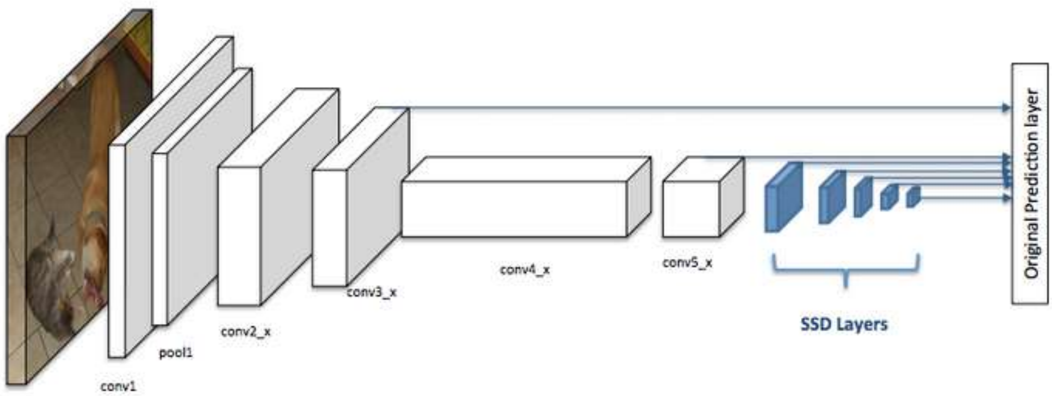


Figure 1.1: Single Shot Multibox Detector (SSD)

When employing SSD (Single Shot MultiBox Detector), the detection process begins with the uniform sampling of frames of varying aspect ratios and sizes at different positions within an image. These frames undergo feature extraction through a convolutional neural network (CNN) for classification. During testing, the algorithm identifies objects in the test images and directly overlays bounding boxes annotated with labels and scores representing category probabilities and position coordinates. A single test operation yields the final detection results, enabling simultaneous prediction across multiple frames.

Evaluation of the SSD algorithm's detection efficacy on individual images hinges on the Intersection over Union (IoU) metric. IoU quantifies the similarity between detected objects and known objects:

- In the training set, IoU is computed from the overlap between bounding boxes generated by the SSD framework and ground truth annotations.
- In the test set, IoU signifies the ratio of the intersection area between the detected bounding box and the ground truth bounding box to their union.

Intersection over Union is expressed as:

IoU=Area of union / Area of intersection

This study on bridge crack detection utilizes a diverse dataset sourced from two distinct repositories: drone surveys and historical inspection reports of bridges. The dataset consists of over 500 high-resolution images obtained through drone surveys equipped with cameras. These images offer detailed perspectives of bridge surfaces captured from various angles and elevations. They depict cracks of varying sizes and patterns naturally occurring on bridge decks, pillars, and support structures. The use of drones ensures comprehensive coverage, revealing cracks that may not be readily visible during ground-level inspections. Additionally, the dataset includes more than 1500 images extracted from historical inspection reports spanning several decades. These images document cracks identified during routine inspections across different bridge types and materials. They encompass a wide spectrum of crack severities and environmental conditions, providing a rich repository of real-world challenges encountered in bridge maintenance and management. To prepare the dataset for machine learning model development, extensive preprocessing steps were undertaken. This included segmentation and annotation of images to delineate crack regions and classify them based on severity levels. The dataset was partitioned into a training set comprising 6000 images and a validation set of 2000 images. This division ensures rigorous evaluation and validation of model performance on unseen data.

The detection results with different IoUs is shown in the figure 1.2

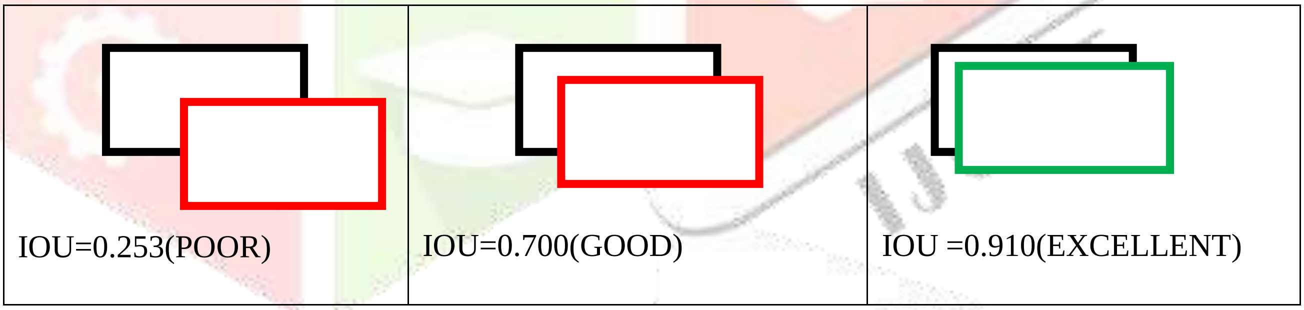


Figure 1.2. The detection results with different IoUs.

Intersection over Union (IoU) Values: Poor (IoU < 0.5): A poor IoU indicates that the predicted bounding box does not closely align with the ground truth crack, suggesting significant localization errors. Good (0.5 ≤ IoU < 0.75): A good IoU suggests moderate alignment between the predicted and actual crack locations, indicating reliable detection with some overlap. Excellent (IoU ≥ 0.75): An excellent IoU indicates high alignment between the predicted and actual crack locations, demonstrating precise detection and accurate localization.

The crack detection, Intersection over Union (IOU) is a critical metric used to evaluate the accuracy of predicted crack regions compared to ground truth (actual) crack regions. An IOU score of 0.253 would be considered poor. This suggests that the predicted crack regions have very little overlap with the actual crack locations marked in the ground truth data. Such a low IOU indicates that the model is not accurately detecting cracks, potentially missing them or identifying false positives. Moving to an IOU of 0.700 signifies good performance. In this case, the predicted crack regions overlap well with the ground truth, indicating that the model is effectively identifying most of the cracks present in the images. An

IOU score of 0.910 is excellent. This implies that there is a very high overlap between the predicted crack regions and the ground truth cracks. A high IOU score like this suggests that the model is accurately and consistently identifying cracks with a high level of precision.

Parameter Setting and Model Training

In the domain of deep learning for bridge crack detection, effective parameter setting and meticulous model training are critical for achieving accurate results. This study leverages a diverse dataset sourced from two primary repositories: high-resolution images obtained from drone surveys and historical inspection reports of bridges. The dataset encompasses over 500 images from drone surveys, capturing detailed views of bridge surfaces from various angles and elevations. These images depict cracks of varying sizes and patterns naturally occurring on bridge decks, pillars, and support structures, providing comprehensive coverage not easily attainable through ground-level inspections alone. more than 1500 images were curated from historical inspection reports spanning several decades. These images document a wide spectrum of crack severities across different bridge types and materials, reflecting the challenges encountered in bridge maintenance and management over time. Parameter Optimization: During the model development phase, several key hyperparameters were carefully tuned based on iterative evaluations using a validation set: Batch Size**:** Due to memory limitations, a batch size of 4 was chosen to ensure efficient GPU computation while maintaining adequate gradient descent accuracy. Learning Rate: The initial learning rate was set to 0.004, a balanced choice between 0.001 and 0.006, facilitating stable convergence and optimal learning speed. Momentum**:** Employing a momentum of 0.9 accelerated gradient descent, enhancing the model's ability to navigate complex optimization landscapes and achieve convergence more rapidly. Weight Decay: To mitigate overfitting and improve generalization, a weight decay of 0.00004 was applied, striking a balance between model complexity and regularization. Activation Function: The ReLU activation function was utilized throughout the network to alleviate gradient vanishing issues during backpropagation, ensuring efficient training and effective feature learning. Training Environment: Model training was conducted on a laboratory server equipped with 2 Intel Xeon CPUs (E5-2696, 2.2 GHz), facilitating robust computational performance. The training process spanned 50,000 iterations, during which the loss function stabilized around 4.5, indicating convergence albeit not reaching ideal theoretical values. Post-training analyses of crack detection results showcased the model's high identification accuracy and robust performance across diverse crack types and environmental conditions.

IV RESULTS AND DISCUSSION

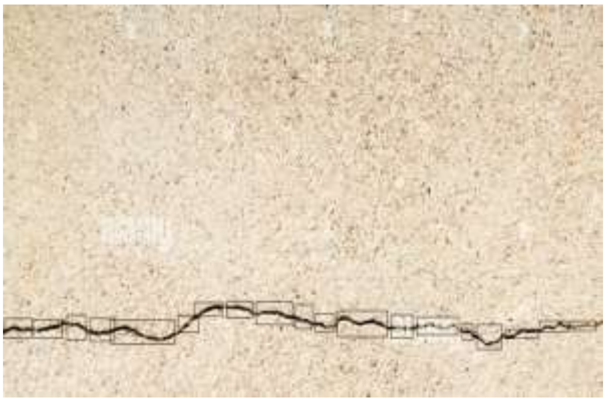
Based on the established crack image dataset, the SSD (Single Shot MultiBox Detector) algorithm was employed to develop a robust crack detection model. The training process utilized a comprehensive dataset comprising 5000 images for training and 2000 images for validation. These images were collected from drone surveys and historical inspection reports, encompassing diverse perspectives and crack types such as vertical, horizontal, slanting, and crossed cracks. During training, the SSD algorithm was optimized using the validation set to adjust model parameters effectively. Post-training, the model's performance was evaluated using sliding window technology on a separate test set to measure its ability to identify cracks accurately under varying environmental conditions. In developing an effective crack detection model, the SSD (Single Shot MultiBox Detector) algorithm was trained using a robust dataset comprised of 5000 training images and 2000 validation images. These images were carefully curated from drone surveys and historical inspection reports, capturing a wide array of crack types including vertical, horizontal, slanting, and crossed cracks commonly found in bridge structures.

Training Iterations: The model underwent rigorous training over 50,000 iterations. This extensive training period was essential to ensure the model achieved convergence, effectively learning the intricate features necessary for accurate crack detection across diverse environmental conditions and crack manifestations.

Threshold Setting: During the evaluation phase on the test set, a threshold value of 0.5 was meticulously applied. This threshold served as a critical criterion to determine the confidence level required for identifying cracks, thereby ensuring reliable and consistent detection performance.

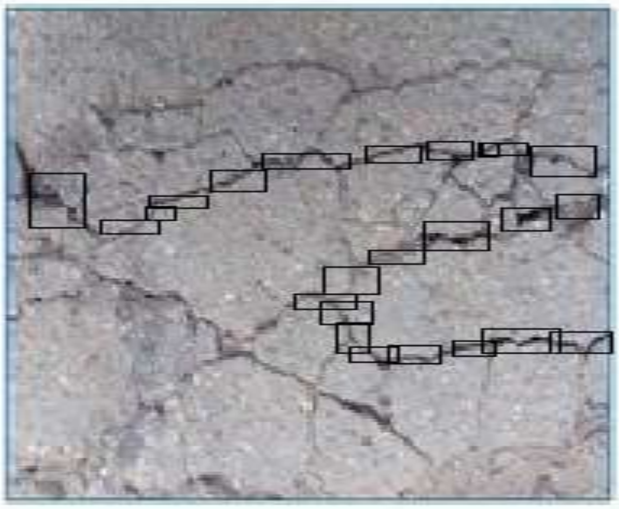
Image Segmentation: To enhance the model's ability to localize cracks with precision, the images were segmented into manageable 20 × 20 dpi patches. These patches were further analyzed at a higher resolution of 120 × 120 dpi, enabling detailed examination and accurate identification of cracks within different structural components of bridges.

a) Vertical Crack



b) Horizontal Crack

c) Slanting Crack



d) Crossed Crack

Figure 1.3. Four kinds of crack detection: (a) vertical crack; (b) horizontal crack; (c) slanting crack; (d) crossed crack.

Precision and recall metrics used to evaluate the performance of crack detection algorithms in image processing and computer vision. Precision measures the accuracy of the algorithm's positive predictions, specifically the ratio of true positives (correctly identified crack pixels) to the total number of pixels predicted as cracks (true positives plus false positives). Mathematically, precision is calculated as

$$\text{Precision} = TP / (TP + FP)$$

where TP represents true positives and FP represents false positives. On the other hand, recall assesses the algorithm's ability to correctly identify all positive instances (crack pixels) in the image. It is defined as the ratio of true positives to the total number of actual positive instances in the image (true positives plus false negatives). Thus, recall is calculated as

$$\text{Recall} = TP / (TP + FN)$$

where FN denotes false negatives. These metrics are crucial as they collectively provide insights into how well an algorithm performs in accurately identifying cracks (precision) and ensuring that most crack pixels are detected (recall), enabling effective assessment and improvement of detection algorithms. The detailed samples of the four situations are presented in Figure 1.3.

Table 1.1: Crack detection results of different samples.

Sample Dataset	Precision	Recall
Bridge Strcutures	86.5%	87.34%

The results obtained from the crack detection algorithm applied to bridge structures reveal a precision of 86.5% and a recall of 87.34%. These metrics indicate a strong performance in identifying cracks within the images analyzed. A precision score of 86.5% signifies that when the algorithm predicts crack pixels, it is correct more than 86% of the time, minimizing false positives. Meanwhile, a recall of 87.34% indicates that the algorithm successfully detects over 87% of all actual crack pixels present in the images, thereby demonstrating its effectiveness in capturing the majority of true positives. These findings highlight the algorithm's robustness in accurately identifying cracks, essential for maintaining the structural integrity and safety of bridge infrastructures. Future enhancements could further optimize the algorithm's precision and recall rates, potentially enhancing its practical applicability and reliability in real-world scenarios.

V CONCLUSION

In evaluating crack detection algorithms for bridge structures, precision and recall metrics are essential indicators of performance. The results demonstrate a high precision of 86.5% and recall of 87.34%, indicating that the algorithm effectively identifies crack pixels with a relatively low rate of false positives and false negatives. This suggests a robust ability to accurately pinpoint crack locations while minimizing both missed detections and erroneous identifications. Such metrics are crucial for ensuring the reliability and efficiency of automated crack detection systems in maintaining structural integrity and safety assessments of critical infrastructure like bridges. Further improvements could focus on reducing false positives to enhance precision even further, thereby refining the algorithm's capability for practical deployment in real-world scenarios.

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