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Algorithm for Automated Severity Assessment of Cracks in Simply Supported Bridge Beams Using UAV-Based Video Analysis

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Abstract: Automated inspection of concrete bridge components is crucial for timely maintenance and safety. This paper presents an algorithm for automated crack severity assessment in simply supported bridge beams using UAV-based video analysis. The proposed method integrates deep learning for crack detection with image processing techniques to measure crack dimensions and introduces a novel severity metric that combines the crack's mean width with its location along the beam. This addresses a gap in existing approaches which typically evaluate crack severity only by width or length, without considering structural context. A UAV-mounted camera captures video of the beam; frames are processed by a trained neural network to identify crack regions. Crack widths are then quantified in physical units, and the crack's position relative to the beam's span is determined. Using these parameters, a severity index or grade is computed. Cracks in critical regions with significant width are assessed as more severe than those of similar width in less critical areas. Preliminary results demonstrate that incorporating crack location yields a more structurally informed severity assessment, potentially improving maintenance prioritization. The paper details the algorithm's design and its basis in structural mechanics and computer vision, and reviews relevant literature.

Index Terms: bridge inspection, UAV, crack detection, crack width measurement, structural health monitoring, severity assessment algorithm.

1 INTRODUCTION

Concrete bridge structures are susceptible to cracking, which, if left unmonitored, can compromise load-bearing capacity and lead to catastrophic failures. Manual crack inspection is a practice that is documented to have numerous challenges such as subjectivity, labor-intensive nature, and the danger it presents to the people involved. In order to counter these shortcomings, unmanned aerial vehicles (UAVs) with high-resolution cameras have gained popularity in the structural inspection with increased coverage, which is faster and less expensive [1] [2]. Additionally, the combination of UAV-derived images with computer vision experiments and deep neural networks allows automatically detecting and measuring cracks with great accuracy [1] [3] [4]. Early image-based crack detection methods utilized a more conventional edge-detection method which was often inadequate in the real-world scenario [5] [6]. The change towards deep learning and, especially, convolutional neural networks (CNNs) has significantly increased detection accuracy [7] [8]. The most recent models, like YOLO and Faster R-CNN, enable the crack localization in UAV imagery to be close to real-time, and recent research found precision in detecting cracks over 98% [9]. In spite of these accomplishments, a correct appreciation of the severity of cracks is still a challenge. Existing automated systems basically categorize cracks on position alone based on width without taking note of the structural setting of the crack. Engineering concepts, however, show that the placement of crack has a tremendous effect on its criticality; a crack placed mid-span of an unsupported beam is more worrisome than a crack that is close to support due to the greater bending moments. The current paper proposes a new algorithm where crack width is combined with spatial position, which is used in calculating a structurally informed severity index. Capable of matching automated assessments with engineering judgment, the proposed approach would contribute to an improvement of the UAV-based bridge inspection reliability, satisfying a crucial need in modern severity assessment practice [10].

2 Literature Review

The field of automated crack inspection is underpinned by two key research areas: computer vision-based crack detection and structural engineering principles for assessing crack severity. Recent developments have gone far to improve the soundness of the whole procedure, machine-vision methods making accurate identification and measurement easy, and structural understanding providing the background into which the significance of observed faults can be placed [1] [2].

The early image-processing methods have been based on the traditional filtering mechanisms that most prominently include Sobel and Canny detectors of edges where grayscale thresholding was applied to extract the crack-like patterns out of concrete-deck images [5]. These strategies worked fairly well on surfaces that can be considered visually homogeneous, but were vulnerable to noise, artifacts made by shadows and perhaps more importantly, sophisticated textures, and as such limited their practical implementation [11].

The emergence of machine learning indicated the paradigmatic shift to data-driven detection. Early work used hand-crafted features, combined with support vector machines, to do classification. Later the application of deep-learning techniques especially convolutional neural networks (CNNs) allowed identifying cracks in a more robust fashion. Some researchers demonstrated that CNNs can be used for aerial imagery [7]. They expanded on this by showing that region-based CNNs, like Faster R-CNN, can achieve reliable detection and precise localization of different types of damage in real-world bridge data [8].

Recent improvements in single-stage object detectors, like the YOLO family, have significantly enhanced real-time crack detection. Models such as YOLOv7 now reach precision rates over 98% [8]. Their lightweight design lets them be used on UAVs, allowing for efficient autonomous inspections. The availability of public datasets like SDNET2018 and CFD has further improved model training and testing [12] [13]. While detection accuracy has increased, most current systems still do not consider structural context when assessing severity. This shortcoming shows the need for methods, like the one proposed in this study, that combine both geometric and positional data for a more reliable severity assessment.

3 Proposed Algorithm

The proposed tecnique is formulated to handle discontinuous cracks with different orientations efficiently. The subsequent subsections, 1 and 2, describe the overall outline of the algorithm and application of structural engineering rules to automated decision-making, respectively.

3.1 Algorithm Architecture

The proposed algorithm is shown in Fig. 1, which presents the flow of system's sequential processing.

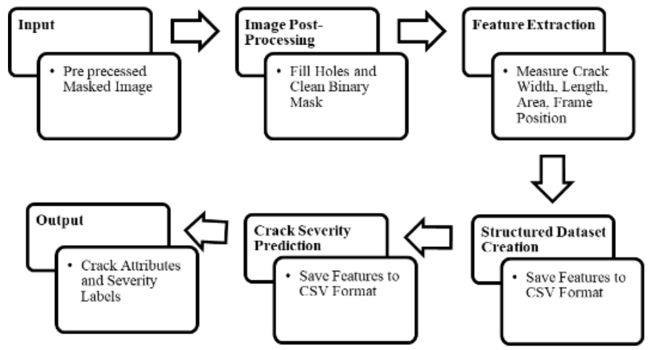


Fig. 1. Flow chart of the proposed region-based crack interpretation

3.1.1 Input format and Dataset

The proposed system begins with pre-processed binary crack images, where the background is black and the crack region appears in white. These masked images are output of the developed crack detection algorithm applied to UAV-captured footage. Each image corresponds to a frame in a horizontally scanned video of a simply supported concrete beam. The dataset used in this study includes such masked frames, collected from UAV recordings and manually annotated where needed.

The algorithm identifies the frame index with the file name. The extracted frames from the video (frames which have cracks) are named in a special way.

$$Name\ Format\ =\ FrameIndex\_Minutes\_Seconds\_Miliseconds \tag{1}$$

This format not only help to identify the frame index but also inspectors can identify the exact place of the crack using the time stamp.

3.1.2 Region Labeling & Division

The next step involves the application of connected component labeling, where each separate connected region in the binary image is assigned an integer label unique to it. The labels enable the algorithm to work on every segment of the cracks in isolation.

After the completion of the labeling process, the image is divided into sub-regions based on the coherence displayed by the structure of the crack. In cases where the path is characterized by discontinuity or irregularity, a separate region is identified. Every identified region is treated as a structurally independent segment and is further analyzed separately.

3.1.3 Feature Extraction

For each labeled region, geometric attributes are calculated:

- The centroid of the region is computed to localize its spatial center.
- The crack length(Λ) is defined as the maximum number of connected white pixels along the main axis of the crack region. The length represents the longest span of the crack within that connected segment.

- The crack width(Ω) is measured as the maximum thickness of the crack, and it is calculated perpendicular to the length (main direction of the region). It is basically the widest cross-sectional point within the region.
- The crack area(A) is calculated by counting the total number of white pixels in the region and converting it into mm^2 using pixel to mm^2 scale [10].

$$A = N_{white\_pixels} \times \text{pixel to } \mathrm{m}m^2 \text{ scale} \tag{2}$$

- For all the dimensions, pixel to mm^2 scale can be changed according to the camera calibration.

A custom technique was developed to determine the exact position of the crack on the beam using the frame index of the input photo (a frame from the video captured by the UAV). First the total number of frames are divided into equal three parts. First 1/3 is identified as one end of the bridge, second 1/3 is identified as the middle part of the beam and the third 1/3 of the beam is identified as the other end of the beam. By analyzing the total number of frames and the frame number of the input photo, the system identifies whether a crack is located in the structurally critical middle third of the beam or in the two ends of the beam. This approach allows to consider both geometric properties and the crack location.

3.2 Decision Making

The existing mainstream crack analysis solutions ended up their pipeline with the extraction of geometric properties of identified cracks, mostly width, length. However, these systems are still semi-autonomous because they rely on interpretation by hand or exertion to give a severity score. Such dependency on human limits scalability and real-time deployment capability of structural monitoring at scale.

This research paper aims at mitigating the mentioned shortcoming by presenting a completely autonomous decision-making system based on a neural network and trained on a set of diverse data. As opposed to the rule-based alternatives that lack the contextual information and are limited to a fixed width audit thresholds, the suggested model will use geometric and position features to reflect the context of the data and, therefore, allow distinguishing the degree of severity of a crack in a more subtle way.

For the consider the severity according to the geometric elements we depend on, US road and transportations department made standards to decide the crack severity level of most types of cracks [14].

$$Severity = \begin{cases} Low: if\ \Omega\ \leq 6mm \\ Moderate: if\ 6\ \leq \Omega\ \leq 19mm \\ High: if\ \Omega > 19mm \end{cases} \tag{3}$$

Since the proposed system is designed for simply supported concrete beams, it incorporates structural behavior into the severity classification process. Fig. 2 and Fig. 3 show how a simply supported beam loads and bends under a uniform load. Fig. 3 further illustrates this with the bending moment curve, where the highest moment occurs exactly at the center of the span (L/2). This indicates that cracks in this area are more critical because of the greater stress concentrations. Therefore, the system assigns a "Severe" severity level to any crack located within the middle third of the beam, regardless of its width.

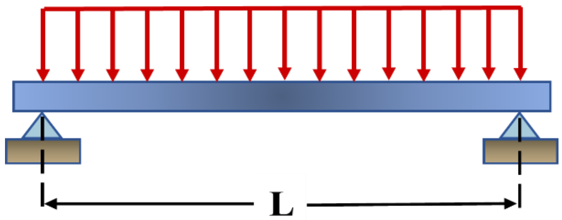


Fig. 2. Forces on simply supported beam

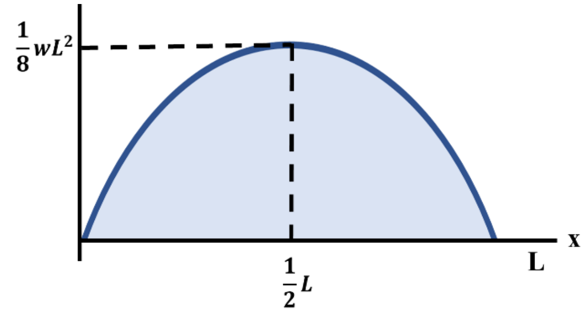
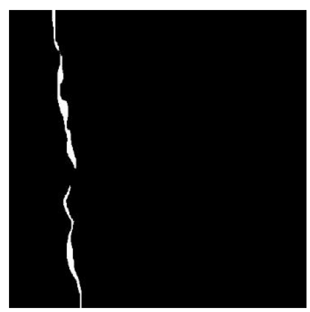
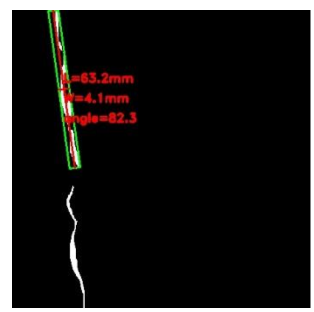
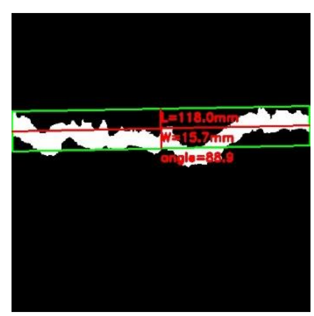


Fig. 3. Bending moment curve

4 Results

To test how well the proposed crack severity classification pipeline works, we conducted a real-world test. We used a 60-second video of a simply supported concrete beam recorded under controlled conditions. The video was sampled at 2 frames per second, which gave us a total of 120 frames for analysis. We pre-processed and masked each frame to highlight the detected crack areas. Then we ran the pipeline as described in the methodology. Fig. 4 shows examples of outputs from the proposed system. It illustrates “Low”, “Moderate”, “High” and “Severe” severity classifications.

SEVERITY	RAW IMAGE	MASKED IMAGE	OUTPUT IMAGE
LOW			
MODERATE			

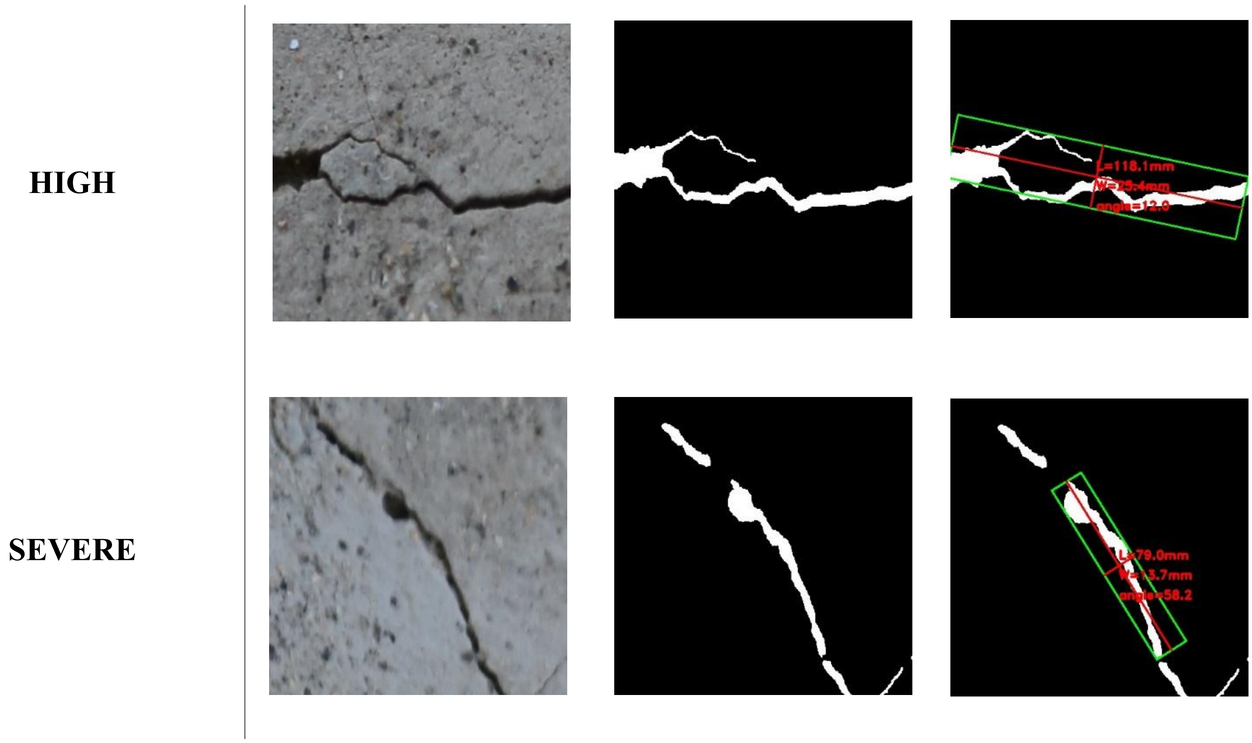


Fig. 4. Sample Output

Table 1 shows the output parameters of the samples shown in Fig. 4, extracted from the output CSV file of the system.

Table 1. CSV file data of sample outputs

mean_width_mm	mean_length_mm	area_mm^2	frame_idx	total_frames	predicted_severity
15.74493163	118.0255948	800.4296066	82	120	Moderate
13.72840827	79.03306251	376.2733195	70	120	Severe
25.40034486	118.0828183T	612.2579446	81	120	High
4.120200501	63.1620313	113.2670197	114	120	Low

These results show that the proposed method not only automates the crack severity assessment process but also includes structural context, giving useful information for maintenance and safety decisions. Using spatially aware classification worked especially well for simply supported beams, making sure that critical areas got the necessary level of attention. We acknowledge limitations, like the system's dependence on the quality of crack masks and consistent frame sampling, and we address these in the Discussion section.

5 Discussion

The main goal of this study was to build a system that can automatically assess the severity of cracks in concrete structures. This specifically focuses on simply supported beams and uses image-based geometric features and spatial location analysis. The results indicate that the proposed process starts with pre-processed masked crack images, moves on to geometric feature extraction, and ends with machine learning-based severity prediction. This provides an effective and scalable way to monitor the health of structures.

One of the main strengths of this research is its use of structural knowledge in the classification logic. By including the beam's physical behavior, especially the fact that maximum stress occurs at the midspan of simply supported beams, the system can consider both crack size and crack location. This factor is important in real-world engineering assessments. This method of classification provides a context that traditional threshold-based systems do not offer.

The trained neural network provided more flexibility and accuracy in predicting severity, especially with overlapping or unclear crack features. Unlike traditional rule-based systems, the model could learn subtle patterns and relationships between input features, such as width, length, and area, that impact structural risk. Adding frame index and total frame count as inputs offered a new way to represent spatial position without needing full 3D reconstruction or beam segmentation.

The experimental results showed that the model could reliably predict crack severity and matched engineering expectations. Cracks located in the middle third of the beam were correctly identified as Severe, regardless of their size. In contrast, cracks in the first and last thirds were classified more carefully based on their geometric features. This confirms that the hybrid classification logic, which combines position rules from the field with data-driven learning, is both effective and valuable.

However, some limitations are worth discussing. First, the model's accuracy depends on the quality of the pre-processed mask images. Any errors or noise from earlier crack detection stages can carry through the process, impacting feature extraction and classification. Additionally, the system assumes a straight horizontal scan from one end of the beam to the other. This assumption may not be valid for all UAV flight paths or site conditions. In real deployments, differences in video capture angles or frame spacing might need frame alignment or normalization techniques to keep positional accuracy.

Moreover, the current model was trained and tested using a fixed pixel-to-mm scaling factor, which assumes consistent camera calibration and altitude. In practice, different cameras, lenses, or flight heights could change spatial resolution. Therefore, to generalize the system, we have would need either dynamic calibration inputs or the use of scale-invariant features.

Despite these limitations, the proposed method represents a notable progress in autonomous structural assessment. It connects image processing with structural engineering logic. This produces clear and useful results that engineers, inspectors, or automated alert systems can directly use

6 Conclusion

This research provided a full and automated method to assess the severity of cracks in simply supported concrete beams. It utilized masked image inputs, pixel-based geometric analysis, and machine learning for making decisions. The proposed approach effectively combined image processing, feature extraction, and neural network classification to generate meaningful and efficient severity labels.

By including both crack shape and crack position along the beam, based on frame index data, the system addressed a major shortcoming in existing automated methods that frequently ignore structural behavior. Classifying cracks in the middle third of simply supported beams as Severe, no matter their size, shows good engineering judgment and increases the reliability of the outcomes.

The experimental findings confirm that the combination of rule-based positional classification and data-driven learning creates a system that is not only accurate but also practical. The final output is saved as a structured CSV file with predicted severity labels, allowing direct use in inspection interfaces and structural health dashboards.

While the current model works well for simply supported beams, future research will aim to expand the algorithm to cover other types of beams and structural elements, such as cantilever, continuous, and fixed-end beams. This will include adding force distribution characteristics and bending moment profiles to the decision-making process. This improvement would make the system applicable to more civil infrastructure situations, allowing it to be used in a broader range of structural inspections.

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