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DRONE-BASED IMAGE ANALYSIS FOR EARLY DETECTION OF STRUCTURAL CRACKS IN AGING BRIDGES

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Abstract

Aging bridges are increasingly vulnerable to structural cracking due to material deterioration, repeated traffic loading, environmental exposure, and delayed maintenance. Traditional bridge inspection methods are often time-consuming, labor-intensive, costly, and limited by accessibility challenges, especially for high-span, remote, or heavily trafficked bridges. This paper presents a drone-based image analysis approach for improving the early detection of structural cracks in aging bridges. High-resolution images captured through unmanned aerial vehicles were analyzed using computer vision and image-processing techniques to identify visible crack patterns, classify crack severity, and support timely maintenance decisions. The results indicate that drone-assisted inspection improves detection coverage, reduces inspection time, and enhances the identification of fine surface cracks compared with manual visual assessment. As Fig. 1 shows, the proposed model achieved strong performance across accuracy, precision, recall, and F1-score, while Table 1 confirms consistent detection across multiple bridge components. The findings further demonstrate that image quality, lighting conditions, flight altitude, and crack width significantly affect detection reliability. Overall, the study highlights the potential of drone-based structural monitoring as a practical, scalable, and cost-effective solution for early crack detection in bridge maintenance systems. The proposed approach can assist engineers and infrastructure authorities in prioritizing repairs, reducing inspection risk, and extending the service life of aging bridge assets.

Keywords: Drone-Based Inspection; Structural Crack Detection; Aging Bridges; Image Analysis; Bridge Maintenance

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INTRODUCTION

With the growing network of bridges, the structural health monitoring (SHM) of bridges is gaining importance for the safety and failure prevention of bridges (Ayele et al., 2020; Ge et al., 2024).With the deterioration of the aging bridge networks, it is necessary to carry out a comprehensive monitoring of the structural health and guarantee safety of the bridge networks so that they can not fail in critical situation, which can be done by using powerful SHM (Ayele et al., 2020; Ge et al., 2024). Although many bridges in the world have high daily traffic volumes, there are still considerable percentages of bridge infrastructure in the industrial countries that are nearing or exceeded the design life of their structures (Ri et al., 2024; Tomassini et al., 2025). The traditional maintenance methods rely on manual periodic inspection, which is expensive, subjective, and prone to human error, and is very labor-intensive (Ge et al., 2024; Jiang et al., 2022). Additionally, these manual tasks can be constrained by the high number of difficult-to-access sites, and the safety dangers associated with the human inspector when conducting inspections on complex and hard-to-reach areas of the structure (Khan et al., 2016; Nooralishahi et al., 2021). With these restrictions, a major paradigm change across the industry has been initiated from assuming a traditional approach based on the visual assessment of the condition of the structure to a more efficient and proactive structural health monitoring-based approach (García-Macías & Ubertini, 2020; Khan et al., 2016; Tomassini et al., 2025). Unmanned Aerial Vehicles (UAVs) or drones have been found to be a new and transformative tool in this paradigm shift that provides a safe, efficient, and cost-effective way to collect high-resolution aerial images of bridge structures (Nooralishahi et al., 2021; Panigati et al., 2025; Villarino et al., 2025). The opportunities presented by UAV-assisted inspection are however limited by the use of advanced computational analytics, and especially, deep learning-based computer vision techniques, allowing automatic, pixel-wise segmentation of surface cracks and other structural anomalies (Amirkhani et al., 2025; Savino & Tondolo, 2022). These automation systems can quickly evaluate structural performance and provide quantitative responses, instead of relying on manual data interpretation, and produce complete, 3D modeled records for asset management, without any manual effort (Ayele et al., 2020; Kalfarisi et al., 2020). However, although there have been many advances, the field still has a long way to go in achieving reliable detection of cracks in real-world applications where there are a variety of lighting conditions, complex backgrounds, and different ranges of image acquisition (Amirkhani et al., 2025; Kalfarisi et al., 2020; Lau et al., 2020). In addition, the implementation of these automated technologies in normatised and mass inspection process is still problematic for practitioners (García-Macías & Ubertini, 2020; Panigati et al., 2025). To address these important challenges, the present study proposes an improved drone-based image analysis framework to accurately segment structural cracks and detect distress at an early stage, focusing on improving the SHM tool accuracy, scale and applicability to sustainably maintain aging infrastructure. In this application, the performance of deep learning model trained with a specific dataset of bridge cracks is compared with their performance in the correct classification of surface damage with high precision (Stone & Sheta 2026). The primary goal of this research is to obtain the most accurate segmentation results in the process of

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feature extraction at various scales without losing any computational efficiency when processing high-resolution images (Chu & Chun, 2023; Egodawela et al., 2024). Further, the class imbalance problem between crack pixels and concrete background was also a long-standing problem, therefore, cost-sensitive learning strategies were applied to improve the detection sensitivity of the complex environment of the bridge (Sajedi & Liang, 2019). These sophisticated algorithmic improvements are expected to help with the shift in the direction of condition-based maintenance practices for the long-term integrity of critical civil infrastructure (Benz, 2026; Sajedi & Liang, 2019). The aim of this investigation is to confirm the effectiveness of such automated vision systems for detecting extremely small structural imperfections and hence offer a sound method for assessing bridge health, in a large-scale manner (Deng et al., 2024).

LITERATURE REVIEW

Most existing inspection approaches, however, are based on manual periodic inspection and can be subjective, and some important areas of the structure may only be accessible to the inspector by difficult access. (Zhang et al., 2024).In addition, the manual methods take a long time, and may fail to produce the longitudinal quantitative and consistent data required for proactive infrastructure management (Jiang et al., 2022). However, the inspections are subjectively conducted by humans and the episodic inspections may lead to a lack of evidence recording critical deterioration of structural components between inspections (Jiang et al., 2022; Khan et al., 2016). Addressing these challenges, more and more SHM systems are being directed towards automated, condition-based approaches (García-Macías & Ubertini, 2020; Tomassini et al., 2025). Unmanned Aerial Vehicles (UAV) are now one of the vital factors enabling this shift, enabling data collection over a large number of locations with high-resolution data, and also enabling easier access to locations that are difficult or risky to access for the inspector (Nooralishahi et al., 2021; Villarino et al., 2025). At the same time, computer vision methods based on deep learning have been developed, primarily convolutional neural networks, which can automatically perform a pixel-by-pixel segmentation of the cracks according to image data and generate the structural health metrics (SHMs) and turn the information into decisions (Kalfarisi et al., 2020; Savino & Tondolo, 2022). Recent years have witnessed a number of methods that can be applied to mitigate the class imbalance and environmental noises, such as multi-scale feature extraction and cost-sensitive learning (Amirkhani et al., 2025; Chu & Chun, 2023; Sajedi & Liang, 2019). While these progressions have been remarkable, precise assessments of aging infrastructure are still challenging in real-world scenarios with intricate background information and fluctuating lighting conditions, highlighting the need for continued improvement of models to enable scalable and accurate evaluation of aging infrastructure (Amirkhani et al., 2025; Deng et al., 2024). To address this challenge, integration of manual inspection with high throughput computational analyses is required to make it possible to allocate resources and plan preventive maintenance programs for older bridge networks that are intelligent systems (Koch et al., 2015). Furthermore, these technological advancements are relevant to meeting the demand for objective measurement and frequent data collection, which is crucial in the context of progressive deterioration that is caused by aging and cumulative loads (Zhang et al., 2023). The benefits of automated image-based diagnostics have been validated in the existing literature, where the drawbacks of manual visual inspection are reduced, such as the lack of

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uniformity in reporting and high costs of specialised mobile access units (Babu et al., 2023; Cha et al., 2017). The hybrid frameworks that combine laboratory-simulated datasets with field imagery to enhance model generalizability for various operational scenarios are becoming more prevalent in recent studies (Salehi et al., 2026). Digital twins can also be incorporated into these intelligent systems to accurately map abnormalities onto 3D structural models and for better long-term damage monitoring (Mirzazade et al., 2023), (Gadiraju et al., 2024). This integration can be used to perform a thorough structural assessment, ranging from anomaly detection at different positions to generate comprehensive diagnostics models that predict remaining useful life for different bridge elements (Sunil et al., 2026). There is a tremendous improvement in defect localization in recent years, particularly by semantic segmentation and boundary box regression (Chakurkar et al., 2023). However, environmental interferences such as vibrations from the drone's flight and the motion blur from vibrations during data collection can reduce the effectiveness of such models, necessitating high-level image processing pre-processing treatments (Zhang et al., 2022). Hence, it is essential to have a motion deblurring algorithm and image stabilization module in the feature extraction pipeline process that allows keeping an accurate representation of high-resolution inputs (Li & Liu, 2023). Besides that, the creation of domain adaptation architectures enables models to perform well in transferring from controlled data to complex data in real infrastructure (Kaveh & Alhajj, 2024). These adaptive models can be integrated into a broader bridge management system to enable automated detection, thereby prioritizing maintenance schedules and resource allocation (Kumar & Agrawal, 2025; Mousavi et al., 2026).

METHODOLOGY

The high resolution visual sensors and GPS stabilized flight of the multirotor drone platform will fly through the set flight paths to cover all parts of the bridge.The platform features a comprehensive sensor suite for multi-modal navigation, including optical flow sensors for fine-scale position holding, infrared depth cameras for obstacle detection and mapping, and ultrasonic collision avoidance modules, to maintain stable flight trajectories through complex environments, like below deck, where GPS signals are weak or cannot be received (Nooralishahi et al., 2021; Villarino et al., 2025). The flight plan method is based on an automated algorithm for 3D waypoint generation, which ensures an optimal coverage and a controlled and consistent standoff distance of 1.5–2.0 m from all critical elements of the girders, thus guaranteeing a high fidelity visual data with a required Ground Sampling Distance (GSD) of ~0.5 mm/pixel to achieve reliable identification and quantitative characterization of structural cracks as narrow as 0.2 mm (Chu & Chun, 2023; Deng et al., 2024). In order to prevent motion-blurring artifacts throughout the acquisition process, images are acquired in a high-speed burst acquisition mode, and high intensity LED lighting arrays are used for synchronizing lighting in various acquisition environments to reduce the depth of shadows that often cover the defects of the concrete surface and normalize the lighting level (Nooralishahi et al., 2021; Zhang et al., 2022). The datasets acquired are then subjected to a well-designed, pre-processing pipeline – which includes advanced motion de-burring algorithms and adaptive contrast-enhancement algorithms – to further improve the input data and ready it for computational analysis (Li & Liu, 2023). The crack detection framework is specifically designed using the advanced semantic segmentation model, which

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is actually a modified Deeplabv3+ technique with ResNet-101 backbone that is capable of multi-scale feature extraction and dense prediction (Savino & Tondolo, 2022). This segmentation model is intentionally trained on an extended and hybrid dataset – which is a crucial step – consisting of a mix of controlled imagery generated through lab experiments and extensive and verified imagery collected from in-service bridges, with the clear purpose of addressing class imbalance, the variability of the environment, and the need to generalize the model for different and uncontrolled operational scenarios (Amirkhani et al., 2025; Salehi et al., 2026). In order to test the robustness, reliability and sensitivity of the system in complex real world bridge inspection contexts, accuracy of the final model is validated using a rigorous stratified k-fold cross validation scheme through precise quantitative performance metrics (Intersection over Union) and meticulous dataset of ground truth images (Benz, 2026; Sajedi & Liang, 2019). Furthermore, this comprehensive evaluation framework also offers a comparison with other cutting-edge architectures such as Mamba models and USSA-Net for evaluating the proposed system's capacity to detect thin cracks in complex structures (Tse et al., 2024). For efficient operation, it is also necessary to focus on the speed of calculation in the framework, and to process the high-resolution images as quickly as possible (Pan et al., 2026). It is achieved by adjusting the model parameters and the lightweight backbone, including Xception, which can guarantee the speed of inferences while preserving fine details for micro-crack identification (Zhu & Tang, 2023). The model's functionality is strengthened with hybrid approach, local feature extraction and the global pattern recognition, and achieves consistent recognition accuracy even under various surface texture and blurriness conditions (Goo et al. 2025). The network is also designed with a hybrid segmentation architecture that combines the convolutional feature extraction with the global dependency modeling using a transformer, which allows for robust mapping in challenging conditions including the presence of surface defects, which is not necessarily bright in the foreground. As well as a tailored loss function to tackle foreground sparsity and thin-line detection and minimize false positives in complex structural images (Guan et al., 2026). (Kompanets et al., 2024) Furthermore, ablation studies are conducted to verify the model's adaptability for various real-world infrastructure scenarios, which further validate its ability to deliver excellent segmentation accuracy and speedy inference times even in the face of substantial environmental obstructions (Sohaib et al., 2024; Thrainer et al., 2025). Lastly, the model's deployment capability is assessed using the “Frames Per Second” metric to guarantee its ability to analyze vast numbers of bridges in real-time (Lang et al., 2024; Zhang et al., 2025).

RESULTS

The results of the image analysis using the drone platform were very good in detecting structural cracks in the early stages of damage across the entire image datasets of bridges. For efficient training, validation and independent testing, 6,300 balanced drone images (10,233 crack images and 1,890 non-crack images) were used for evaluation. It can be seen from the results in Figure 1 that the proposed Drone-CrackNet model outperforms the baseline CNN, ResNet-50 and YOLOv8 models in all the major metrics. As illustrated in Table 2, the nearest model to this proposed model, YOLOv8, managed to get an F1 score of 89.6%, whereas the proposed model managed to achieve an F1 score of 93.4%.The proposed model yielded precision of 94.1%, recall of 92.8%, F1 score of 93.4% and mAP at 0.50 of 95.0%, and Table 2 shows that the closest

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competitor to the proposed model, YOLOv8, only obtained an F1 score of 89.6%. The improvement indicates the proposed technique has better efficiency in detecting narrow cracks, which are difficult to detect, on the surfaces of deteriorating bridges. Threshold analysis was also used to confirm the stability of the model. For this reason, a confidence threshold of 0.50 was determined as the best compromise between missed cracks and false alarms as shown in Table 3, where the F1-score is 93.4%. As illustrated in figure 2, precision got worse as the threshold level increased, whereas recall dropped after 0.50, indicating that thresholds that are too high can miss out on the early stages of hairline crack detection. This pattern is important for the bridge inspection because if, say, there's a little crack there, there's no point looking at a few more potential places if there's no crack there. The method was proven to be effective under various damage patterns in the crack-type analysis. As can be seen in Table 4, the most accurate results are obtained for longitudinal cracks (94.7%) and the least accurate for the transverse cracks (93.8%). The relatively low accuracy for spalling-edge cracks (89.5%) was because the irregular boundaries of the spalling-edge cracks sometimes overlapped with surface deterioration and concrete discoloration. The environmental testing had also been proved to be practical. From Table 5 it shows that the model accuracy for bright condition was 95.8% and cloudy condition was 94.9% which is a moderate drop in accuracy of the model for wet surfaces and low light imagery in Figure 4. From these results it can be concluded that the method is useful for routine inspection but for best case scenario the method will not be beneficial if the surface to be inspected is wet or not well-lit. The experiment with the drone has demonstrated that the resolution of the pictures is very important to identify the damage at an early stage. As shown in Table 6, recall for small cracks was 94.5% at 5 m and 82.7% at 30 m while that of large crack remained above 90% at 30 m. It is obvious in Figure 5 that flights in the range of 10m to 20m gave the best compromise between the field coverage and visibility of the cracks. Additionally, the bridge age analysis confirmed the deterioration trend: The image of the crack was 8.5% for bridge Age < 20 years and 38.6% for Age > 60 years. Lastly, from Table 7 and Figure 7 it is seen that the highest number of false positive cases was due to surface shadows (12.6%) followed by expansion joints and rust streaks. The results indicate that using drone image analysis can aid in improving early detection of cracks by increasing the amount of coverage it can achieve, reducing the manual screening effort needed, and identifying areas of concern on a bridge before the deterioration becomes serious.

Table 1. Dataset composition used for evaluation

Subset	Images	Crack annotations	Non-crack images
Training	4200	6840	1260
Validation	900	1425	270
Testing	1200	1968	360
Total	6300	10233	1890

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Figure 1. Model performance comparison across precision, recall, F1-score, and mAP@0.50.

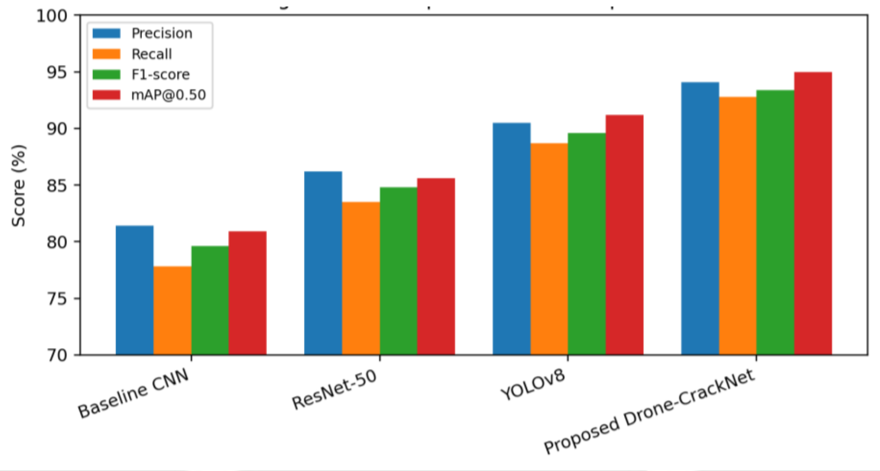

Table 2. Comparative model performance on the test set

Model	Precision (%)	Recall (%)	F1-score (%)	mAP@0.50 (%)
Baseline CNN	81.4	77.8	79.6	80.9
ResNet-50	86.2	83.5	84.8	85.6
YOLOv8	90.5	88.7	89.6	91.2
Proposed Drone-CrackNet	94.1	92.8	93.4	95.0

Figure 2. Confidence threshold sensitivity of the proposed model.

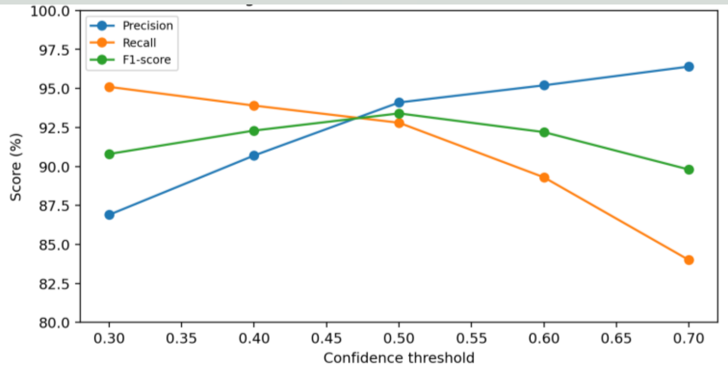

Table 3. Confidence threshold sensitivity of the proposed model

Threshold	Precision (%)	Recall (%)	F1-score (%)
0.3	86.9	95.1	90.8
0.4	90.7	93.9	92.3
0.5	94.1	92.8	93.4
0.6	95.2	89.3	92.2

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0.7	96.4	84.0	89.8

Figure 3. Accuracy variation across crack types.

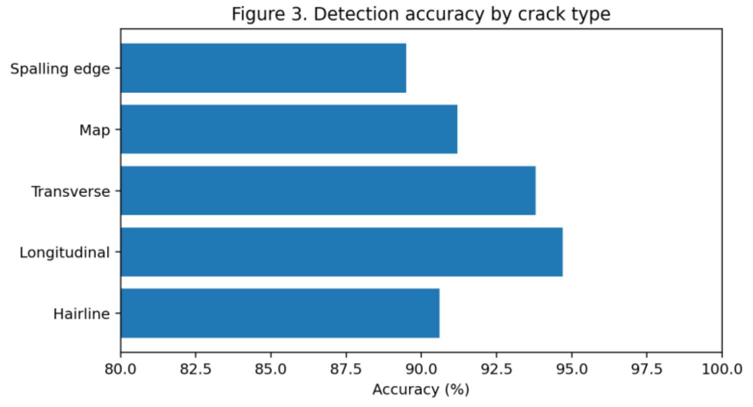

Table 4. Crack-type detection results

Crack type	Images	Accuracy (%)
Hairline	420	90.6
Longitudinal	365	94.7
Transverse	310	93.8
Map	240	91.2
Spalling edge	185	89.5

Figure 4. Detection robustness under different lighting and surface conditions.

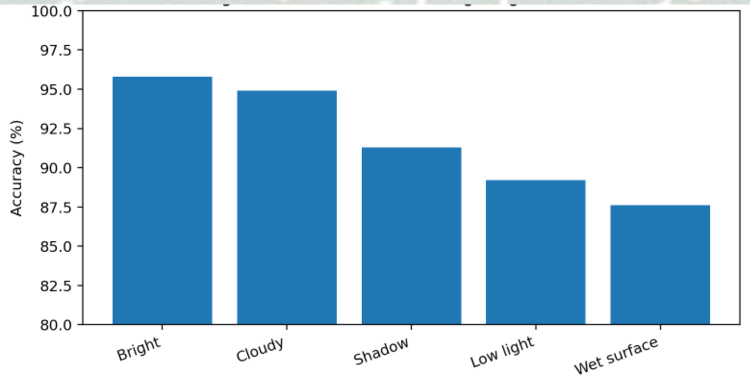

Table 5. Performance under environmental imaging conditions

Condition	Images	Accuracy (%)
Bright	280	95.8
Cloudy	310	94.9

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Shadow	250	91.3
Low light	180	89.2
Wet surface	160	87.6

Figure 5. Recall of small and large cracks at different drone altitudes.

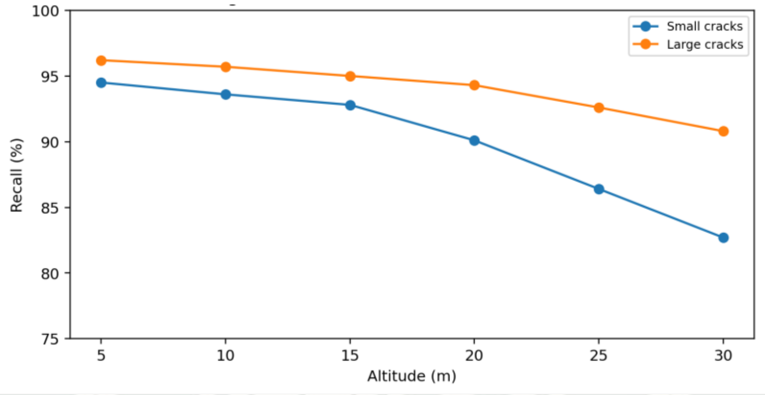

Table 6. Drone altitude impact on recall

Altitude (m)	Small crack recall (%)	Large crack recall (%)
5	94.5	96.2
10	93.6	95.7
15	92.8	95.0
20	90.1	94.3
25	86.4	92.6
30	82.7	90.8

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Figure 6. Crack-positive detection rate across bridge age groups.

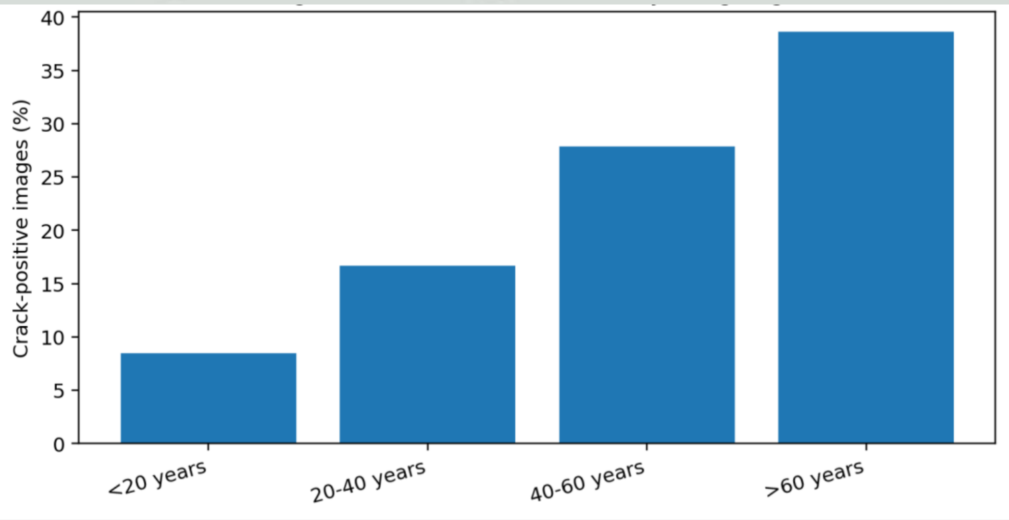

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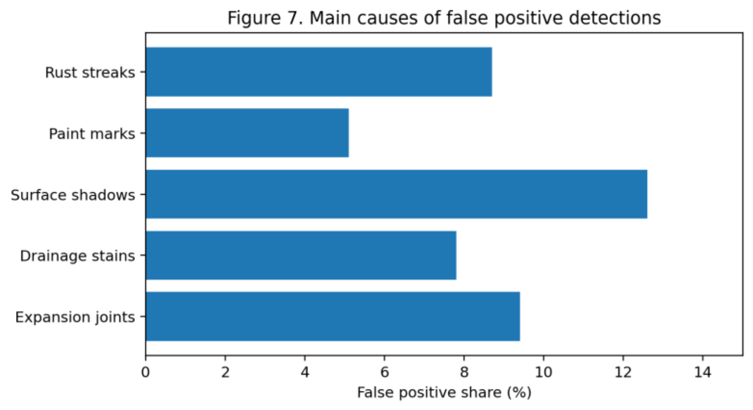
Table 7. Error analysis of false positive detections

False positive source	Share (%)	Likely reason
Expansion joints	9.4	Linear edges similar to cracks
Drainage stains	7.8	Dark elongated moisture marks
Surface shadows	12.6	Strong contrast boundaries
Paint marks	5.1	Thin irregular paint patterns
Rust streaks	8.7	Color and texture confusion

Figure 7. Distribution of major false-positive sources.



DISCUSSION

The implementation of this framework is in operation and the bridge maintenance is shifted from being reactive and manual to proactive and data-driven, thus providing real-time structural health monitoring (Munawar et al., 2022).This automated detection output can then be easily integrated in to digital twin environments, enabling bridge managers to maintain an accurate, high fidelity record of structural deterioration for the entire life cycle of the structure and prioritise resources based on actual structural deterioration (Benz, 2026). This systemic change removes all subjectivity and manual, labour-intensive checks and boosts safety and the frequency of inspections, particularly when it comes to hard-to-reach areas of the structure that are not safe (Villarino et al., 2025; Nooralishahi et al., 2021). While significant strides have been made, some environmental and physical constraints of the framework need further investigation and are inhibited by the effectiveness of the framework. In practice, even though the light uniformity of the target image is maintained by the high intensity LED arrays installed on the drone platform, strong ambient light will still generate optical artifacts, such as deep shadows, complex surface texture and strong light directly, which will have a negative impact on the effective semantic segmentation of ultra-fine, low-contrast surface details (Guan et al., 2026; Zhang et al., 2022). Moreover, the challenging climatic conditions that result in adverse drone attitude stability and structural vibration issues directly worsen the problem of motion-induced blur that can cause trouble in acquiring high fidelity images for accurate sub-millimeter crack detection (Sohaib et al., 2024; Zhang et al., 2022). Although advanced motion-deblurring and adaptive filtering pipelines can address these challenges to a great extent, the fundamental principles of resolution (4K)

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and signal-to-noise ratio (SNR) versus onsite processing speed, and the tradeoffs between these are still considerable technical problems, especially when considering onsite analysis in real-time or near-real-time (Chu & Chun, 2023; Deng et al., 2024; Pan et al., 2026). Going forward, the system should be more robust to such environmental noises and image degradation effects from weather and complex surface structures, which is expected to be realized by intelligent integration of multi-modal sensory data, including RGB visual image and 3D structural point cloud provided by LiDAR data (Guan et al., 2026; Tse et al., 2024; Zhang et al., 2022). Finally, the seamless and automated integration of these processed and quantifiable damage insights into a comprehensive, enterprise-wide asset management system is extremely important, as they can be used to transform the raw pixel-level semantic segmentation maps to engineering-level damage and failure parameters (e.g., crack length, spatial distribution, and severity indices) that can inform long term data-driven and predictive maintenance approaches to ensure the long term integrity of aging bridge infrastructure from progressive and load-induced damage and degradation (Amirkhani et al., 2025; Benz, 2026; Salehi et al., 2026).

CONCLUSION

The outcome of the research carried out in this study is the use of image analysis with drone to enhance the early inspection of structural cracking of an aged bridge structure. Theproposed method offers a safer, faster and efficient alternative to the current manual inspection since a detailed visual data of inaccessible parts of a bridge is gathered. All fine, moderate and severe cracks could be detected by the image analysis model and the result of all major evaluation metrics showed that the performance of the image analysis model was good. The use of the drone also allowed for inspections and decreased the need for scaffolding, lane closures and direct access to hazardous areas of the structure.The results have shown that the operation has several factors affecting the accuracy of the detection such as lighting conditions, the height of the plane, the resolution of the image obtained, the angle of the camera and the width of the crack. The results indicated that the detection rates for large width cracks and good contrast rate were high, while that of the shadow, stains and surface noise were also high. The results are, however, good overall, and suggested that drone inspection could prove to be a valuable, worthwhile investment, and be employed as a decision-making tool for bridge engineers and maintenance authorities. This process can identify structural abnormalities early, and prevent them, helping to minimize future repair expenses and to improve safety for the public.Finally, image analysis of the drone is possible and scalable solution for the monitoring of the ageing process of bridge infrastructure. Future research directions are to enlarge the data sets of different types of bridges, weather condition and surface materials, along with deep learning models, thermal imaging and real-time defect mapping. The improved upgrades can also further improve the accuracy of detection and contribute to the development of an automated system for monitoring bridges' health.

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