AI-Powered Digital Twins of Concrete Bridges for Enhanced Asset Management

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SUMMARY

Ensuring the long-term sustainability of bridge assets is crucial, but manual inspections are often time-consuming, laborious, and can be hazardous. These issues can be addressed by leveraging Artificial Intelligence (AI) with Digital Twin technology for enhanced monitoring and maintenance. This approach automates defect identification, reduces field time, and simplifies generating repair documentation, shifting from traditional to proactive, data-driven asset management.

In this study, the condition assessment of concrete bridge decks involves three steps: data acquisition, interpretive analysis, and visualization. Autonomous Unmanned Aerial Vehicles (UAVs) are utilized to capture high-quality images of the bridge, which are then stitched into 3D models using photogrammetry. Deep Learning algorithms detect defects such as cracking and spalling in these images, significantly reducing manual inspection time.

The Digital Twin is visualized in an Asset Management Portal (AMP), providing stakeholders with a clear, interactive representation of the bridge's condition. This enables timely interventions and historical tracking of defects. By leveraging UAVs, photogrammetry, and ML/AI, the transformative potential of Digital Twins in Structural Health Monitoring can be fully realized.

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INTRODUCTION

Bridge inspection methods have evolved significantly over the years, ranging from invasive methods to various Nondestructive Evaluation (NDE) techniques to perform comprehensive assessment of concrete bridge decks. Comparative studies conducted on conventional NDE methods, including ground-penetrating radar, the chain drag method, and impact echo, underlined their respective advantages and limitations in assessing bridge deck conditions [1, 2]. Researchers emphasized the importance of employing at least two NDE methods to achieve robustness and efficiency [3]. However, these methods are susceptible to the subjectivity of the inspector, are highly time-consuming for large-scale bridges, involve areas that are difficult to access, and often necessitate long-time traffic disruptions [4]. These studies collectively underscore the progression and diversification of bridge deck inspection methods, paving the way for more advanced and automated approaches in asset lifecycle management. Macchi et al. endorsed the incorporation of Digital Twins (DT) into structural health monitoring for two main purposes: (1) forecasting the performance and long-term behavior of the system and ensuring data continuity throughout the various lifecycle phases, and (2) improving the decision-making process for predictive maintenance and repairs [5].

Coupling with the emerging technologies such as advanced Machine Learning / Artificial Intelligence (ML / AI) techniques and Computer Vision (CV) algorithms, researchers have explored DT technology to enhance bridge asset management and maintenance [6]. This technology offers better communication among stakeholders and supports decision-making through the versatility of ML / AI. For instance, Perry et al. proposed an automated bridge inspection framework, supporting Bridge Information Modeling (BrIM) in the current Geographic Information System (GIS)-based asset management systems of state-departments of transportation [7]. Their framework demonstrated the ability to identify and quantify structural issues using images taken by an Unmanned Aerial Vehicle (UAV), highlighting its superiority over traditional human visual inspection techniques. Rios et al. systematically reviewed state-of-the-art knowledge on integrating DT in bridge management [8]. They highlighted the consensus on adopting DT for bridge management and identified gaps in software inoperability and anomaly detection algorithm performance. More recently, Kong et al. coupled the photogrammetry technology with DT for health monitoring of a historical bridge structure [9]. They demonstrated the effectiveness of UAV images in building DTs as well as utilizing DT for predictive analytics by detecting time-varying structural damage. Williams et al. introduced a specialized web platform for asset management involving DT of concrete cooling towers with automated detection of defects such as cracks and spalls [10]. It empowers the stakeholders with having a centralized platform where communication is made easier, showing significant promise in enhancing the monitoring, analysis, and maintenance of concrete cooling towers.

This paper presents a practical use case of an AI-enabled asset management platform for concrete bridge decks with automation capabilities. This paper is structured into several sections. Section 2, "Means and Methods," details the methodologies and techniques employed in the study, including the integration of Deep Learning-based CV algorithms with DT technology to monitor and manage concrete bridge assets. This section outlines the data collection processes and the analytical frameworks used to interpret the data. Section 3, "Results and Discussion," presents the findings of the study, highlighting the effectiveness of AI-powered DTs in predicting maintenance needs and identifying structural issues before they become critical. Section 4, "Conclusions," summarizes the key takeaways from the study, emphasizing the benefits of using AI with DT for proactive asset management and describes future work to further enhance the technology's capabilities.

MEANS AND METHODS

This paper explores a case study of three bridges, two of which are reinforced concrete and part of a cloverleaf interchange, and the third one being a prestressed concrete bridge. General information regarding these bridges is provided in Table 1.

TABLE I. GENERAL CHARACTERISTICS OF EACH BRIDGE CASE STUDY.

Case	Date of Construction	Date of Rehabilitation	Length (ft)	Width (ft)	# of Spans
Bridge 1	1971	2007	202.5	48.0	2
Bridge 2	1973	2007	202.5	48.0	2
Bridge 3	1981	N/A	168.5	54.0	3

A three-step procedure involving Data Acquisition, Data Analysis, and Data Visualization was followed to generate a DT for each bridge. This procedure, along with its inputs, constraints, methods, and outputs, was depicted in Figure 1.

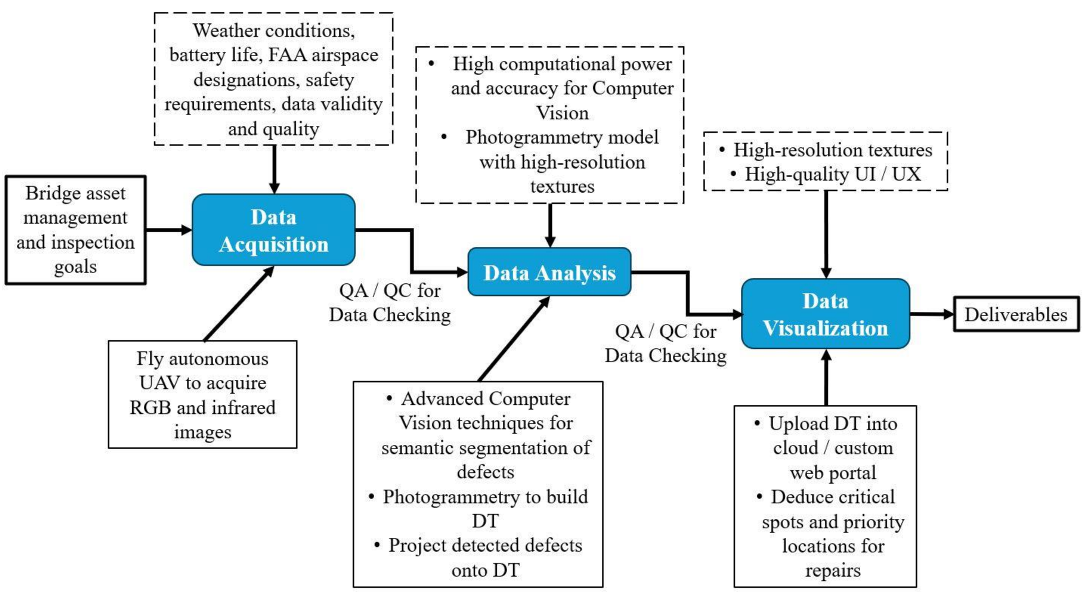


Figure 1. Diagram depicting the three-step framework of DT, along with their inputs, constraints (dashed outline), methods, and outputs.

Data Acquisition with Autonomous UAVs

A Skydio X10 UAV was deployed, capable of autonomous flight and obstacle avoidance, making it highly efficient for capturing both 2D surfaces and 3D spaces. The UAV operates using a standalone controller and is equipped with standard and infrared cameras to capture both visible red-green-blue (RGB) and thermal imagery, respectively for detecting surface and subsurface defects. The resolution of each RGB image is 9248 x 6944. With a battery life of over 40 minutes, the UAV can maintain optimal performance at a typical distance of 30 feet from the surface, which is ideal for detecting concrete cracks as small as 1/32-inch in width. A 30-ft distance-to-surface with 80% overlap and sidelap was utilized between adjacent images, following a path similar to the illustration in Figure 2. Overlap and sidelap ratios larger than the general practice were chosen to ensure the successful alignment of infrared images.

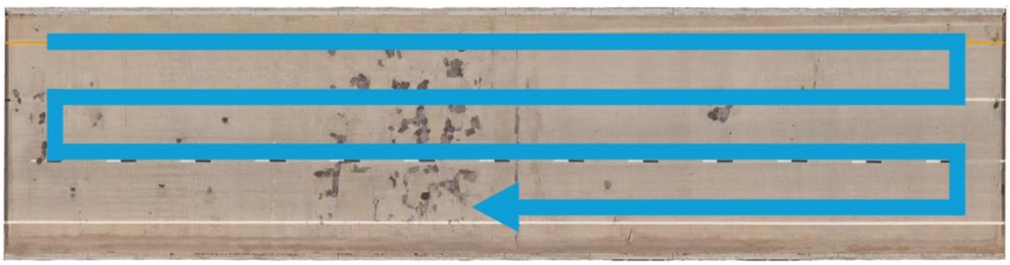


Figure 2. Typical scan path for the autonomous drone, illustrated on one of the bridges of interest.

To ensure the safety of UAV operations and minimize the risks of accidents, flying over vehicles was actively avoided. A visual line of sight was maintained at all times to be able to quickly react to any potential hazards. Scan parameters for drone surveys of each bridge are summarized in Table II.

TABLE II. SCAN PARAMETERS

Case	Scan Area (ft^2)	Flight Time (min)	# of Images
Bridge 1	11,813	16	828
Bridge 2	11,572	18	809
Bridge 3	6,906	10	515

In this study, surface defects include concrete cracking, spalling, exposed reinforcement, corrosion staining, and efflorescence. Subsurface defects of focus are concrete deck delaminations, particularly those that are not yet visible. Rapid heating and cooling on concrete deck surfaces create temperature differentials between pristine and delaminated concrete, which can be measured by infrared thermography under certain weather conditions [11]. In this case, infrared thermography is employed by using the procedure in ASTM D4788 as a guide to monitor subsurface defects [12].

Data Fusion with Photogrammetry

The high-resolution images collected with the UAV can be stitched together to build high-resolution 3D models and 2D orthomosaic images. The following steps were taken in conjunction with photogrammetry software, to fully automate model building and visualization of collected images:

- (i) Identify distinctive image features as key points in each image and match them across overlapping images
- (ii) Consistent matches observed in at least two images become tie points and are used to estimate camera poses. The resulting sparse point cloud and camera network for Bridge 2 are shown in Figure 3.
- (iii) Create depth maps with calibrated camera parameters for a high-density point cloud that captures color and fine geometric detail
- (iv) Convert the dense cloud into triangular meshes with mesh decimation and smoothing
- (v) Overlay high-resolution textures onto the triangular mesh to demonstrate photorealistic details and colors.

Figure 3. Tie points in 3D, obtained by stitching the images together.

These steps utilize parallel processing, in which the sparse point cloud is partitioned into multiple sub-chunks and submitted as separate tasks to multiple servers, thereby significantly accelerating the overall processing. For each bridge, the entire photogrammetry process takes approximately one hour. A similar procedure was carried out to stitch infrared camera images together to generate a thermal map of each bridge.

Data Analysis with Computer Vision

The RGB images obtained by the UAV are then analyzed using AI-enabled Computer Vision (CV) algorithms, specifically a model from the U-Net family, to perform multi-class semantic segmentation. The U-Net architecture, originally developed for biomedical image segmentation, is distinguished by its symmetric encoder-decoder design, a principle that continues to underpin many of its modern variants [13]. The encoder uses special filters called convolutional layers to look at each image in detail and then uses a technique called max-pooling to make the image smaller and smaller. As the image gets smaller, the model learns more complex features from it. The decoder, on the other hand, is the opposite and it takes the small, detailed image from the encoder and gradually decompresses it while connecting back to the encoder at various stages to bring back some of the original information and not to lose important details from the image. In this study, this model was trained using the Adam optimizer with a learning rate of 0.00001 [14]. Pre-trained weights obtained from a large and diverse dataset were utilized as a starting point to fine-tune on the UAV RGB image dataset. The full dataset is composed of several thousands of annotated images, split into 80% for training and 20% for validation. Data augmentation techniques, including rotation, scaling, and flipping, were applied to the images to enhance the robustness of the dataset. The classes for segmentation labels in this model are Cracking and Spalling. A combination of the cross-entropy loss function, focal loss, and dice loss was used to measure the discrepancy between predictions and ground truth.

Data Visualization with Asset Management Portal

A custom web portal was developed to facilitate asset management for enhanced decision-making. During this step, defects identified by AI are projected into the 3D model space, effectively illustrating them on the DT of the bridge. The web portal facilitates continuous monitoring of the bridge's condition by generating / updating DT through periodic inspections, enabling us to track defects over time and enabling predictive analytics. This comprehensive approach aids the stakeholders in maintaining an up-to-date record of the bridge's health.

RESULTS AND DISCUSSION

Evaluation metrics such as the F1 score and Intersection over Union (IoU) were used to assess the performance of the fine-tuned U-Net model. The best model yielded an F1 score of 0.60 and an IoU score of 0.42 for validation of predicting spalling in concrete. The results demonstrate that the identification of various types of defects on concrete surfaces (see Figure 4(a)) is made possible and the integration of UAV technology with ML / AI models enhances the reliability and efficiency of monitoring. A sample image selected from the testing set is depicted along with ground truth for its defects and predicted masks in Figures 4(b) and 4(c). The masks of exposed reinforcement, corrosion staining, and efflorescence defects are displayed in these figures to provide a visual context and demonstrate the model’s broader segmentation capabilities with the ongoing development.

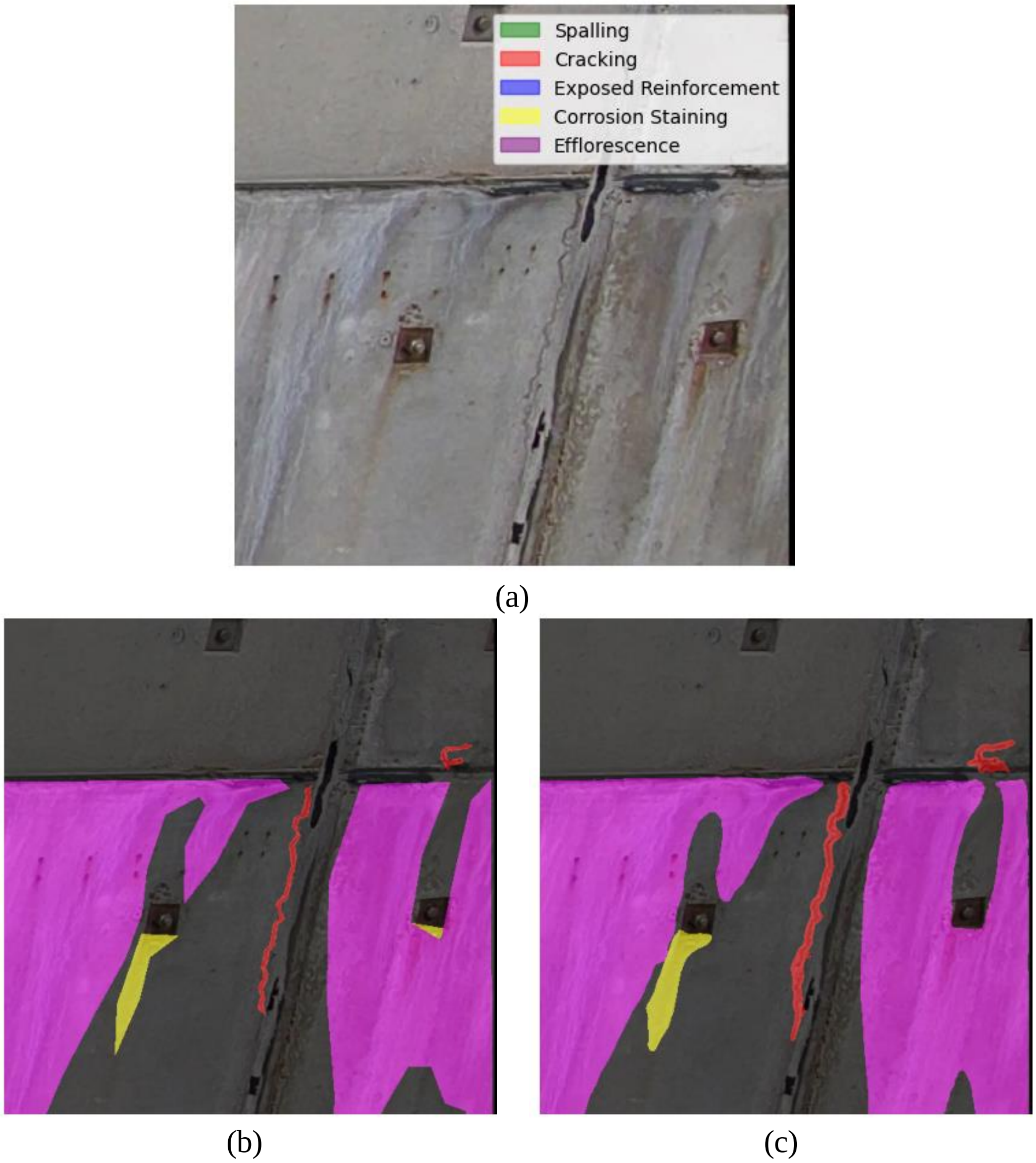
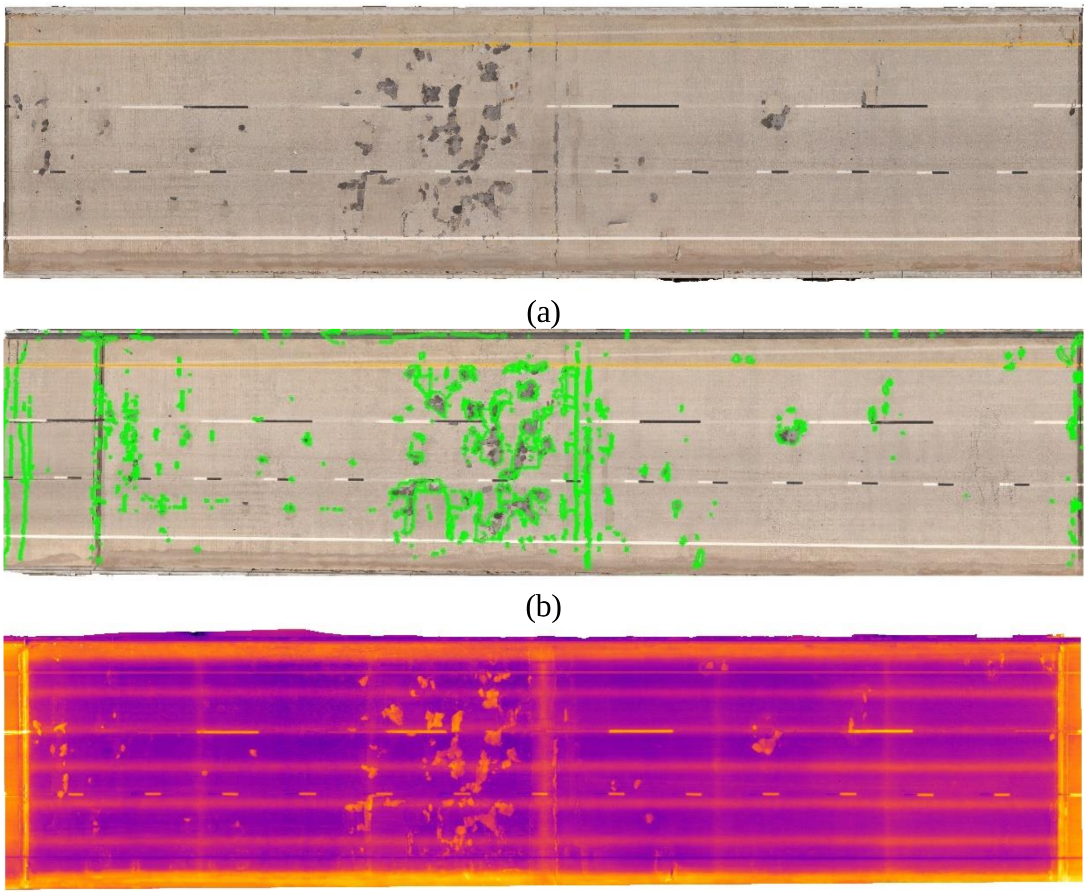


Figure 4. (a) Example image from the full dataset that is used for training and validation, (b) the same image overlaid with defects that were previously annotated as ground truth, and (c) the same image overlaid with the predicted masks via the multiclass segmentation model.

Due to cracks being significantly narrower compared to the other defects in concrete, metrics depending on segmented areas such as IoU are not reliable for evaluating the performance of the U-Net model in this case. A better method for measuring the crack detection accuracy is to compare the quantity of identified cracking in macro scale: Benchmarking the total crack length computed by AI with hand calculations for estimating the quantity showed that the error in crack length measurement was less than 5%.

In the case of infrared thermography, identification of defects was conducted manually. Evidence of delaminations was detected on all three bridges, sometimes in locations around visible distress and sometimes not. The top view of Bridge 2 is shown as an example in Figure 5(a), along with the same view overlaid with defects identified by AI in Figure 5(b), and the thermal map of the bridge deck surface is given in Figure 5(c).



(a)

(b)

(c)

Figure 5. (a) Detailed orthomosaic image of Bridge 2 built by stitching images together, (b) defects predicted by AI illustrated on the orthomosaic image, and (c) thermal map of Bridge 2 created by stitching infrared images together.

The CV technique successfully identified surface defects on the concrete deck, as shown in Figure 5(b). The thermal map in Figure 5(c) highlights hot spots indicating delaminations. Delaminations appear as bright or “hot” areas in the infrared image during daytime testing, when the sun heats up the surface unevenly. We found evidence of delaminations on all three bridges, sometimes in locations around visible distress and sometimes not.

The AMP is a cloud-based web platform that efficiently visualizes and calculates the quantity of each defect, as seen in Figure 6. A benchmark study was done to determine the accuracy of the computed quantities, and it was found that the CV algorithm shows superiority in calculating the quantities with high accuracy over estimations carried out by an engineer.

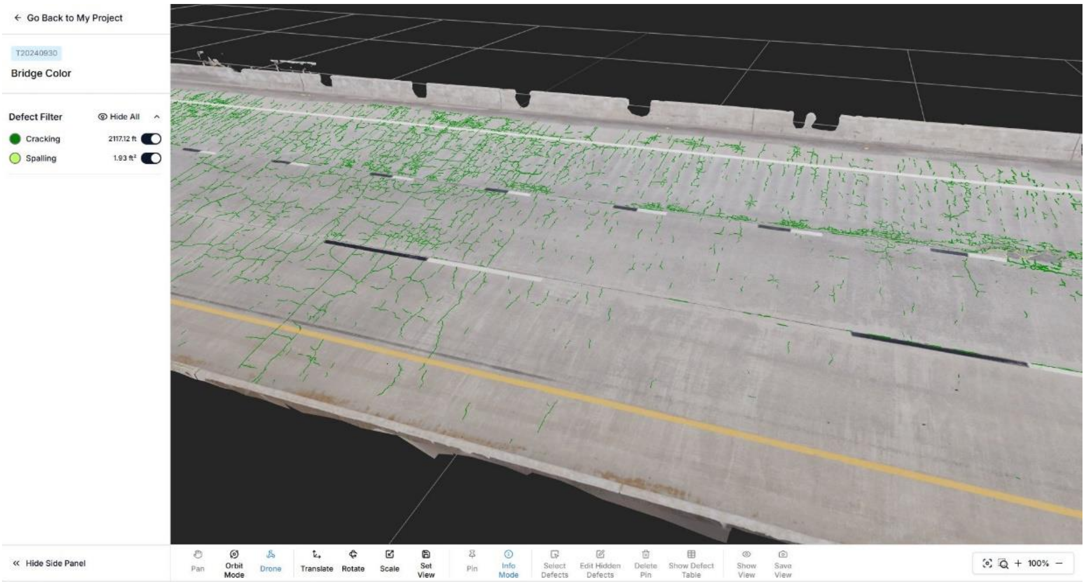


Figure 6. Snapshot from the AMP illustrating DT with the visualization features.

The advanced user interface features of the DT platform not only provide better visualization capabilities but also enable improved communication among stakeholders. These features include highlighting high-priority repair locations, manually adding / modifying / deleting / tagging defects, setting views, and taking snapshots.

CONCLUSIONS

This paper demonstrates a three-step process that can be successfully adopted for building a DT with automated defect identification. This empowers human workers with not having the need for manual, repetitive, often strenuous, and occasionally hazardous tasks, allowing them to focus on asset management and maintenance. Additionally, updating DT via periodic inspections allows the stakeholders to track defect conditions over time, which can be leveraged for predictive analytics.

In the future, new ML / AI models will be developed for infrared images for automated identification of delamination in concrete structures. Existing models will also be extended into different materials such as steel.

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