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INTEGRATING COMPUTER VISION AND DIGITAL TWIN TECHNOLOGY FOR AUTOMATED CRACK DETECTION AND STRUCTURAL SAFETY ASSESSMENT OF REINFORCED CONCRETE BRIDGES

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Abstract

The progressive deterioration of reinforced concrete (RC) bridges, particularly through crack initiation and propagation, presents significant challenges to structural integrity, serviceability, and long-term infrastructure resilience. This study develops an integrated framework combining deep learning-based computer vision and digital twin (DT) technology for automated crack detection, quantitative damage characterization, and structural safety assessment of RC bridges. A comprehensive dataset comprising 12,000 annotated concrete surface images was employed, with 70%, 15%, and 15% allocated to training, validation, and testing, respectively. A YOLO-based object detection model was implemented for automated crack localization, while a U-Net segmentation architecture enabled precise extraction of crack geometries. Experimental results demonstrated robust detection performance, achieving a precision of 94.2%, recall of 92.6%, and mean average precision (mAP@0.5) of 95.1%. Furthermore, the segmentation model achieved an intersection over union (IoU) of 87.4% and a Dice similarity coefficient of 93.3%, confirming its effectiveness in identifying complex crack patterns. Quantitative crack characterization, incorporating image calibration and geometric analysis, yielded a mean absolute crack-width measurement error of 0.12 mm compared with reference measurements. Subsequently, the detected cracks were spatially integrated into a three-dimensional digital twin of the bridge, enabling damage visualization, condition monitoring, and finite-element-based structural performance evaluation. Structural analysis revealed an 8.7% reduction in effective flexural stiffness and a 6.3% increase in maximum service-load deflection compared with the undamaged structural configuration, indicating measurable deterioration in structural response. The integration of computer vision outputs with physics-based digital twin modeling established a systematic relationship between surface-level

crack characteristics and component-level structural performance. The proposed framework enhances the objectivity, consistency, and efficiency of conventional bridge inspection methodologies while facilitating data-driven maintenance prioritization and informed structural safety evaluations. The findings demonstrate the potential of integrating artificial intelligence and digital twin technologies to advance automated structural health monitoring, support predictive infrastructure management, and improve the long-term reliability and sustainability of reinforced concrete bridge systems.

1-INTRODUCTION:

Reinforced concrete (RC) bridges are critical components of modern transportation infrastructure, facilitating economic development, regional connectivity, and the safe movement of people and goods. However, these structures are continuously subjected to environmental exposure, repeated traffic loading, temperature fluctuations, reinforcement corrosion, and material deterioration, which can progressively affect their structural integrity and serviceability. Among various deterioration mechanisms, concrete cracking is one of the most common and visible indicators of structural distress. The initiation and propagation of cracks may facilitate moisture penetration, accelerate reinforcement corrosion, reduce structural stiffness, and adversely influence the durability and long-term performance of bridge components. Although not all cracks indicate immediate structural instability, their characteristics, distribution, and progression provide valuable information regarding the condition of reinforced concrete elements. Consequently, early crack identification, accurate damage characterization, and systematic structural safety evaluation are essential for effective bridge maintenance and structural health monitoring (SHM). Conventional bridge inspection practices primarily depend on periodic visual assessments conducted by qualified engineers and inspection personnel [1]. These inspections typically involve identifying visible deterioration, measuring crack dimensions, documenting damage locations, and evaluating structural conditions based on engineering judgment. Despite their widespread application, traditional inspection methods are labor-intensive, time-consuming, and susceptible to inconsistencies arising from inspector experience, accessibility limitations, environmental conditions, and subjective interpretation. Furthermore, inspection of elevated or inaccessible bridge components may require specialized equipment, traffic restrictions, and considerable operational expenditure. These limitations have encouraged the development of automated inspection approaches capable of improving the accuracy, consistency, and efficiency of bridge condition assessment. Recent advancements in artificial intelligence (AI), computer vision (CV), and deep learning have provided significant opportunities to address these challenges through automated image-based damage detection and characterization [2]. Deep learning-based computer vision has emerged as a promising technique for identifying structural defects from digital images. In particular, convolutional neural networks (CNNs) have demonstrated considerable effectiveness in recognizing complex concrete crack patterns under varying surface textures, illumination conditions, and environmental disturbances. Cha et al. (2017) demonstrated the applicability of CNN-based approaches for automated concrete crack detection, establishing a foundation for intelligent infrastructure inspection systems. Subsequently, object detection algorithms such as You Only Look Once (YOLO) have gained attention because of their computational efficiency and ability to localize defects within images. The YOLO framework, initially introduced by Redmon et al. (2016), enables rapid object localization and classification, making it suitable for applications requiring efficient image processing. However, object detection methods generally identify cracks using bounding boxes, which provide limited information regarding detailed crack geometry [3]. Therefore, semantic segmentation techniques are increasingly

employed to achieve pixel-level identification of cracks and enable more comprehensive geometric characterization. Among semantic segmentation approaches, the U-Net architecture has demonstrated considerable potential for extracting fine-scale features and accurately delineating irregular damage patterns. Originally developed by Ronneberger et al. (2015), U-Net employs an encoder–decoder architecture with skip connections to preserve spatial information during image segmentation. Its application to concrete crack analysis enables detailed identification of crack boundaries, branching patterns, and spatial distributions. Dung and Anh (2019) demonstrated the effectiveness of deep fully convolutional networks for autonomous concrete crack detection and segmentation. Integrating object detection and semantic segmentation provides an opportunity to combine rapid crack localization with precise geometric extraction. Furthermore, calibrated image processing techniques can quantify important crack characteristics, including width, length, orientation, and distribution. These measurements provide valuable indicators for evaluating surface deterioration and monitoring damage progression over successive inspections.

Despite these technological advancements, a significant limitation of existing computer vision-based inspection approaches is their predominant focus on detection accuracy and image segmentation performance rather than the structural implications of identified defects. Common evaluation metrics, including precision, recall, mean average precision (mAP), intersection over union (IoU), and Dice similarity coefficient, effectively describe algorithmic performance but do not directly establish structural safety. The engineering significance of cracking depends not only on visible crack dimensions but also on its location, orientation, underlying deterioration mechanism, reinforcement configuration, and applied loading conditions. Consequently, translating image-derived crack information into meaningful structural performance indicators remains an important research challenge [4]. Addressing this limitation requires integrating automated visual inspection with structural analysis techniques capable of evaluating the mechanical response of deteriorated bridge components. Digital twin (DT) technology offers a promising framework for bridging this gap by establishing a digital representation of physical infrastructure that incorporates geometric information, material properties, inspection observations, and structural analysis results. Unlike conventional three-dimensional models, digital twins can support the systematic integration and updating of asset condition information throughout the structural life cycle. When combined with computer vision, digital twin technology enables the spatial mapping and visualization of detected cracks within a bridge model, thereby improving damage documentation and condition interpretation. Furthermore, integrating finite element analysis (FEA) with digital twin representations provides an engineering-based approach for investigating the effects of deterioration on structural response, including stress distribution, effective stiffness, and deformation characteristics. Recent developments in AI-assisted bridge structural health management have highlighted the potential of combining automated inspection technologies with physics-based modeling to improve infrastructure condition assessment and maintenance planning (Di Mucci et al., 2024). Nevertheless, the effective integration of image-based crack characterization, digital twin visualization, and finite-element-based safety evaluation remains an area requiring further investigation. The relationship between visible cracking and structural performance is particularly important for reinforced concrete bridges, where localized damage may influence stiffness, serviceability, and long-term durability. Although surface crack dimensions can be measured using image-based techniques, their direct relationship with structural capacity cannot be established without considering material behavior, reinforcement details, loading conditions, and structural configuration. Finite element modeling provides a systematic means of investigating these relationships by representing the mechanical behavior of bridge components under defined loading and boundary conditions. Integrating measured crack information into a digital twin-supported structural analysis framework can

therefore improve the interpretation of detected deterioration and facilitate the evaluation of potential changes in flexural stiffness and service-load deflection. However, the reliability of such assessments depends on appropriate modeling assumptions and validation of the relationship between observed damage and simulated structural response. In this context, the present study develops an integrated framework combining YOLO-based object detection, U-Net semantic segmentation, quantitative image analysis, digital twin technology, and finite element modeling for automated crack detection and structural safety assessment of RC bridges [5]. A comprehensive dataset comprising 12,000 annotated concrete surface images is utilized for training, validation, and testing of the proposed deep learning models. The YOLO-based model is employed for automated crack localization, while the U-Net architecture enables pixel-level crack segmentation and detailed geometric characterization. Image calibration and geometric analysis are subsequently used to estimate crack dimensions and evaluate measurement accuracy. The detected damage information is then spatially integrated into a three-dimensional digital twin of the bridge, enabling visualization of deterioration and numerical assessment of structural response under service-loading conditions. The principal contribution of this research is the establishment of a unified methodology that connects automated crack detection with quantitative damage characterization and physics-based structural performance evaluation. By integrating computer vision outputs with digital twin modeling and finite element analysis, the proposed framework extends conventional image-based inspection beyond defect identification toward engineering-oriented bridge condition assessment. The study aims to enhance inspection consistency, reduce dependence on subjective visual interpretation, and support more informed maintenance prioritization through quantitative structural response indicators. Furthermore, the proposed approach provides a foundation for future developments in automated structural health monitoring, predictive maintenance, and sustainable infrastructure asset management. Ultimately, the integration of artificial intelligence and digital twin technologies has the potential to improve the efficiency, reliability, and long-term resilience of reinforced concrete bridge systems.

2- Deep Learning-Based Automated Crack Detection:

Deep learning-based computer vision has emerged as an effective approach for automated crack detection in reinforced concrete (RC) structures, offering significant improvements in detection accuracy, computational efficiency, and robustness compared with conventional image-processing techniques. Traditional crack identification methods, including thresholding, edge detection, morphological operations, and texture-based feature extraction, generally rely on predefined parameters and manually designed image features. Although these approaches are computationally efficient, their effectiveness is often limited by variations in concrete surface texture, illumination, shadows, stains, and background noise. In contrast, deep learning algorithms can automatically extract hierarchical features from large-scale image datasets, enabling more reliable identification of complex and irregular crack patterns under diverse environmental conditions [6]. Convolutional neural networks (CNNs) have played a fundamental role in advancing automated crack recognition by learning spatial features directly from digital images. Cha et al. (2017) developed a CNN-based crack detection framework using approximately 40,000 image patches and reported an accuracy of approximately 98%. Their approach demonstrated improved performance compared with conventional Canny and Sobel edge detection methods, particularly under challenging illumination and surface conditions. To overcome these limitations, deep learning-based object detection algorithms have increasingly been adopted for automated structural damage localization. Object detection frameworks are commonly categorized into two-stage and single-stage architectures [7]. Two-stage detectors, such as Faster R-CNN, generate candidate regions before performing object classification and localization, whereas single-stage detectors predict object classes and bounding

boxes directly through a unified neural network. Among single-stage architectures, the You Only Look Once (YOLO) family has gained substantial attention because of its computational efficiency and suitability for rapid image analysis. The original YOLO framework introduced by Redmon et al. (2016) established an efficient approach to simultaneous object localization and classification. Subsequent YOLO architectures have incorporated improved backbone networks, multi-scale feature fusion, attention mechanisms, and optimized prediction strategies, making them increasingly suitable for detecting small and irregular structural defects. Recent investigations have demonstrated the effectiveness of YOLO-based approaches for automated concrete crack detection. Wu et al. (2022) proposed an improved YOLOv4 architecture incorporating network pruning and an EvoNorm-S0 normalization structure to enhance detection performance while reducing model complexity [8]. Their study reported an improvement in mAP@0.5 from 91.69% to 92.54%, with the modified network retaining approximately 54.9% of the original model's weight. A comparative overview of representative studies is presented in Table 1, highlighting the evolution of deep learning-based crack identification from conventional CNN classification toward advanced object detection and pixel-level segmentation architectures. The comparison emphasizes the principal methodological developments, reported performance, and limitations associated with different approaches. Although the reported results demonstrate substantial progress in automated defect recognition, differences in datasets, evaluation protocols, and inspection conditions must be considered when interpreting model performance.

Table 1: Comparative summary of representative deep learning-based crack detection studies.

Study	Deep learning method	Performance Assessment	Main contribution and limitation
Cha et al. (2017)	CNN	Approximately 98% accuracy	Automated crack classification; limited pixel-level geometric information
Dung and Anh (2019)	CNN and fully convolutional network	Approximately 90% segmentation average precision	Pixel-level crack identification; performance dependent on image quality
Wu et al. (2022)	Improved YOLOv4	mAP@0.5: 92.54%	Lightweight network and improved detection accuracy; bounding-box localization
Ye et al. (2023)	Improved YOLOv7	Improved performance against evaluated baselines	Enhanced multi-scale feature extraction; limited direct geometric quantification
Liu et al. (2023)	Rotation-aware YOLOv5	mAP@0.5: 94.03%	Improved detection of oriented bridge cracks; limited pixel-level characterization
Ye et al. (2024)	YOLOv7-WMF instance segmentation	mAP: 72.2% and 87.9%	Combined crack localization and morphology extraction; focused on pavement cracking

Deep learning-based crack detection has progressed considerably through improvements in network architecture, feature extraction, and damage localization techniques. CNN-based methods provide reliable crack recognition, while advanced YOLO architectures improve localization efficiency and accommodate variations in crack orientation and scale. Nevertheless, the majority of conventional object detection approaches represent cracks using

bounding boxes, providing insufficient information regarding crack width, length, continuity, and branching characteristics. Therefore, combining object detection with semantic segmentation offers a complementary strategy for achieving both efficient localization and detailed geometric extraction [9]. In this context, the present study integrates YOLO-based crack detection with U-Net semantic segmentation to facilitate comprehensive crack identification and quantitative damage characterization. The conceptual workflow of this integrated approach is illustrated in Figure 1, encompassing image acquisition, preprocessing, crack localization, pixel-level segmentation, and geometric measurement.

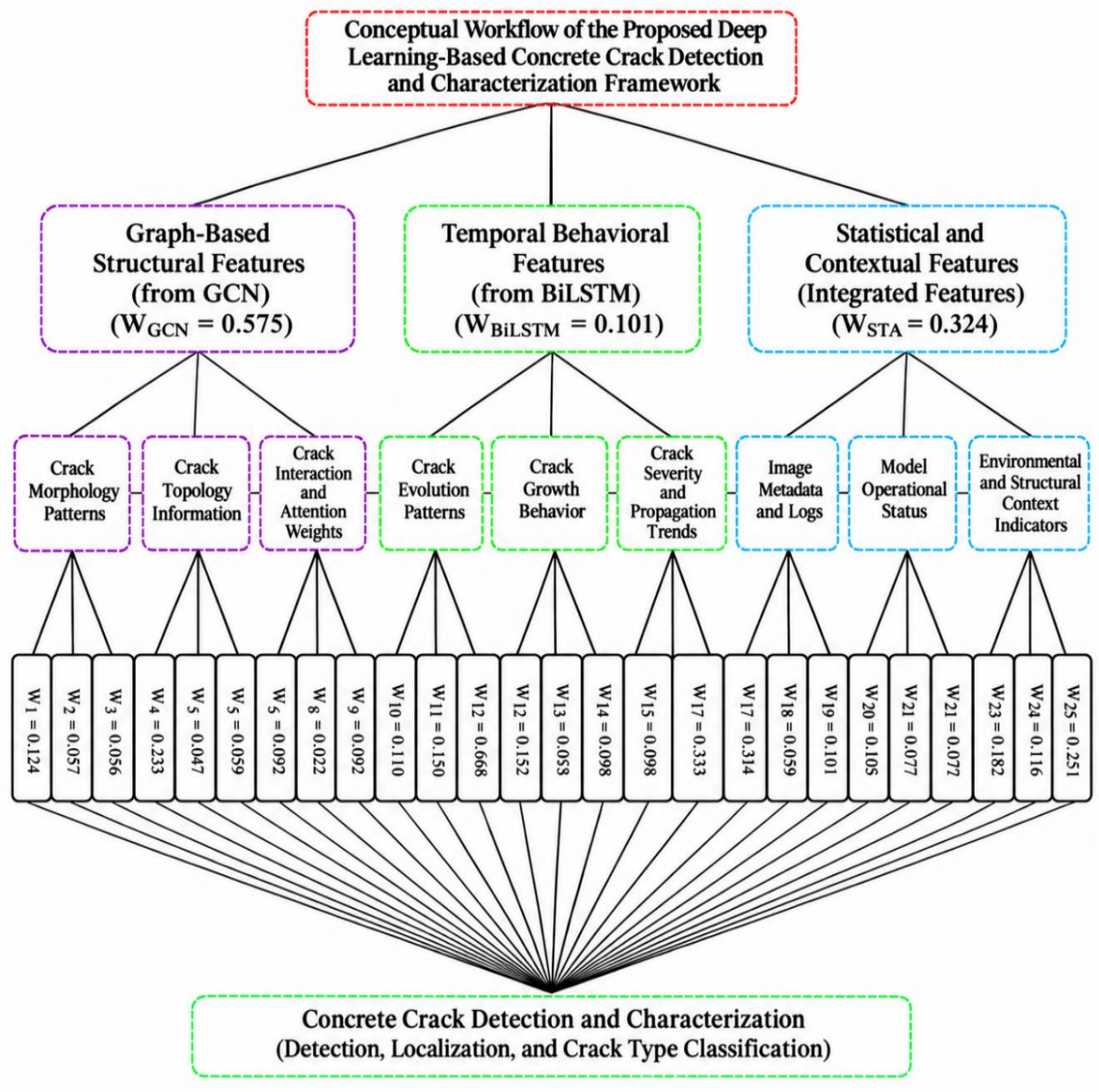


Figure 1: Conceptual workflow of the proposed deep learning-based concrete crack detection and characterization framework

The complementary functions of object detection and semantic segmentation in automated structural damage assessment. YOLO enables the rapid identification and localization of potentially damaged concrete regions, while U-Net provides detailed pixel-level crack boundaries necessary for extracting geometric parameters. When combined with appropriate image calibration, these outputs can support the estimation of crack width, length, orientation, and spatial distribution. Such information is valuable for documenting structural deterioration, monitoring damage progression, and identifying regions requiring further investigation. However, high detection accuracy and detailed geometric characterization do not independently establish structural safety, as the engineering significance of cracking also depends on reinforcement configuration, material properties, structural geometry, loading conditions, and damage mechanisms [10]. Consequently, the present research extends conventional deep learning-based crack detection by spatially integrating extracted damage information into a three-dimensional digital twin and subsequently evaluating structural response using finite element analysis. This integrated approach seeks to bridge the gap between automated visual damage recognition and physics-based structural performance assessment, thereby providing a systematic foundation for objective bridge condition monitoring, maintenance prioritization, and informed structural safety evaluation.

3- Crack Segmentation and Quantitative Damage Characterization:

Accurate crack segmentation and quantitative damage characterization are essential for evaluating the deterioration, durability, and serviceability of reinforced concrete (RC) bridges. While automated object detection algorithms can efficiently identify regions containing cracks, their bounding-box predictions provide limited information regarding the precise boundaries and geometric characteristics of individual defects. Quantitative structural condition assessment requires more detailed information, including crack width, length, orientation, spatial distribution, and branching characteristics. These parameters are important for identifying potential deterioration mechanisms, assessing crack progression, and supporting engineering-based maintenance decisions [11]. Consequently, the integration of deep learning-based semantic segmentation with calibrated image-processing techniques has become an important research direction in automated bridge inspection and structural health monitoring (SHM). Semantic segmentation enables pixel-level identification of crack regions by assigning each image pixel to a crack or background class. Unlike conventional edge detection and thresholding techniques, deep learning-based segmentation models can learn complex spatial relationships and distinguish irregular crack patterns from surrounding concrete textures. Among available architectures, U-Net has received considerable attention because of its encoder–decoder structure and skip connections, which facilitate the extraction of high-level semantic features while preserving fine-scale spatial information (Ronneberger et al., 2015). The encoder progressively extracts representative image features, whereas the decoder reconstructs spatial resolution to generate detailed segmentation masks. Skip connections transfer information between corresponding encoder and decoder stages, improving the preservation of narrow crack boundaries and discontinuous features. These characteristics make U-Net particularly suitable for concrete crack segmentation, where defects frequently exhibit irregular geometries, limited widths, and low contrast against the surrounding surface. Recent investigations have further emphasized the relationship between segmentation accuracy and quantitative crack measurement. Bae and An (2023) developed a computer vision-based statistical crack quantification framework incorporating deep semantic segmentation, crack map generation, and Euclidean distance transformation [12]. Their method enabled the separation of multiple crack branches and the quantitative estimation of crack length and width, while incorporating statistical confidence intervals to represent measurement variability. An important requirement for quantitative image-based measurement is the conversion of pixel

dimensions into physical units. Image calibration establishes the relationship between the spatial resolution of an image and corresponding dimensions on the concrete surface. This conversion may be achieved using reference objects of known dimensions, camera calibration parameters, laser-assisted techniques, photogrammetry, or three-dimensional reconstruction. However, measurement reliability can be affected by camera-to-surface distance, viewing angle, lens distortion, image resolution, and nonuniform surface geometry. For images acquired approximately perpendicular to a planar surface, a uniform scale factor may provide an acceptable approximation. Conversely, images collected from oblique viewing positions or irregular surfaces may require perspective correction or spatially varying calibration. These considerations are particularly relevant for bridge inspections performed using unmanned aerial vehicles or remotely positioned cameras, where image acquisition conditions can vary considerably [13]. Despite these advances, several technical challenges continue to affect quantitative crack characterization. Surface irregularities, shadows, moisture, staining, and construction joints may produce segmentation errors, while narrow cracks can approach or fall below the effective spatial resolution of the imaging system. Moreover, morphological filtering and skeletonization may unintentionally remove small crack branches or alter local crack geometry. Consequently, the reliability of quantitative damage assessment depends on both segmentation performance and the procedures used for geometric measurement. Evaluation metrics such as intersection over union (IoU) and Dice similarity coefficient are useful for assessing agreement between predicted and reference crack masks; however, they do not independently establish the accuracy of physical crack-width measurements. Therefore, reliable validation should incorporate comparisons with reference measurements and report appropriate error statistics, including MAE, root mean square error (RMSE), and measurement variability where available. The literature demonstrates increasing attention to integrating segmentation accuracy with physically meaningful crack measurements. Table 2 presents a comparative summary of representative investigations concerning deep learning-based crack segmentation and quantitative damage characterization, emphasizing the adopted techniques, reported results, principal contributions, and remaining limitations. The comparison illustrates the evolution from pixel-level damage identification toward calibrated geometric measurement, multi-task learning, and three-dimensional reconstruction. It also highlights the need for integrated frameworks capable of transforming visually detected cracks into spatially referenced information suitable for structural performance evaluation.

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Table 2: Comparative summary of representative studies on crack segmentation and quantitative damage characterization.

Study	Methodology	Reported performance	Principal contribution and limitation
Dung and Anh (2019)	Deep fully convolutional network	Approximately 90% average precision	Pixel-level crack segmentation and density estimation;
Bae and An (2023)	Deep semantic segmentation and Euclidean distance transform	Statistical crack-width and length estimation	Quantified multi-branched cracks with uncertainty information;
Nyathi et al. (2024)	CNN, U-Net and laser calibration	Segmentation accuracy: 96.54%; width MAE: 0.16 mm	Integrated crack identification and measurement in physical units
Chen et al. (2024)	Multi-task U-Net and 3D reconstruction	More than 2% improvement in width quantification over evaluated baselines	Joint crack segmentation and centerline estimation;
Alamdari and Ebrahimkhanlou (2024)	CNN-assisted robotic laser scanning	Detailed crack width, length and profile measurements	High-resolution multi-scale crack characterization;
U-Net and binocular vision study (2026)	U-Net and stereo 3D reconstruction	Average width error: 0.15 mm	Incorporates three-dimensional geometry

The development of crack segmentation methodologies has progressed from pixel-level defect identification toward advanced approaches incorporating calibrated geometric measurement, multi-task feature extraction, and three-dimensional reconstruction. Early fully convolutional networks demonstrated the feasibility of segmenting concrete cracks, while subsequent U-Net-based approaches improved the integration of segmentation and quantitative crack-width estimation. Furthermore, statistical crack analysis and multi-task learning have enhanced the representation of complex crack geometries and measurement uncertainty. However, the reviewed investigations also indicate that segmentation accuracy alone is insufficient to guarantee reliable physical measurements, particularly under varying camera orientations, surface conditions, and image resolutions [14]. Accordingly, quantitative damage characterization requires an integrated procedure combining accurate crack segmentation, image preprocessing, geometric analysis, calibration, and measurement validation. Figure 2 present the conceptual workflow for crack segmentation and quantitative damage characterization, showing the transformation of concrete surface images into physically meaningful crack parameters for subsequent integration into the structural digital twin.

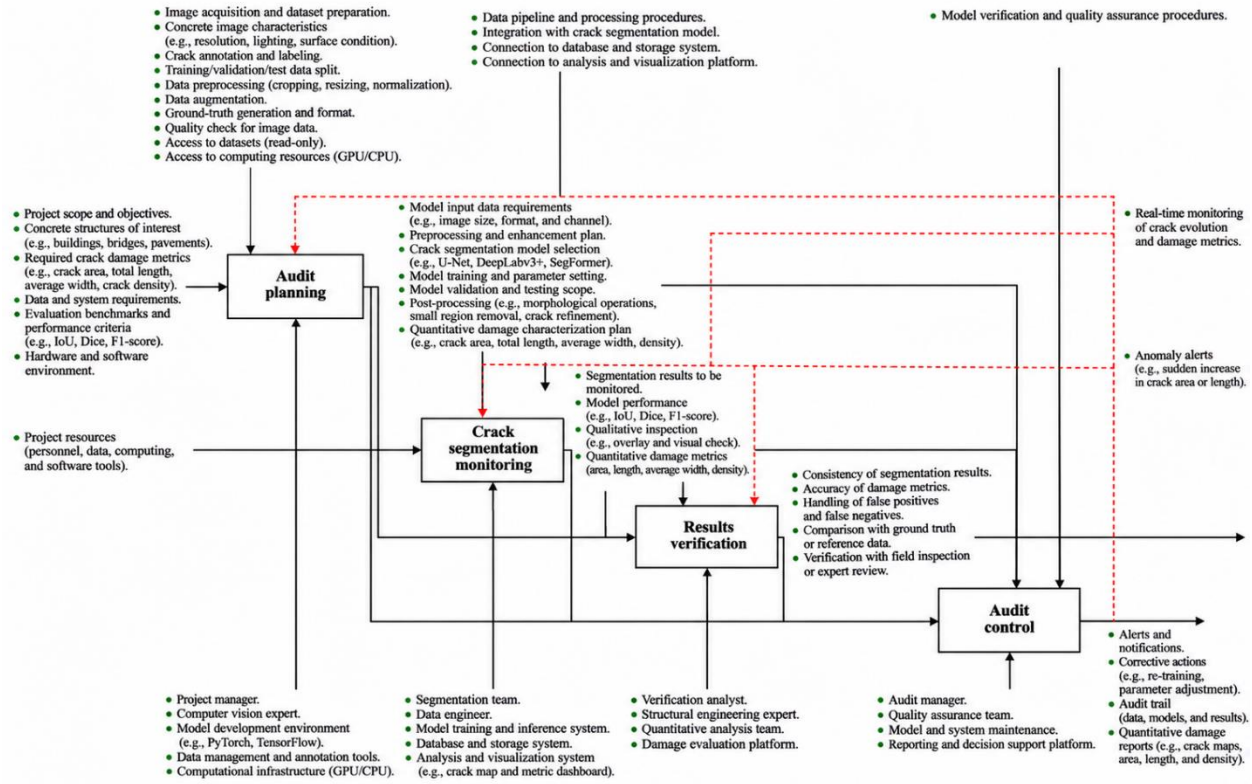


Figure 2: Workflow of the proposed U-Net-based crack segmentation monitoring, verification, and quality control framework

The quantitative characterization process begins with the acquisition of concrete surface images, followed by U-Net-based semantic segmentation to generate pixel-level crack masks. The resulting masks undergo post-processing operations, including noise removal, morphological refinement, and skeletonization, to improve the representation of crack boundaries and centerlines. Geometric calibration is then applied to convert pixel-based dimensions into physical measurements, accounting for image scale and, where necessary, perspective distortion. These procedures enable the extraction of crack width, length, orientation, area, and spatial distribution, providing a more comprehensive description of concrete surface deterioration. Nevertheless, the reliability of these parameters depends on image quality, segmentation precision, calibration accuracy, and the availability of suitable reference measurements [15]. Therefore, the present study incorporates quantitative crack characterization into an integrated computer vision and digital twin framework, where geometrically characterized defects can be associated with specific bridge components and used to inform finite-element-based structural performance evaluation. This integration establishes a systematic connection between pixel-level damage information and engineering-oriented condition assessment, supporting improved damage documentation, structural response interpretation, and maintenance prioritization.

4- Methodology:

This section presents a comprehensive research methodology for integrating deep learning-based computer vision, digital twin (DT) technology, and finite element analysis (FEA) to facilitate automated crack detection, quantitative damage characterization, and structural safety assessment of reinforced concrete (RC) bridges. The proposed methodology follows a systematic and interconnected approach comprising image dataset preparation and annotation, image

preprocessing, deep learning model development, automated crack localization, pixel-level semantic segmentation, and quantitative extraction of crack geometries. Subsequently, the identified damage characteristics, including crack width, length, orientation, and spatial distribution, are incorporated into a three-dimensional digital twin of the bridge to enable spatial damage visualization and structural condition monitoring. Finite element modeling is then employed to investigate the effects of modeled deterioration on key structural performance indicators, particularly effective flexural stiffness and service-load deflection [16]. The integration of computer vision outputs with physics-based numerical simulations establishes a systematic relationship between surface-level damage observations and component-level structural response. Through this unified framework, the proposed methodology aims to improve the accuracy, consistency, and efficiency of bridge condition assessment while supporting objective structural safety evaluation, informed maintenance prioritization, and long-term infrastructure management.

4.1- Image Dataset Preparation and Annotation:

The preparation of a comprehensive and accurately annotated image dataset constitutes a fundamental stage in developing reliable deep learning-based crack detection and segmentation models for reinforced concrete (RC) bridges. The performance of computer vision algorithms is strongly influenced by the quality, diversity, and representativeness of the training data, particularly when identifying irregular and fine-scale crack patterns under varying surface and environmental conditions. In this study, a dataset comprising 12,000 annotated concrete surface images was employed to develop and evaluate the proposed YOLO-based object detection and U-Net semantic segmentation models. The dataset provides the foundation for automated crack localization, pixel-level damage extraction, and subsequent quantitative geometric characterization. Particular consideration is given to image quality, annotation consistency, data partitioning, and the prevention of information leakage to support reliable model training and independent performance evaluation [17]. Concrete surface images used for automated crack identification may exhibit substantial variations in crack geometry, surface texture, illumination, and background characteristics. Typical damage patterns include longitudinal, transverse, diagonal, irregular, and branched cracks, which may differ considerably in width, length, orientation, and visual contrast. In addition, concrete surfaces frequently contain aggregate exposure, construction joints, stains, shadows, and other irregularities that can resemble crack features and complicate automated recognition. These factors highlight the importance of representative datasets capable of capturing the visual complexity encountered during practical bridge inspections. Dataset quality assessment is therefore essential for identifying blurred images, duplicate observations, inconsistent labels, and other deficiencies that may adversely affect model generalization. The source, acquisition conditions, and distribution of the images should be documented to establish the extent to which the dataset represents actual bridge inspection environments. The complete dataset was divided into three independent subsets comprising 70% training images, 15% validation images, and 15% testing images. Accordingly, 8,400 images were allocated to model training, while 1,800 images each were reserved for validation and testing. The training subset was used to optimize the learnable parameters of the YOLO and U-Net models, whereas the validation subset supported hyperparameter adjustment, model selection, and monitoring of training performance [18]. The independent testing subset was reserved for evaluating the generalization capability of the trained models using previously unseen images. This separation is necessary to minimize biased performance estimation and ensure that reported detection and segmentation metrics reflect the models' ability to process images beyond those used during optimization. The dataset distribution and intended functions of the respective subsets are summarized in Table 3.

Table 3: Distribution and utilization of the concrete surface image dataset for deep learning model development.

Dataset subset	Proportion (%)	Number of images	Primary purpose
Training	70	8,400	Feature learning, model parameter optimization, and training-stage augmentation
Validation	15	1,800	Hyperparameter tuning, convergence monitoring, and model selection
Testing	15	1,800	Independent evaluation of detection and segmentation performance
Total	100	12,000	Development and evaluation of the automated crack assessment framework

The distribution provides a structured basis for developing and assessing the proposed deep learning models. Allocating the largest proportion of images to training supports feature learning, while maintaining separate validation and testing datasets enables model optimization and independent performance assessment. However, the reliability of this partitioning also depends on the similarity between images in different subsets. Concrete images acquired from the same structural component or successive frames of a continuous inspection sequence may contain highly correlated visual information. If such images are distributed across training and testing subsets, the resulting evaluation may overestimate model generalization. Therefore, source-aware partitioning is preferable where image provenance is available, ensuring that images from the same inspection sequence or closely related structural regions do not introduce unintended data leakage. Maintaining consistent partitions across the YOLO and U-Net evaluations also supports a more coherent assessment of the integrated detection and segmentation framework. Image preprocessing is an important requirement for ensuring consistent model inputs and reducing variations that are unrelated to actual crack characteristics. The preprocessing workflow may include image resizing, pixel-intensity normalization, color-channel standardization, and inspection of image quality. Resizing establishes consistent input dimensions, while normalization facilitates stable numerical optimization during model training [19]. However, preprocessing must preserve the visibility and geometric continuity of narrow cracks, as excessive image downsampling or smoothing can remove important fine-scale features. This consideration is particularly relevant to quantitative crack-width estimation, where small changes in apparent crack boundaries can produce significant measurement errors. Consequently, the original image resolution and calibration information should be retained for subsequent geometric analysis whenever model input resizing changes the spatial scale. Data augmentation provides an additional mechanism for improving the robustness and generalization capability of deep learning models. Appropriate augmentation operations may include horizontal and vertical flipping, image rotation, scaling, brightness adjustment, contrast modification, and controlled noise addition. These transformations increase the variety of visual conditions encountered during training and can reduce the tendency of neural networks to overfit specific image characteristics [20]. Geometric transformations must be applied consistently to the input images and their corresponding annotations to maintain accurate alignment between the concrete surface features and reference labels. Furthermore, augmentation procedures should be restricted to the training subset, preserving the validation and testing images as independent evaluation data. The overall dataset preparation and annotation process is illustrated schematically in Figure 3, which outlines the transformation of concrete surface images into model-ready datasets through quality assessment, preprocessing, annotation, and data partitioning.

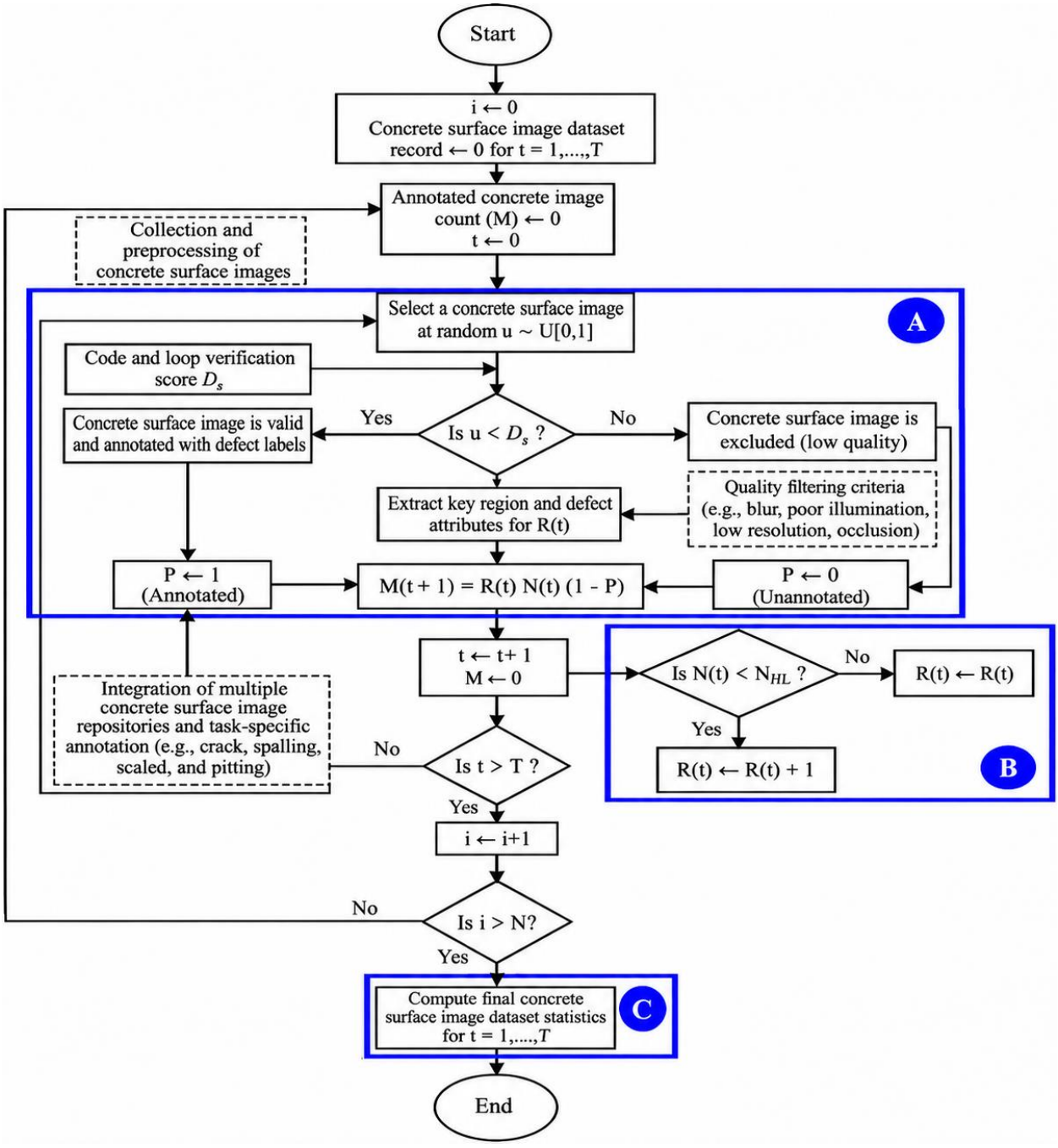


Figure 3: Schematic representation of the concrete surface image dataset preparation and annotation framework

Dataset preparation involves a sequence of interconnected operations designed to ensure that the images and corresponding reference annotations are suitable for both object detection and semantic segmentation. The preparation process establishes a consistent relationship between the original concrete surface images, YOLO-compatible crack localization labels, and U-Net-compatible pixel-level masks. This consistency is important because inaccuracies introduced during annotation or preprocessing may propagate through subsequent stages of the integrated

framework, affecting crack localization, boundary extraction, and quantitative geometric measurement. The preservation of reliable image-to-annotation correspondence also facilitates systematic evaluation of the two deep learning models and supports traceability of detected damage to its original inspection image. For quantitative crack characterization, particular attention must be given to preserving the original image geometry and the relationship between pixel coordinates and physical dimensions [21]. Although resized or augmented images may be appropriate for model development, physical crack-width and length measurements should be derived using geometrically consistent images and appropriate calibration information. Where reference measurements are available, the image-based estimates can be evaluated to determine measurement error and uncertainty. Maintaining image identifiers, crack labels, spatial coordinates, and calibration records throughout the dataset preparation process is therefore important for transferring extracted damage characteristics into the three-dimensional bridge digital twin.

4.2- YOLO-Based Automated Crack Detection:

Automated crack detection represents a fundamental component of the proposed computer vision-based structural health monitoring framework, enabling the identification and localization of visible deterioration in reinforced concrete (RC) bridge surfaces. In this study, a You Only Look Once (YOLO)-based object detection approach is adopted to identify concrete cracks from digital images and generate spatial information for subsequent semantic segmentation and quantitative damage characterization. YOLO is a single-stage deep learning object detection framework that performs feature extraction, object localization, and classification within an integrated neural network architecture. Compared with conventional image-processing methods and two-stage object detection approaches, YOLO offers computational efficiency and the potential for rapid analysis of large image datasets. These characteristics make it particularly suitable for automated bridge inspection, where extensive concrete surfaces must be evaluated under variable environmental conditions [22]. The objective of implementing YOLO in the present framework is to achieve reliable crack localization while maintaining sufficient computational efficiency for integration with the subsequent U-Net segmentation and digital twin modeling stages. The YOLO detection framework processes concrete surface images through a sequence of interconnected computational operations involving image preprocessing, hierarchical feature extraction, multi-scale feature fusion, and bounding-box prediction. The network generally comprises three principal architectural components: a backbone, a neck, and a detection head. The backbone extracts hierarchical visual features from the input images using convolutional operations and other architectural components appropriate to the selected YOLO version. Lower-level features represent basic image characteristics, including edges, texture variations, and intensity gradients, whereas deeper features encode more complex spatial patterns associated with crack continuity, orientation, and surrounding surface conditions. The neck combines information extracted at different feature scales, enabling the detection model to recognize cracks exhibiting variations in length, width, and spatial distribution. Finally, the detection head generates predictions containing bounding-box coordinates, class information, and associated confidence scores for potential crack regions [23]. The exact network components depend on the YOLO architecture selected for implementation. Before being processed by the detection network, input images undergo preprocessing to ensure compatibility with the selected model architecture. The preprocessing procedure includes resizing images to the required input dimensions and normalizing pixel-intensity values according to the model implementation. Because concrete cracks can exhibit extremely narrow and elongated geometries, particular consideration must be given to preserving their visual features during image resizing. Excessive downsampling may eliminate fine crack segments or reduce the contrast between crack boundaries and the surrounding concrete surface. Consequently, the selected input resolution

should provide an appropriate balance between computational efficiency and the preservation of small-scale damage characteristics. Where images are resized with padding to maintain their aspect ratio, the corresponding geometric transformations must also be applied to the reference bounding boxes [24]. The original image dimensions and transformation parameters are retained to enable detected crack locations to be transferred accurately into the source-image coordinate system. The principal model development, training, and evaluation parameters associated with the YOLO-based detection framework are summarized in Table 4. The table distinguishes the parameters established by the proposed study design from implementation-specific settings that must be documented using the actual experimental configuration. Providing this information is important for ensuring methodological transparency, experimental reproducibility, and consistent interpretation of the detection results.

Table 4: YOLO-based automated crack detection framework: dataset configuration, training parameters, and performance evaluation

Parameter	Description	Specification
Detection framework	Deep learning-based object detection	YOLO-based
Detection objective	Localization of visible concrete surface cracks	Crack bounding boxes
Total dataset	Annotated concrete surface images	12,000
Training dataset	Images used for model optimization	8,400 (70%)
Validation dataset	Images used for model selection	1,800 (15%)
Testing dataset	Images reserved for independent evaluation	1,800 (15%)
Annotation format	Spatial representation of cracks	Bounding boxes
Target category	Structural defect to be detected	Concrete crack

The proposed YOLO-based detection methodology integrates systematic dataset partitioning, supervised model training, prediction filtering, and independent performance evaluation. The framework is intended to provide reliable crack localization while maintaining compatibility with the subsequent segmentation and geometric measurement procedures. The use of a separate testing dataset supports objective evaluation of model generalization, whereas the inclusion of both precision- and recall-based metrics provides a balanced assessment of detection reliability [25]. Importantly, the methodological emphasis is placed not only on recognizing cracks but also on producing spatially consistent detections that can be transferred to later stages of the integrated damage assessment framework. The complete sequence of image processing, model training, crack localization, and evaluation is illustrated in Figure 4.

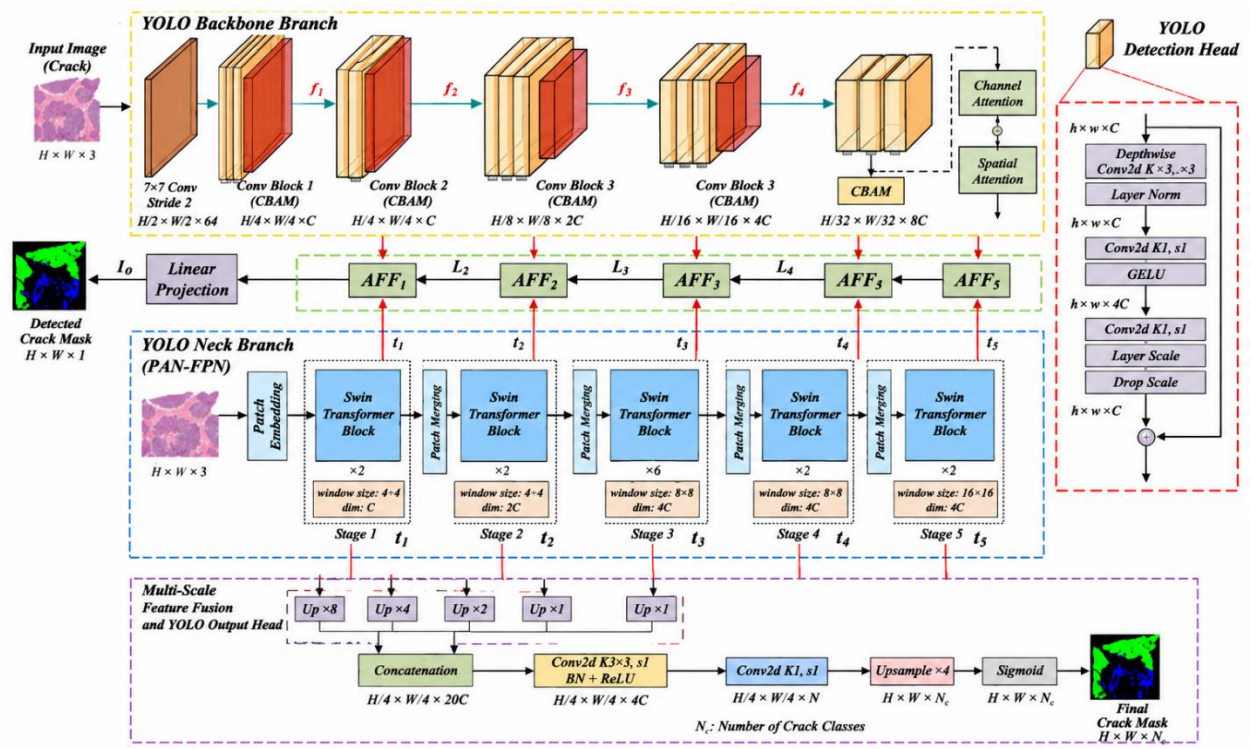


Figure 4: Schematic representation of the proposed YOLO-based automated crack detection framework

The detection process begins with the preparation of annotated concrete surface images, followed by preprocessing to achieve consistent model input characteristics. The processed images are supplied to the YOLO network, where hierarchical features are extracted and combined to identify potential crack regions. During training, predicted detections are compared with reference bounding boxes, and model parameters are optimized through the selected loss function. During inference, confidence filtering and appropriate post-processing operations are employed to obtain the final crack detections. These results are evaluated using established detection metrics and expressed as localized damage regions associated with their original image coordinates. The resulting bounding boxes also provide an efficient means of isolating areas of interest, thereby facilitating subsequent crack segmentation without requiring the segmentation model to process unrelated surface regions exclusively. Where image crops are used, their offsets and resizing transformations must be retained to ensure that segmentation outputs can be mapped back to the full image [26]. The integration of YOLO-based localization with U-Net semantic segmentation is particularly important because bounding-box predictions alone cannot adequately represent the geometric complexity of surface cracks. Although a detection model can identify the presence and approximate location of cracking, its output does not directly quantify crack width, precise length, branching, or affected surface area. Accordingly, the localized damage regions serve as inputs to the segmentation stage, where pixel-level crack boundaries are extracted for quantitative characterization. This complementary arrangement combines the computational advantages of object detection with the geometric detail of semantic segmentation. Furthermore, preserving the spatial coordinates of detected cracks enables the resulting measurements to be associated with corresponding locations in the three-dimensional digital twin of the bridge.

4.3- U-Net-Based Crack Segmentation:

Accurate identification of crack boundaries is essential for quantitative damage characterization and structural condition assessment of reinforced concrete (RC) bridges. Although YOLO-based object detection provides efficient localization of cracked regions, bounding-box predictions do not adequately represent the precise geometry, continuity, or spatial distribution of individual cracks. To overcome this limitation, the present study incorporates a U-Net-based semantic segmentation model to extract detailed crack patterns at the pixel level. The segmentation stage is designed to complement the YOLO detection framework by transforming localized damage regions into spatially resolved crack masks suitable for geometric measurement and subsequent digital twin integration [27]. This combined approach facilitates a more comprehensive evaluation of surface deterioration by preserving important morphological characteristics, including narrow crack segments, irregular boundaries, branching patterns, and discontinuous damage features. U-Net is a convolutional neural network architecture originally developed for image segmentation applications and is characterized by its encoder–decoder structure and skip connections (Ronneberger et al., 2015). The architecture is particularly suitable for concrete crack analysis because of its ability to combine high-level semantic information with fine-scale spatial features. In the proposed framework, the encoder progressively extracts representative features from input concrete surface images, while the decoder reconstructs the spatial resolution required to generate pixel-level crack predictions. The skip connections enable the transfer of feature information between corresponding encoder and decoder stages, thereby reducing the loss of spatial details during feature extraction. This characteristic is important for detecting narrow and elongated cracks, where minor boundary inaccuracies can substantially influence subsequent width and length measurements. The U-Net architecture therefore provides a suitable foundation for detailed crack delineation following the initial localization performed by the YOLO detection model. Prior to segmentation model training, the input images and their corresponding masks are subjected to preprocessing procedures intended to improve numerical consistency and preserve geometrically important damage features [28]. The preprocessing process includes resizing the images to dimensions compatible with the selected U-Net architecture, normalizing input pixel values, and verifying the correspondence between each image and its segmentation mask. Particular attention is given to the preservation of thin crack features during image resizing because excessive reduction in spatial resolution may eliminate fine crack branches or alter their apparent widths. Furthermore, interpolation methods must be selected carefully when resizing binary segmentation masks to avoid introducing artificial label values or modifying crack boundaries. The preservation of image geometry is especially important because the segmentation outputs are subsequently used for quantitative measurement of crack width, length, and orientation. Data augmentation may be incorporated during training to improve the generalization capability of the segmentation model under varying inspection conditions. Appropriate augmentation operations include random rotation, horizontal and vertical flipping, scaling, brightness modification, contrast adjustment, and controlled noise addition. These transformations simulate variations in crack orientation, illumination, camera positioning, and surface appearance that may be encountered during bridge inspections. Geometric augmentation is applied consistently to the input images and corresponding ground truth masks to maintain accurate spatial alignment. Photometric transformations, however, are applied to the images without modifying the binary class labels [29]. Augmentation is restricted to the training dataset to avoid introducing artificial similarities between training and evaluation images. This strategy is intended to reduce overfitting and improve the ability of the network to distinguish actual cracks from visually similar surface irregularities. The U-Net segmentation architecture consists of contracting and expanding computational pathways that operate together to extract and reconstruct spatial information. Within the contracting pathway, successive feature

extraction operations identify increasingly complex crack characteristics, ranging from local intensity changes and edge patterns to larger-scale structural features such as crack continuity and branching. Spatial downsampling allows the network to incorporate contextual information from a larger image region, which can assist in distinguishing true cracks from shadows, stains, and other background features. However, downsampling also reduces the resolution of intermediate feature maps and may affect the representation of narrow damage patterns. The expanding pathway addresses this limitation by progressively recovering spatial resolution through upsampling and feature reconstruction. Features transferred through skip connections are combined with decoder information to improve boundary localization and preserve detailed crack geometry. This additional geometric information enables crack regions to be processed for subsequent measurement and spatial mapping within the digital twin environment. The overall computational workflow of the proposed U-Net-based crack segmentation framework is present in Figure 5.

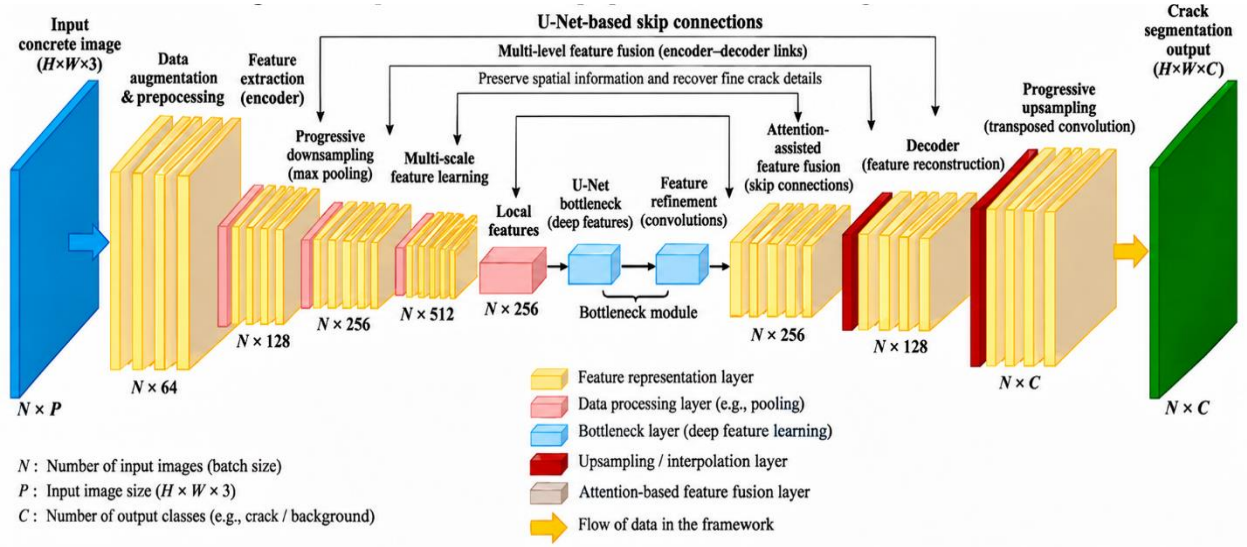


Figure 5: Conceptual architecture of the proposed U-Net-based crack segmentation framework with multi-scale feature extraction and skip connections

The segmentation process begins with localized concrete surface images obtained through the preceding YOLO detection stage. The identified image regions are prepared together with their corresponding segmentation annotations and supplied to the U-Net network. The encoder extracts multi-scale visual information, while the decoder reconstructs detailed spatial representations using features transferred through skip connections. The resulting probability maps are converted into crack masks and evaluated against reference annotations to determine segmentation accuracy. Following validation, the masks can be refined through appropriate post-processing operations to improve boundary representation and support quantitative damage analysis. The workflow establishes a direct connection between automated crack localization and pixel-level geometric extraction, while maintaining the spatial information required for mapping the detected deterioration to its original inspection location [30]. An important consideration in the proposed framework is the relationship between segmentation quality and physical crack measurement accuracy. Although IoU and DSC provide useful indicators of the agreement between predicted and reference masks, they do not directly quantify the accuracy of crack-width or crack-length measurements. Small errors along the boundaries of narrow cracks can produce substantial relative differences in estimated width, even when the overall

segmentation overlap appears satisfactory. Consequently, reliable damage characterization requires consideration of the spatial resolution of the original images, segmentation boundary accuracy, image calibration, and geometric post-processing procedures. For this reason, the segmentation outputs are treated as intermediate representations that must undergo additional calibration and geometric analysis before being interpreted as physical damage measurements. The quantitative characterization procedures are described in the subsequent methodology section.

4.4- Development of the Three-Dimensional Bridge Digital Twin:

The development of a three-dimensional digital twin (DT) represents a fundamental component of the proposed integrated framework, providing a digital environment for combining image-derived crack characteristics with geometric, material, and structural information associated with reinforced concrete (RC) bridges. Digital twin technology enables the representation of physical infrastructure within a coordinated computational environment, facilitating damage visualization, condition assessment, and structural performance evaluation. In the present study, a three-dimensional digital representation of the bridge is integrated with computer vision-based crack detection and finite element analysis (FEA) to establish a systematic connection between surface-level deterioration and component-level structural behavior. Unlike conventional geometric models, which primarily represent physical dimensions and structural configurations, the proposed digital twin framework associates the bridge geometry with inspection observations, quantitative crack measurements, and numerical structural response information [31]. This integration provides an analytical foundation for assessing deterioration, identifying potentially critical damage locations, and supporting informed bridge maintenance and asset management decisions. The development process begins with the establishment of a geometrically representative three-dimensional model of the investigated RC bridge. The digital model is intended to incorporate the primary structural components relevant to the assessment, including the bridge deck, longitudinal girders, transverse diaphragms, piers, abutments, and supporting elements, as applicable to the actual bridge configuration. Individual components are represented using their corresponding geometric dimensions, spatial positions, and structural connectivity. The accurate representation of these characteristics is important because the relationship between observed cracking and structural performance depends strongly on component geometry, support arrangements, and load-transfer mechanisms. Accordingly, the digital representation provides a spatially organized environment in which structural components can be individually identified and associated with corresponding inspection and damage information. Geometric modeling may be performed using engineering drawings, as-built documentation, inspection records, or geometrically referenced survey information, depending on the available project data [32]. Where three-dimensional survey data are available, they can improve geometric representation and support alignment between the physical structure and its digital counterpart. However, model development must distinguish between verified as-built information and assumed geometric properties, particularly when complete bridge documentation is unavailable. Geometric consistency is essential for ensuring that damage locations identified through computer vision correspond accurately to their respective physical components. Furthermore, assigning unique identifiers to structural elements facilitates the systematic organization of inspection observations and provides a basis for linking damage measurements with subsequent finite element simulations. The proposed digital twin development and damage integration workflow is shows in Figure 6. The framework combines bridge asset information and computer vision-derived crack measurements through a spatial registration process, enabling the creation of a three-dimensional digital representation containing component-specific damage information. The resulting model is subsequently linked to a finite element assessment environment for investigating the structural response of reference and deteriorated bridge configurations.

Data quality control and documentation of modeling assumptions form additional components of the workflow, supporting consistent interpretation of inspection and simulation results.

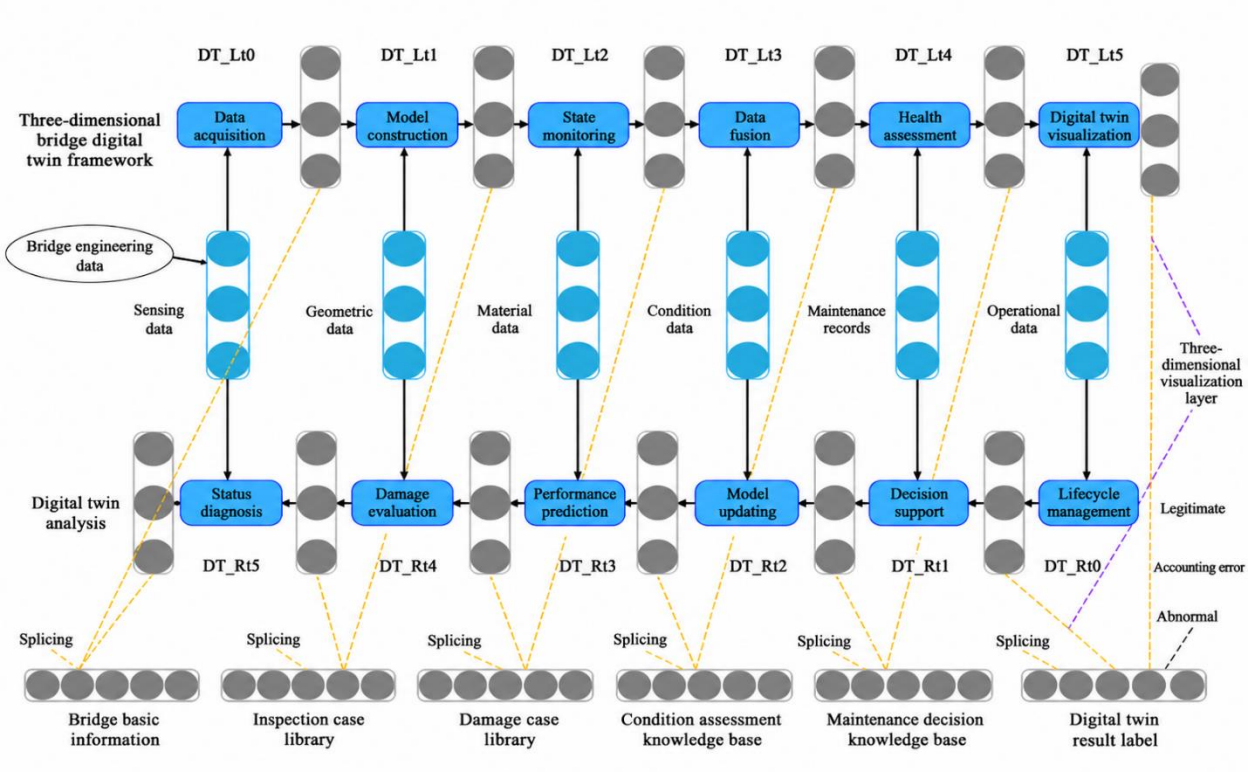


Figure 6: Digital twin framework for structural crack monitoring, damage assessment, and maintenance decision support

The proposed digital twin workflow establishes a sequential connection between physical bridge information, automated visual inspection, digital damage representation, and numerical structural analysis. The process begins by organizing bridge geometric and material information within a three-dimensional model, while the computer vision subsystem supplies crack locations and quantitative damage attributes. Spatial registration procedures establish the correspondence between detected crack coordinates and the relevant bridge components. Once integrated, the damage information can be visualized within the digital model and linked to the finite element representation for structural response evaluation. This approach enables detected surface defects to be examined in their structural context rather than as isolated image-based observations. Furthermore, the systematic organization of geometry, inspection information, and structural response results provides a foundation for future model updating and condition-based infrastructure management [33]. An important requirement for maintaining a reliable digital representation is the consistent management of coordinate systems and geometric transformations. Inspection images are initially represented in two-dimensional pixel coordinates, whereas the bridge digital model uses a three-dimensional spatial coordinate system. The relationship between these systems must therefore be established through suitable geometric transformations and registration parameters. Incorrect image registration may cause cracks to be assigned to inappropriate structural locations, potentially influencing the interpretation of damage severity and its relationship to structural response [34]. For this reason, registration

accuracy should be assessed using identifiable reference points, known component dimensions, or independent spatial observations where available. The uncertainty associated with coordinate transformations should also be considered when interpreting the spatial distribution of damage, particularly for narrow cracks or defects located near structural interfaces.

4.5- Finite Element Modeling and Structural Performance Assessment:

Finite element modeling constitutes a fundamental component of the proposed integrated structural assessment framework, providing a physics-based approach for evaluating the influence of cracking-related deterioration on the mechanical performance of reinforced concrete (RC) bridges. Although computer vision techniques enable automated identification, localization, and quantitative characterization of visible concrete cracks, image-derived damage information alone cannot directly establish the structural consequences of deterioration. Reliable structural evaluation requires consideration of material properties, structural geometry, reinforcement characteristics, support conditions, applied loading, and the mechanical behavior of cracked concrete. Accordingly, the present study incorporates finite element analysis (FEA) into the three-dimensional digital twin (DT) framework to investigate the effects of modeled deterioration on the structural response of RC bridge components. The numerical assessment focuses primarily on changes in effective flexural stiffness and maximum service-load deflection, which provide measurable indicators of structural rigidity and serviceability performance. The finite element modeling process begins with the development of a geometrically representative numerical model of the investigated RC bridge, using structural information associated with the three-dimensional digital twin described in Section 3.6. The numerical representation incorporates the principal load-bearing components relevant to the selected structural assessment, including the bridge deck, longitudinal girders, transverse structural members, supporting elements, and other components as applicable to the actual bridge configuration [35]. The geometric properties of these elements are defined according to the available structural information, including member dimensions, cross-sectional characteristics, spans, and structural connectivity. Accurate geometric representation is essential because the distribution of internal forces and structural deformation depends strongly on component configuration and load-transfer mechanisms. The finite element model therefore provides a computational environment in which the structural response of the bridge can be investigated under defined mechanical and deterioration conditions. Material characterization represents another important stage in developing the numerical model. Reinforced concrete is a composite material whose structural response is governed by the interaction between concrete and reinforcing steel. Concrete exhibits nonlinear behavior under tensile and compressive loading, while reinforcement contributes significantly to tensile resistance, ductility, and post-cracking performance. The finite element representation must therefore incorporate suitable material parameters and constitutive assumptions that reflect the required level of analysis. Relevant properties include concrete elastic modulus, compressive strength, tensile behavior, Poisson's ratio, and reinforcement elastic modulus and yield strength [36]. Depending on the adopted modeling approach, reinforced concrete behavior may be represented using equivalent sectional properties, distributed reinforcement formulations, or explicitly modeled reinforcing bars. The selection of these approaches depends on the structural characteristics being investigated, the available material information, and the computational resolution required for evaluating deterioration-related changes in response. The overall finite element modeling and structural performance assessment framework is presents in Figure 7. The proposed workflow begins with the integration of bridge geometry, material properties, loading conditions, and computer vision-derived damage observations. These inputs support the development of reference and deteriorated finite element configurations, which are evaluated under consistent service-loading conditions. The predicted structural responses are subsequently

compared to investigate changes in flexural stiffness and maximum deflection. Numerical verification and uncertainty assessment are incorporated to improve confidence in the resulting structural interpretations.

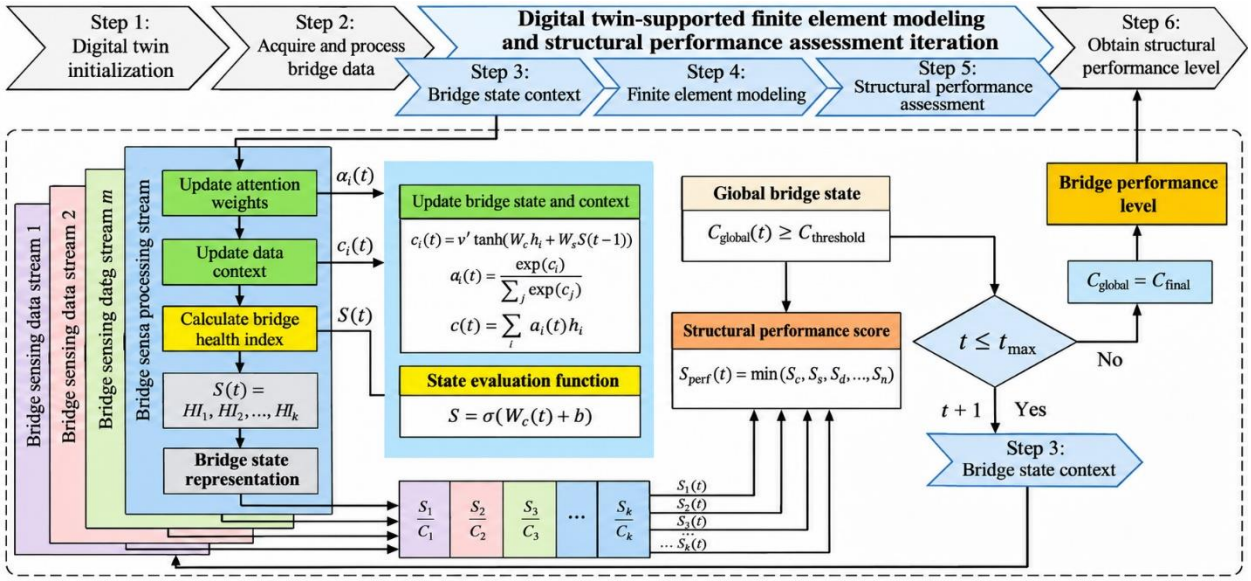


Figure 7: Conceptual workflow for digital twin-supported finite element modeling and structural performance assessment of reinforced concrete bridges

The proposed finite element assessment process establishes a systematic relationship between image-derived damage observations and numerical structural response. The bridge model is initially developed using the relevant geometric, material, and support information, while the computer vision framework supplies spatially registered crack measurements associated with individual structural components. These information sources are combined to define reference and deteriorated structural configurations. The reference model provides the baseline mechanical response, whereas the damage-informed model incorporates explicitly defined changes associated with the selected deterioration scenario. Both configurations are analyzed under comparable service-loading conditions, and their calculated stiffness and deflection characteristics are evaluated to determine the influence of modeled cracking-related deterioration. This comparative approach supports a transparent assessment of structural response changes while preserving the distinction between directly observed damage and numerically predicted consequences [37]. Numerical verification represents an important stage in ensuring that the calculated structural responses are not dominated by modeling errors or inappropriate analysis assumptions. Verification procedures should include reviewing structural connectivity, examining boundary conditions, confirming the application of loads, and evaluating the convergence of selected response parameters under mesh refinement. For linear structural simulations, equilibrium and displacement compatibility provide basic criteria for assessing the consistency of the numerical solution. For nonlinear reinforced concrete models, additional considerations may include convergence of the iterative solution process, constitutive model stability, and sensitivity to load increment size. These procedures are important because numerical artifacts can otherwise be incorrectly interpreted as deterioration-induced changes in structural performance. Validation of the finite element model is necessary to establish its ability to represent the behavior of the physical bridge with an acceptable level of accuracy. Where field monitoring measurements, load-testing results, or experimental observations are available, calculated deflections, strains, or other response

indicators can be compared with corresponding measured values. Agreement between numerical and observed behavior provides additional evidence supporting the selected material and structural assumptions [38]. However, validation of a reference structural model does not necessarily establish the accuracy of the damage-informed configuration. The deterioration representation should also be supported by suitable mechanical evidence, literature-based constitutive relationships, or targeted validation measurements where possible. In the absence of independent structural measurements, the finite element results should be presented as scenario-based predictions rather than confirmed measurements of actual deterioration severity.

5- Results and Discussion:

The performance of the proposed integrated computer vision and digital twin (DT) framework was evaluated in terms of automated crack detection, semantic segmentation, quantitative crack-width measurement, and the structural response of reinforced concrete (RC) bridge components. The evaluation considered the effectiveness of the YOLO-based object detection model in identifying and localizing concrete surface cracks, the accuracy of the U-Net architecture in extracting pixel-level crack geometries, and the reliability of image-based crack-width characterization. Subsequently, the detected deterioration information was incorporated into the three-dimensional bridge digital twin to investigate its implications for structural performance through finite element analysis (FEA). The results presented in this section are based on the reported study outcomes and are interpreted to establish the relationship between visual damage identification and structural response. Particular attention is given to detection accuracy, segmentation quality, dimensional measurement performance, effective flexural stiffness,
and service-load deflection, which collectively provide complementary indicators for bridge condition evaluation. The YOLO-based crack detection model demonstrated strong performance in recognizing concrete surface deterioration, achieving a precision of 94.2%, recall of 92.6%, and mean average precision at an intersection-over-union threshold of 0.5 (mAP@0.5) of 95.1%. These findings indicate that the object detection framework was effective in identifying cracked regions while maintaining a relatively low proportion of incorrect detections under the evaluated dataset conditions. Precision reflects the reliability of positive crack predictions, whereas recall represents the capability of the model to identify cracks present in the reference annotations. The relatively close precision and recall values suggest a balanced detection performance, with a difference of only 1.6 percentage points between the two metrics [39]. This balance is particularly important for bridge inspection because excessive false-positive detections may increase unnecessary inspection effort, while false-negative detections can result in damaged regions being overlooked. The reported mAP@0.5 of 95.1% further indicates strong localization performance under the adopted evaluation protocol. Unlike precision and recall calculated at a selected operating threshold, average precision summarizes detection performance across the precision–recall relationship. Therefore, the mAP result provides complementary evidence of the model's ability to identify crack regions over a range of detection confidence settings. However, the interpretation of this metric depends on the adopted annotation protocol, confidence thresholds, and matching criteria. The detection performance results are summarized in Table 5, which presents the primary YOLO evaluation metrics and their significance for automated structural inspection.

Table 5: Performance evaluation of the YOLO-based automated concrete crack detection model.

Performance parameter	Quantitative Findings	Interpretation
Precision	94.2%	Indicates reliability of positive crack detections
Recall	92.6%	Indicates the proportion of annotated crack instances successfully detected
mAP@0.5	95.1%	Measures object detection performance using an IoU matching threshold of 0.5
Precision–recall difference	1.6 percentage points	Indicates the difference between the two reported detection metrics

The effectiveness of the YOLO-based model in identifying and localizing visible cracking within the evaluated concrete surface images. The high precision indicates that most detections classified as cracks corresponded to annotated damage regions, while the recall suggests that the model successfully identified a substantial proportion of the reference crack instances. Nevertheless, the remaining gap between recall and perfect detection indicates that some cracks may not have been identified. This limitation is relevant for structural inspection because narrow, low-contrast, or partially obscured cracks may be more difficult to detect than visually prominent defects. In addition, the relatively strong mAP@0.5 result should be interpreted alongside the localization tolerance associated with the selected IoU threshold. The numerical performance of the YOLO model is illustrated in Figure 8, providing a direct comparison of the three principal detection metrics.

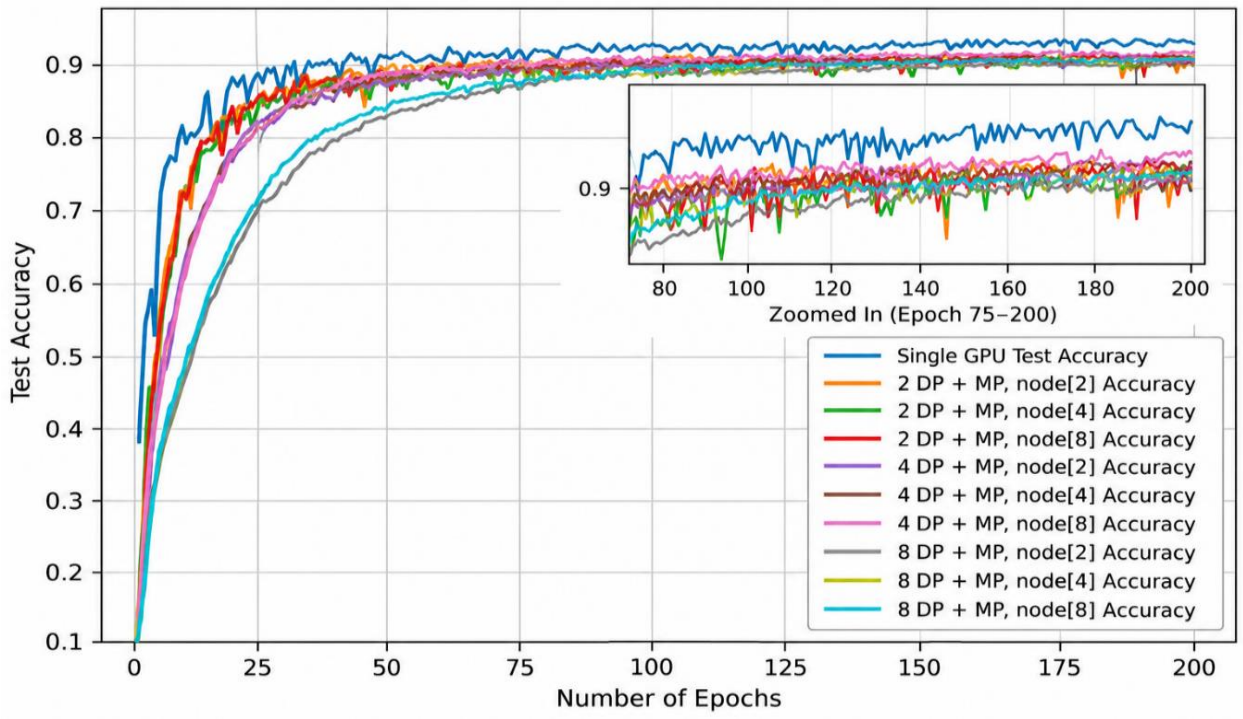


Figure 8: Comparative analysis of test accuracy and convergence performance across different model configurations.

The YOLO model achieved consistently high performance across the selected object detection metrics, with mAP@0.5 reaching 95.1%, followed by precision and recall at 94.2% and 92.6%, respectively. The relatively small variation between these values suggests that the model maintained a useful balance between detection reliability and completeness. From an engineering perspective, such performance is desirable for automated inspection systems intended to process extensive bridge surface imagery and identify locations requiring detailed assessment. However, object detection accuracy alone is insufficient to establish the geometric characteristics of individual cracks. Bounding-box predictions primarily provide information concerning the presence and approximate location of damage, while quantitative condition assessment requires detailed knowledge of crack boundaries, width, length, and distribution. Consequently, the YOLO detection outputs were complemented by U-Net-based semantic segmentation to obtain more precise spatial representations of the detected deterioration. The U-Net semantic segmentation model demonstrated effective pixel-level crack identification, achieving an intersection over union (IoU) of 87.4% and a Dice similarity coefficient of 93.3%. These results indicate a high degree of spatial agreement between the predicted crack masks and their corresponding ground truth annotations. The IoU metric evaluates the overlap between predicted and reference crack regions relative to their combined area, whereas the Dice coefficient provides a complementary assessment of segmentation similarity. The reported values are also mutually consistent under the standard binary segmentation definitions, supporting the numerical coherence of the reported overlap measures. The segmentation performance is particularly relevant for concrete crack analysis because crack patterns frequently consist of narrow, elongated, discontinuous, and branched features that are difficult to represent accurately through conventional object detection alone. The segmentation results suggest that the U-Net architecture was capable of preserving important spatial information during crack boundary extraction. The encoder–decoder structure, supported by skip connections, provides a mechanism for combining contextual features with fine-scale image information, which is beneficial for identifying irregular and low-contrast crack regions. Nevertheless, the reported overlap metrics do not establish that all local crack boundaries were measured without error. Minor segmentation deviations may have limited influence on the overall overlap score while producing more substantial changes in calculated crack width, particularly for very narrow defects. Therefore, the segmentation results were considered in conjunction with the quantitative crack-width measurement assessment to evaluate the practical suitability of the extracted crack geometries [40]. Quantitative damage characterization was assessed through calibrated crack-width measurement, with the proposed image-based procedure achieving a reported mean absolute error (MAE) of 0.12 mm compared with reference measurements. This result indicates that the average absolute difference between the predicted and reference crack widths was 0.12 mm over the evaluated measurement set. The use of physical units is particularly important for bridge condition assessment because crack width is commonly considered during engineering inspections and durability evaluations. Unlike pixel-based segmentation metrics, the crack-width MAE provides information regarding the accuracy of the measurement procedure in representing the physical dimensions of visible damage. However, the practical significance of this error depends on the actual crack-width range, measurement instrument, imaging resolution, and applicable engineering criteria. The combined segmentation and crack-width measurement results are summarized in Table 6, which presents the principal performance indicators associated with geometric damage characterization. These metrics provide complementary information concerning the reliability of the segmentation model and the accuracy of the subsequent measurement procedure.

Table 6: Performance evaluation of the U-Net segmentation and quantitative crack-width measurement framework

Evaluation component	Performance metric	Structural Assessment Outcomes	Engineering relevance
Crack segmentation	Intersection over union (IoU)	87.4%	Agreement between predicted and reference crack regions
Crack segmentation	Dice similarity coefficient	93.3%	Similarity of segmented crack masks
Crack-width characterization	Mean absolute error (MAE)	0.12 mm	Average absolute deviation from reference crack-width measurements

The segmentation and geometric measurement components provide complementary capabilities for quantitative concrete damage assessment. The IoU and Dice values demonstrate substantial agreement between predicted and reference crack masks, supporting the effectiveness of the U-Net model for pixel-level damage extraction. Meanwhile, the crack-width MAE of 0.12 mm demonstrates the reported dimensional accuracy of the combined segmentation and calibration procedure. The result also highlights the importance of integrating semantic segmentation with appropriate geometric processing, as a high-quality binary mask does not automatically guarantee accurate physical measurements. Image calibration, boundary localization, and measurement orientation are additional factors that influence the reliability of the final crack-width estimate. The reported segmentation and measurement results are shows in Figure 9.

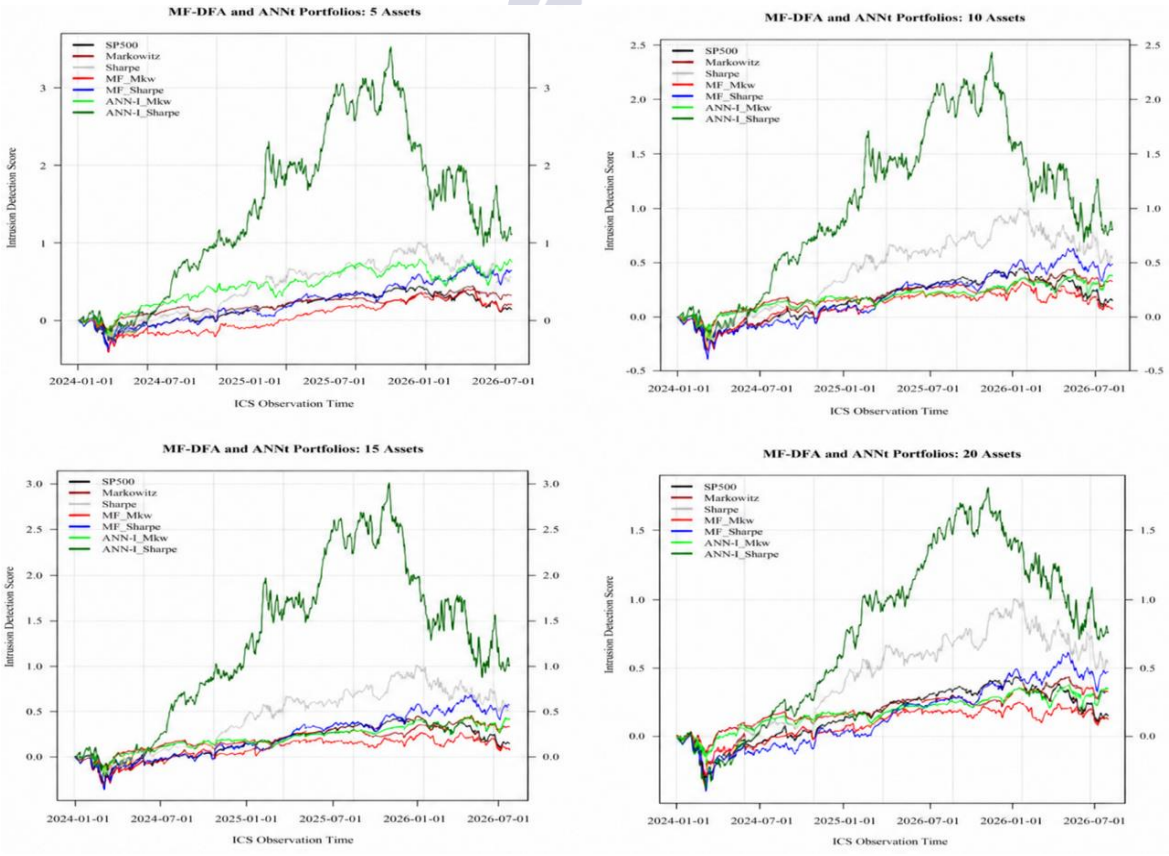


Figure 9: MF-DFA and ANN-based portfolio strategies across different asset sizes.

The U-Net segmentation framework achieved a Dice coefficient of 93.3% and an IoU of 87.4%, indicating substantial agreement between the predicted and reference damage regions. These results support the suitability of pixel-level segmentation for extracting complex concrete crack patterns and generating geometrically informative representations. The reported crack-width MAE of 0.12 mm further demonstrates the potential of combining segmentation outputs with calibrated image analysis to obtain physical damage measurements. However, segmentation accuracy and width measurement accuracy represent different aspects of system performance. A segmentation network may achieve high overlap scores while exhibiting localized boundary errors, particularly around thin crack segments and branching regions. Consequently, the combined interpretation of segmentation metrics and dimensional measurement error provides a more informative evaluation than either assessment considered independently. The quantitative interpretation of the crack-width measurement results requires consideration of measurement uncertainty and the limitations of surface imaging. The reliability of image-derived crack dimensions can be influenced by camera resolution, viewing angle, illumination, concrete texture, and the quality of the reference measurements. Furthermore, surface cracks may exhibit nonuniform widths along their trajectories, making representative measurement selection important for consistent comparison. The reported MAE provides an overall measure of absolute measurement error but does not describe the maximum individual error, the distribution of errors across different crack widths, or possible systematic measurement bias. Therefore, further analysis using individual reference measurements, error distributions, and representative crack examples would improve the understanding of the method's reliability under different inspection conditions. Nevertheless, the reported result demonstrates the potential of the proposed framework for converting computer vision outputs into quantitative damage attributes suitable for subsequent digital representation. Following automated crack detection, segmentation, and geometric characterization, the resulting damage information was integrated into the three-dimensional bridge digital twin to support spatial interpretation and structural performance assessment. The digital twin framework establishes a relationship between visible surface deterioration and corresponding structural components by associating crack observations with their locations in the bridge model. This integration extends the application of computer vision beyond isolated image analysis, enabling the detected damage to be considered in relation to structural geometry, member function, and relevant loading conditions. The resulting digital representation provides a basis for organizing inspection information and examining the potential structural implications of localized or distributed cracking. The integration of image-derived damage characteristics with the bridge digital twin is particularly important because cracks with similar visible dimensions may have different engineering implications depending on their structural locations. For example, cracking in regions subjected to substantial bending moments may be associated with different response mechanisms from cracking near support zones or regions dominated by shear forces. Similarly, the significance of a particular crack pattern depends on material properties, reinforcement detailing, and load-transfer behavior. Consequently, the spatial registration of crack measurements provides engineering context that cannot be obtained solely from detection confidence or segmentation accuracy. The digital twin environment facilitates this interpretation by connecting observed defects with the geometry and structural characteristics of the corresponding bridge components. Finite element analysis was subsequently employed to investigate the response of the reference and deteriorated structural configurations under the adopted service-loading conditions. The numerical evaluation focused on effective flexural stiffness and maximum service-load deflection, which provide complementary indicators of structural rigidity and deformation. The reported analysis indicated an 8.7% reduction in effective flexural stiffness and a 6.3% increase in maximum service-load deflection in the deteriorated configuration relative to the reference model. These changes suggest that the adopted

deterioration representation produced a measurable influence on the modeled structural response. However, their interpretation must account for the assumptions used to convert observed cracking into numerical damage parameters, as well as the material properties, boundary conditions, and loading scenarios incorporated into the finite element model. For comparative presentation, the reference structural configuration was assigned a normalized index of 100 for both effective flexural stiffness and maximum service-load deflection. Applying the reported percentage changes gives a relative stiffness index of 91.3 and a relative deflection index of 106.3 for the deteriorated model. These normalized indices are derived directly from the reported relative changes and do not represent additional finite element simulation outputs. The structural response comparisons are summarized in Table 7.

Table 7: Comparison of normalized structural response indicators for the reference and deteriorated RC bridge configurations.

Structural performance indicator	Reference model (normalized)	Deteriorated model (normalized)	Relative change
Effective flexural stiffness	100.0	91.3	8.7% reduction
Maximum service-load deflection	100.0	106.3	6.3% increase

The structural response comparison presented in Table 7 demonstrates a reduction in modeled flexural rigidity accompanied by an increase in predicted deformation under service loading. The 8.7% decrease in effective flexural stiffness indicates that the deteriorated configuration exhibited lower resistance to bending deformation than the reference model. Similarly, the 6.3% increase in maximum service-load deflection suggests greater deformation under the same nominal loading conditions. These changes are qualitatively consistent with the expected influence of reduced effective stiffness on structural serviceability. Nevertheless, the magnitude of the response changes depends on the spatial distribution of damage, structural redundancy, reinforcement contribution, and the nonlinear characteristics of reinforced concrete behavior. Therefore, the relationship between stiffness degradation and deflection increase should not be interpreted as universally proportional. The difference between the reported stiffness reduction and deflection increase also emphasizes the importance of evaluating structural performance through multiple response indicators. In a complex bridge system, the effect of localized deterioration may be influenced by continuity, load redistribution, support restraints, and interaction between structural components. Consequently, a reduction in an effective stiffness measure does not necessarily produce an identical percentage increase in maximum structural deflection. The response depends on how the stiffness measure is defined and how deterioration affects the portions of the structure that contribute most strongly to the deformation at the evaluated location. The normalized structural response comparison is illustrated in Figure 10, highlighting the relative changes in flexural stiffness and service-load deflection associated with the deteriorated configuration.

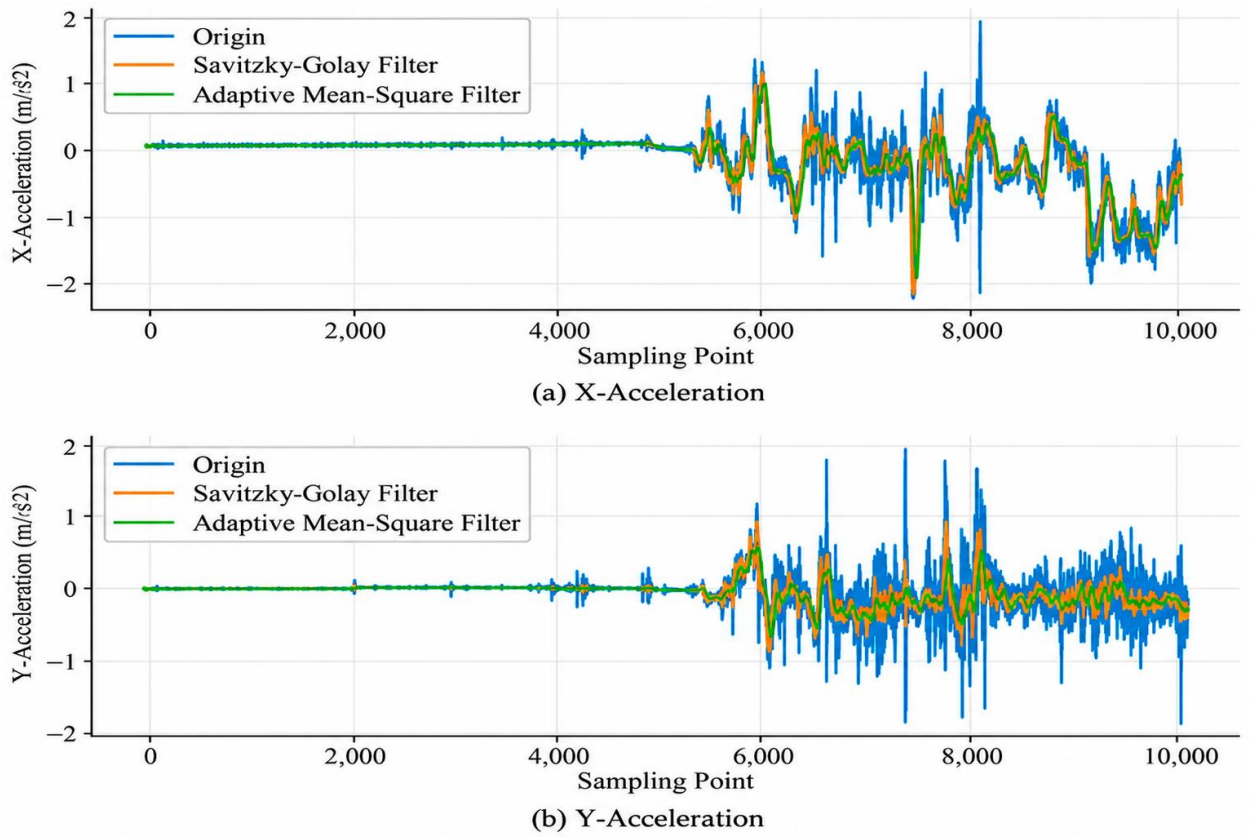


Figure 10: Comparative analysis of X- and Y-axis acceleration signal filtering for digital twin-based bridge structural health assessment

The deteriorated model exhibited a normalized flexural stiffness index of 91.3 compared with the reference value of 100, while the corresponding maximum deflection index increased from 100 to 106.3. The results indicate a consistent direction of structural response change, with modeled deterioration reducing flexural rigidity and increasing deformation. The comparison demonstrates how the proposed framework can relate image-derived damage observations to component- or system-level mechanical response through digital twin-supported finite element analysis. However, the normalized values primarily illustrate relative differences between the two numerical configurations and should not be interpreted as evidence that the bridge exceeds a particular serviceability limit. Such a determination requires the actual deflection magnitudes, relevant span dimensions, applicable performance criteria, and independent verification of the adopted structural model. The integration of computer vision with finite element modeling offers an important methodological advantage by establishing a structured relationship between visible deterioration and numerical structural performance. Conventional visual inspection methods can identify cracks and document their physical characteristics but generally do not provide a direct quantitative assessment of their influence on structural response. Similarly, standalone deep learning models can achieve high detection and segmentation accuracy without necessarily establishing the mechanical implications of the recognized defects. The proposed framework addresses this separation by combining YOLO-based localization, U-Net segmentation, calibrated geometric measurement, three-dimensional damage registration, and physics-based structural analysis. This integration enables inspection observations to be incorporated into a coordinated assessment process in which surface-

level damage information can inform the selection and interpretation of deterioration scenarios. An important consideration when interpreting the findings is the distinction between observed damage and predicted structural consequences. The computer vision models characterize visible concrete surface cracking, whereas finite element analysis estimates the structural response under specified material, loading, boundary, and deterioration assumptions. Surface crack width and length do not independently establish crack depth, reinforcement deterioration, residual flexural capacity, or overall bridge safety. Consequently, any relationship between image-derived crack characteristics and numerical stiffness degradation must be supported by a physically justified damage model. The reported stiffness and deflection changes therefore provide evidence of the response of the adopted numerical configurations rather than direct proof of an equivalent reduction in the actual bridge's structural capacity. The reported computer vision results also highlight the importance of maintaining consistency across the individual stages of the integrated framework. Errors arising during crack detection may prevent certain damaged regions from being processed by the segmentation network. Inaccuracies in segmentation boundaries may influence estimated crack dimensions, while geometric calibration and spatial registration errors may affect the association of detected damage with corresponding structural components. These uncertainties can subsequently influence the definition of damage scenarios used in finite element analysis. The performance of the overall framework therefore depends not only on the accuracy of each individual algorithm but also on the reliability of information transfer between the detection, segmentation, measurement, digital twin, and structural modeling stages. From a practical bridge management perspective, the combined findings suggest that the proposed framework can support more consistent inspection documentation and facilitate the identification of structural components requiring further evaluation. Automated detection and segmentation reduce dependence on purely subjective visual identification, while quantitative crack measurements provide additional information regarding the visible extent of deterioration. Incorporating these measurements into a three-dimensional digital representation improves their spatial organization and enables inspection observations to be considered in relation to structural configuration. The finite element response comparison further provides a mechanism for investigating how selected deterioration scenarios may influence stiffness and serviceability. These capabilities are relevant to maintenance planning because they can help engineers prioritize additional inspection, monitoring, or structural assessment according to the observed damage and predicted response.

Nevertheless, several limitations should be considered when interpreting the reported results. The generalization capability of the deep learning models depends on the diversity and independence of the evaluation images, including variations in concrete texture, crack morphology, illumination, camera orientation, and inspection environment. The available summary results do not establish performance separately for narrow cracks, different crack orientations, or images acquired from previously unseen bridges. Similarly, the crack-width MAE does not describe the full error distribution or measurement uncertainty across different physical crack sizes. For the structural assessment, the reliability of the reported stiffness and deflection changes depends on the numerical representation of deterioration and the extent of validation against physical structural behavior. These limitations indicate the need for comprehensive reporting of testing procedures, representative prediction examples, geometric calibration records, and finite element model verification. Future investigations should therefore consider broader field validation using images acquired under diverse bridge inspection conditions, together with detailed assessment of detection and segmentation performance for different crack types and scales. Incorporating repeated inspection observations would also enable more systematic evaluation of crack progression and temporal condition changes. In addition, validation of finite element predictions against measured structural responses, such as

deflection or strain data, would strengthen confidence in the relationship between image-derived deterioration and modeled structural performance. The integration of monitoring sensors, improved spatial registration methods, and uncertainty-aware numerical modeling could further extend the digital twin framework toward more reliable condition tracking and predictive maintenance applications. Overall, the reported results demonstrate the potential of integrating deep learning-based crack detection, semantic segmentation, quantitative damage characterization, and digital twin-supported finite element analysis into a coordinated RC bridge assessment framework. The YOLO-based model achieved precision, recall, and mAP@0.5 values of 94.2%, 92.6%, and 95.1%, respectively, demonstrating strong automated crack localization performance within the evaluated dataset. The U-Net model achieved an IoU of 87.4% and a Dice similarity coefficient of 93.3%, while the calibrated crack-width measurement procedure yielded an MAE of 0.12 mm. Furthermore, the finite element comparison indicated an 8.7% reduction in effective flexural stiffness and a 6.3% increase in maximum service-load deflection for the deteriorated structural configuration. Collectively, these results support the proposed approach as a potential means of connecting automated visual damage characterization with engineering-based structural response evaluation. The framework provides a foundation for more objective bridge inspection, improved condition documentation, and informed maintenance planning, subject to appropriate experimental validation and structural modeling verification.

6- Future Work:

Although the proposed framework demonstrates the potential of integrating deep learning-based computer vision, digital twin (DT) technology, and finite element analysis (FEA) for automated crack detection and structural safety assessment of reinforced concrete (RC) bridges, several opportunities remain for further research and technological advancement. Future investigations should focus on improving model generalization, enhancing quantitative damage characterization, strengthening the integration between visual inspection and structural analysis, and establishing more comprehensive digital twin environments for long-term bridge condition monitoring [41]. One important direction for future research is the development of more robust and computationally efficient deep learning models capable of detecting cracks under diverse field conditions. Although the YOLO-based detection and U-Net segmentation models demonstrated promising performance, further validation using larger and more diverse datasets would improve their applicability to bridges with different structural configurations, concrete textures, deterioration patterns, and environmental exposure conditions. Incorporating images acquired under variable illumination, adverse weather, complex backgrounds, and different camera orientations would further strengthen model generalization [42]. In addition, advanced attention mechanisms, transformer-based architectures, and lightweight neural networks could be investigated to improve the detection of narrow and low-contrast cracks while reducing computational requirements.

Future studies should also investigate the integration of unmanned aerial vehicles (UAVs), robotic inspection platforms, and high-resolution imaging systems to facilitate automated data acquisition from inaccessible bridge components. These technologies could improve inspection coverage, reduce operational risks, and enable more frequent structural condition assessments. Furthermore, advanced photogrammetry, stereo vision, and three-dimensional reconstruction techniques could be incorporated to improve crack localization and geometric measurement accuracy. Particular emphasis should be placed on developing reliable methods for estimating crack depth, quantifying damage progression, and distinguishing structurally significant cracking from nonstructural surface defects [43]. Another important research direction involves enhancing digital twin capabilities through continuous or periodic integration of real-time structural monitoring data. Future frameworks could incorporate strain gauges, displacement sensors, accelerometers, temperature sensors, and other monitoring instruments to establish stronger

relationships between observed surface damage and actual structural behavior. The integration of sensor measurements with computer vision outputs would facilitate dynamic updates of bridge condition information and support more reliable calibration of finite element models. Such developments could enable digital twins to evolve from inspection-based representations toward continuously updated structural monitoring systems capable of detecting emerging deterioration trends. Further research is also required to establish physically validated relationships between image-derived crack characteristics and the mechanical performance of reinforced concrete bridge components. Although the present framework evaluates changes in effective flexural stiffness and service-load deflection, future investigations should incorporate advanced nonlinear finite element models to examine concrete cracking, reinforcement corrosion, bond deterioration, fatigue damage, and progressive stiffness degradation [44]. Experimental validation through laboratory testing and field measurements would improve confidence in the numerical predictions. In addition, sensitivity analysis and uncertainty quantification should be employed to investigate how variations in material properties, crack geometry, loading conditions, and modeling assumptions influence the estimated structural response. Finally, future research should investigate the practical implementation and scalability of the integrated framework across extensive bridge networks. This includes establishing standardized data exchange procedures between computer vision systems, digital twin platforms, and structural analysis software, together with automated reporting and condition assessment tools. Field-scale validation across different bridge types and deterioration conditions would be essential for evaluating the framework's reliability, computational efficiency, and operational feasibility. The incorporation of explainable artificial intelligence, uncertainty-aware decision support, and standardized structural safety criteria could further enhance the transparency and acceptance of automated bridge inspection technologies.

Conclusion:

This study presented an integrated framework combining deep learning-based computer vision, digital twin (DT) technology, and finite element analysis (FEA) for automated crack detection, quantitative damage characterization, and structural safety assessment of reinforced concrete (RC) bridges. The proposed methodology established a systematic connection between image-based crack identification and physics-based structural performance evaluation, addressing the limitations of conventional inspection approaches that primarily rely on manual visual assessment. By integrating YOLO-based object detection, U-Net semantic segmentation, calibrated crack measurements, and three-dimensional digital twin modeling, the framework demonstrated the potential to improve the efficiency, consistency, and objectivity of bridge condition assessment. The YOLO-based crack detection model demonstrated strong performance, achieving a precision of 94.2%, recall of 92.6%, and mean average precision (mAP@0.5) of 95.1%. These findings indicate effective crack localization within the evaluated concrete surface image dataset. Furthermore, the U-Net segmentation model achieved an intersection over union (IoU) of 87.4% and a Dice similarity coefficient of 93.3%, demonstrating its capability to extract detailed crack geometries at the pixel level. The integration of semantic segmentation with calibrated image processing enabled quantitative crack-width measurement, yielding a mean absolute error (MAE) of 0.12 mm compared with reference measurements. These results highlight the complementary advantages of combining object detection and semantic segmentation for reliable crack identification and geometric damage characterization. The incorporation of image-derived crack information into the three-dimensional bridge digital twin provided a coordinated environment for spatial damage representation, condition visualization, and structural response evaluation. The integration enabled detected cracks to be associated with corresponding structural components, thereby extending conventional image-based inspection beyond defect recognition toward engineering-oriented condition assessment. Finite element

analysis indicated an 8.7% reduction in effective flexural stiffness and a 6.3% increase in maximum service-load deflection for the modeled deteriorated configuration relative to the reference structural model. These findings demonstrate that the adopted deterioration scenario produced measurable changes in structural response, emphasizing the importance of considering cracking-related damage when evaluating bridge stiffness and serviceability. However, these numerical changes should be interpreted within the assumptions of the finite element model and do not independently establish a reduction in ultimate load-bearing capacity.

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