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# Remote collaborative framework for real-time structural condition assessment using Augmented Reality

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ABSTRACT

Civil structures worldwide are confronted with a growing threat of structural deterioration, aggravated by various factors such as climate change, population growth, and increased traffic. The latent nature of these issues often leads to undetected vulnerabilities until a catastrophic failure occurs, resulting in substantial losses. To address this challenge, there is a critical need for improved structural monitoring, condition assessment, and maintenance practices. Traditional inspection methods, relying on visual estimation and heavy equipment for inaccessible areas, present formidable obstacles to inspectors. These methods impede the safe and fast examination of structural damage, complicating tracking of structural deterioration, and hindering efficient condition assessment. Recognizing these challenges, this paper proposes a remote collaborative framework to enhance the efficiency of structural inspections by leveraging the capabilities of Augmented Reality (AR), QR code, and 5G network. The proposed framework centers on real-time remote collaboration among on-site and off-site inspectors, aiming to elevate safety, accessibility, and overall inspection efficacy. The integration of real-time data sharing and collaboration facilitates immediate decision-making, enabling inspectors to proactively address structural vulnerabilities and prevent potential failures. This study concludes that the proposed framework effectively facilitates real-time structural condition assessment for on-site AR users. Simultaneously, off-site web users can instantly track the progression of data over time through the utilization of 5G technology. The proposed advanced AR framework effectively demonstrates real-time structural condition assessment through a lab-scale experimental beam and a full-scale bridge.

## 1. Introduction

Civil structures worldwide face an increasing challenge of structural deterioration due to various factors, including climate change, growing populations, and traffic, that are often not detected until a catastrophic failure occurs. In fact, the American Infrastructure Report Card of 2021ASCE Infrastructure Report Card [3] indicated that one-third of America's infrastructure is at risk of rapid deterioration. In Canada, the Canadian Society for Civil EngineeringCSCE Infrastructure Report Card [14] stated that around 9,600 bridges and tunnels are in poor condition. To mitigate the risk of structural deterioration and subsequent economic loss, real-time structural monitoring, condition assessment, and maintenance can provide detailed information and help prevent future failures [34,31,38,1]. Conventional inspection approaches, such as visual estimation and the use of heavy equipment to perform inspections in inaccessible areas, pose significant challenges for inspectors by hindering safe, speedy, and accurate examination of structural damage, while also complicating the task of tracing structural conditions and obstructing efficient structural condition assessment in the inspection process [19,36,33]. For example, inspectors at the construction site collect data using time-intensive techniques that require the setup of heavy expensive equipment, and this data is not processed until weeks later off-site in an office setting. The motivation of the proposed research stems from the significant challenge of limited data accessibility and the lack of real-time collaboration between on-site and off-site users that prevents quick decision-making regarding the condition of the structure. Recently, researchers have developed advanced solutions leveraging Augmented Reality (AR) to overcome traditional inspection techniques for greater efficiency in the inspection process [8,35,37,39]. These studies include integrating 3D models of civil structures for enhanced visualization [20,7,32], and incorporating user interaction with structural data for improved data management [25,15,24]. However, existing

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studies limit the usage scope by relying on predefined 3D models, failing to facilitate real-time remote collaboration between off-site and on-site users, and impeding ongoing data evaluation over time by omitting the ability to update data during the inspection. Therefore, there is an emergent need to establish a robust framework to elevate the efficiency of monitoring during structural inspections, enhancing safety, and improving accessibility through real-time remote collaboration between inspection teams while providing access to updated 3D models that include most recent damage information for on-site inspectors.

Consequently, this paper proposes a framework that harnesses the capabilities of AR to streamline structural inspection processes and enhance the maintenance capacity, ultimately contributing to safer and more resilient infrastructure worldwide. To achieve these objectives, this paper: 1) enables real-time remote structural condition assessment using AR and cloud storage, 2) empowers users to collect new data in real-time and store it immediately for further maintenance, and 3) allows users to visualize new data alongside historical data in a real-time framework accessible through a web application. Leveraging cloud storage and a real-time web application facilitates seamless remote collaboration among inspectors employing multiple HL devices by improving data accessibility during inspections. This framework not only enables real-time on-site inspector cooperation but also improves collaboration with off-site colleagues, which expedites decision-making processes for enhanced efficiency.

The remainder of the paper is organized as follows: it begins with an introduction to the related work, presents the background technologies, proceeds to explain the proposed methodology, provides details about the hardware and software of the proposed framework, and concludes by presenting and discussing the experimental results of SHM of two relevant use cases including an experimental and full-scale structure.

## 2. Related work

AR technology is an emerging technological advancement that is a part of the computer-mediated reality technologies that integrate virtual elements such as holograms, text, and 3D objects into the real environment [30,11,18]. This technology was integrated into a head-mounted display (HMD) to superimpose computational outputs in a physical environment through real-time measurement [13]. In the last few years, researchers have developed similar applications aimed at maximizing the benefits of AR across various areas, including construction, maintenance, manufacturing, and education [42,35].

For example, Park et al. [28] developed a defect management system for civil structures by integrating BIM models and AR. During the work process, the site manager uses a mobile device with a defect collection template to gather and rectify defect data, storing it in an ontology-based database. When preparing a defect management plan for a new project, the site manager searches for crucial information using ontology linked to the work schedule. For field inspection, the site manager provides markers that contain defect information to trade workers, who attach them to assigned locations for checking core control factors. After task completion, images of finished work are sent to the site inspector for feedback via mobile device. However, the markers cannot be remotely exchanged between managers and workers in real-time, but they are rather exchanged physically which delays the inspection process. In a similar study, Zhou et al. [43] presented a framework that allows inspectors on-site to analyze differences in structural conditions of tunnels. The system works by superimposing a BIM model onto a real structure using a physical marker to locate the real structure. Once the BIM model is superimposed, the inspector can examine any differences in displacement between the baseline BIM model and the real structure that would indicate damage or concern in the structure. This enables inspectors to make informative decisions during the inspection process. However, the system does not store data remotely limiting real-time data acquisition and dynamic BIM model usage.

Implementing a different approach, Huang et al. [20] developed an AR system to visualize finite element analysis of structures. The system utilizes sensor data to create a hologram of the virtual structure that is projected on a real structure, which helps the user visualize the effect of different loads. Bahri et al. [6] contributed to developing a system that seamlessly integrates 3D Building Information Modelling (BIM) into an AR environment using Microsoft HoloLens (HL). Leveraging the spatial mapping feature of HL, the system scans the environment to obtain real-world coordinates and projects BIM models in front of the user. Users can interact with these models by moving, resizing, or rotating them. However, a significant limitation arises as the BIM models must be predefined within Unity, a cross-platform game engine for creating interactive 3D experiences before deployment to the HL. This static nature implies a lack of flexibility, preventing real-time incorporation or updates of BIM models without a complete deployment in AR.

Brito et al. [7] introduced an enhanced approach for visualizing BIM models using an HL1 headset that includes adding inspection reports to a 3D model. The proposed system uses the Industry Foundation Classes (IFC) file format as the input data for the models, which allows users to select sub-models of a whole 3D model. The proposed system allows the user to fill out an inspection/damage report about the model and save it to be viewed later. This approach enables inspectors to view BIM models and their corresponding inspection reports on-site and directly compare the data from the report to the current condition of the structure. However, the framework assumes no internet connectivity on construction sites, it uses a local file to store the existing and updated data, which hinders real-time collaboration, as any updates made are exclusively reflected locally on a specific HL device, with no immediate shared visibility. In another study, Raimbaud et al. [32] developed a BIM-based mixed reality application for the supervision of construction projects. The application uses BIM data to create a virtual model of the construction site, which is overlayed on the physical environment using mixed-reality technology. This allows supervisors to view the construction progress in real-time and identify potential issues before they create major problems. This system does not use an AR headset for visualization of models on-site, instead, it allows the supervisor to remotely view the site through real-time video inputs captured with a drone, where the BIM models are projected into the real environment and the AR scene is displayed on a computer screen. Introducing another approach, Mirshokraei et al. [25] worked on a web-based structural quality management system using BIM and AR. The system allows inspectors to view BIM models projected onto the real structure. For example, the user can use the AR device to view the augmented formwork on a reinforced beam and assess its quality. However, the data associated with the BIM models cannot be updated in real-time on the construction site.

Cao et al. [9] established an architecture for map navigation and air quality data visualization using a 5G network and AR. The system collects data from sensing devices and sends them to an edge server, which acts as the transfer point between the sensors and the AR device, then it processes the sensor data and sends them to the HL. Although this study does not focus on structural inspections, it provides a detailed approach to evaluating the performance of data transfer between the server and HL using a 5G vs. LTE network. This study concludes that the 5G network is the best option for real-time map navigation.

Expanding on previous BIM-related studies, Deng et al. [15] proposed an integrated management framework leveraging BIM and an SQL database. This framework, designed as a visual system, facilitates safety measures, early warnings, and bridge monitoring. The approach utilized Revit as the primary development platform and seamlessly integrated visual warning and monitoring information management plug-ins through an API. The resulting framework enhanced the visualization of bridge monitoring data and had the capability to document early warning information, transmitting it to the relevant personnel. However, this approach does not support remote collaboration between on-site and off-site users, which hinders the decision-making process and assessment of civil structures. In another study, Klauer and Plaß [21] presented a methodology for capturing as-built BIM models using AR and AI-based classification of the captured point cloud data. The study aims to provide an efficient and accurate way of creating as-built BIM models using AR technology. The methodology involves capturing the point cloud data of the as-built environment using an AR-enabled mobile device. The point cloud data is then processed using a machine learning algorithm (i.e., YOLO) to classify and identify different elements of the as-built environment, such as walls, windows, and doors. The classified data is then used to create a BIM model of the as-built environment. This enables inspectors to automate the classification process of building components which creates a possibility to save such information for future reference. While this study yielded positive outcomes, it falls short in real-time capability, requiring an initial scanning of point clouds that must be manually provided to the classification model.

Building on data-maintenance applications from Brito et al. [7], Maharjan et al. [24] developed a framework that enables data access and inspection in SHM. The system allows inspectors to scan a Quick Response (QR) code corresponding to different objects (e.g. bridges) and load data as a PDF file for visualization. The system uses a cloud database to store information. This application allows inspectors to use sensors such as strain gauges for bridges and view real-time strain time series in an online web application. This work enables inspectors to visualize information through PDF files or real-time plots. However, the plots only display readings from the current session and lack the capability to track sensor data over time. Additionally, the system does not support the presentation of 3D model structures or offer the flexibility to update data within the AR environment. As a result, inspectors are required to update the data manually before visualizing it on-site. In another study, Liu et al. [23] introduced a system that integrates BIM and AR with drone-based inspection. The system works by scanning the building structure using a drone, and the inspector examines the video feed of the scanning process to look for any defects. The inspector can view the live video recording and the BIM model at the same time. They can also capture screenshots when a defect is detected and mark any defects present in the real structure on the corresponding BIM model location. However, this system does not allow real-time collaboration between on-site and off-site inspectors as there is no real-time interaction between both teams, and it requires office equipment to monitor the drone inspection which is only available for off-site users.

Nguyen et al. [27] proposed an approach that uses an AR system based on BIM models to facilitate bridge inspections by visualizing models and data about bridge conditions using HL1. The BIM modeling involves developing a 3D model of the asset from bridge geometric information using Revit and Dynamo. The user interface (UI) allows the user to visualize the BIM model and cloud-based documentation, while the cloud storage allows users to access information about damages that exist in the BIM model and map it to the AR environment. However, this work also has the BIM models predefined inside the Unity project, which means that new or updated models need to be added inside the Unity project and deployed again to the HL, which limits the usage of the system on construction sites as users do not have access to the code to redeploy it.

In contrast to the discussed studies, Ashour et al. [4] presented a novel approach to using BIM and AR technologies to enhance the positioning of 3D models using deep learning (DL). The system uses LiDAR to scan the building structure and create a 3D BIM model, it then utilizes DL algorithms to detect the real location of the structure to project the 3D model on the actual structure. However, this approach does not utilize these steps inside the developed AR application: the LiDAR scan and aligning the generated 3D model inside the Unity project are conducted before the application is deployed to the AR device. In a similar vein to Ashour et al. [4], Al-Sabbag et al. [2] implemented an AR-enabled SHM system using DL for damage segmentation to measure the area of the damage in real-time. However, this approach does not save the measurements performed over time which prevents a thorough assessment of the health of structures. On the other hand, Carbonari et al. [10] described the development and testing of a mixed reality application for on-site assessment of building renovation by projecting 3D models on actual structures. The methodology involves developing a mixed reality application using Unity 3D that is deployed to the HL, which allows users to visualize and interact with 3D models of building designs overlaid onto the physical environment. The system utilizes a mobile device and Near-Field Communication (NFC) tag, which stores real-world coordinates that are sent to the HL when scanned by the mobile device to align the models in an AR environment for condition assessment. The application also includes features such as data collection and visualization, which enable users to assess and analyze the building's condition and make informed decisions about the renovation process. The developed system allows users to preload multiple models which means that users can visualize multiple models instead of one in the app, however, new models need to be preloaded to the Unity project beforehand. Also, external devices (mobile, NFC cards) are required to align the BIM models.

In recent studies, Cho et al. [12] developed an interactive system for BIM alignment and assessment in AR through QR codes. The system communicates with a database on a server to retrieve BIM models and display them in AR view with the HL2. QR codes serve as the mechanism to align the BIM model in the AR environment. When the real environment that has a QR code is scanned, it is compared with the virtual environment in the database, and then the BIM model is aligned with the real object in the real environment. However, BIM models on the cloud need to have a virtual QR code object that can be compared to the real QR code to overlay the model in the correct position, this may not be practical as in most cases BIM models do not include a virtual QR code object, especially when the 3D model is a 3D scanned object of the real structure. Park et al. [29] utilizes cloud storage for exchanging BIM models and defect records. The framework exchanges data using fiducial markers that contain location information to superimpose models in the AR scene, these markers also contain a tag identification number that is used to retrieve the corresponding defect information and display it to be viewed by the inspector, but this information cannot be updated in real-time by these inspectors. In Awadallah and Sadhu [5], a damage inspection using AR is developed that utilizes an ML model to classify cracks, spalling, concrete joints, and pitting in civil structures. This system integrates an interactive measurement tool that quantifies the severity of damages by enabling inspectors to measure the length, area, and perimeter of damages. However, this system does not track the historical measurement data over time or store them in remote cloud storage, which limits remote collaboration, and it lacks integration of 3D BIM models for detailed structure visualization.

Moving beyond data maintenance, Mohammadkhorasani et al. [26] constructed a robust framework that integrates computer vision with AR to automate crack detection and localization. Their work utilizes a video processing algorithm that enables crack detection in near real-time by analyzing live video capture instead of images. The live capture of the video is transferred to a cloud database, where it is analyzed by a computer vision algorithm, which returns feature points of the fatigue crack as an output. These feature points are projected over the crack location in the AR environment. This automates the damage severity measurement process for a more accurate inspection process. However, the results show that the system accurately segments damages at a 0.5 m distance from the damage location, but this is not feasible in field applications. This system also does not enable the integration of 3D models. Combining BIM visualization and maintenance with ML, Um et al. [41] proposed a framework that enables BIM visualization and maintenance using AR by simplifying 3D models for fast performance. The framework processes 3D models using an ML algorithm that reduces the complexity of the model's point cloud, which leads to a smoother visualization experience in the AR environment. Although this framework enables an improved inspection experience, it is limited in terms of data that the inspector can visualize and maintain regarding the BIM models, which limits the possibility of conducting a thorough and

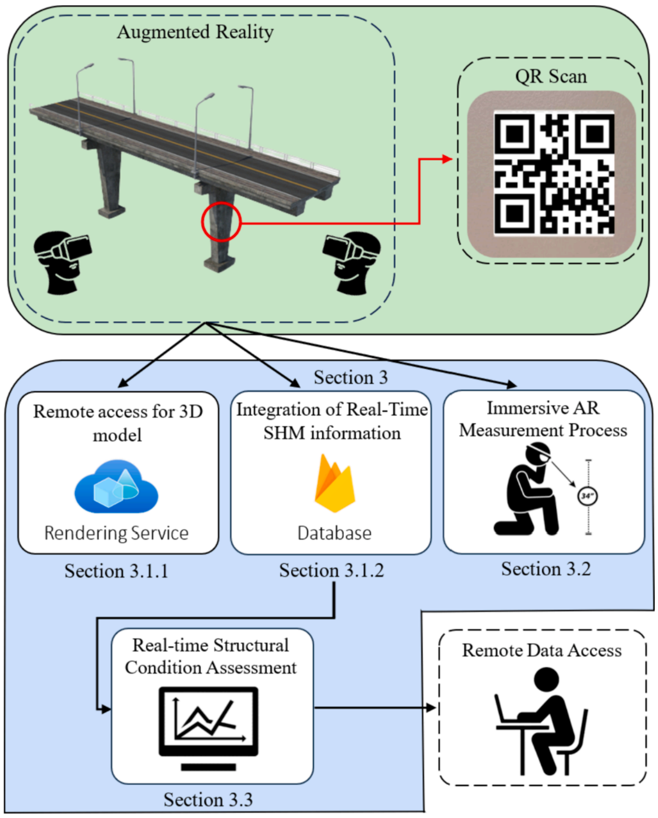



**Fig. 1.** Overview of the proposed AR framework.

detailed inspection.

Based on the above literature review, it is evident that the existing work restricts the scope of the inspection process by confining the inspectable 3D models only to predefined BIM models [6,10,12,20,26,27], preventing real-time remote inspection of structural conditions [43,7,9,15,21,29], and depriving immersive update and visualization of previous and current data [2,5,16,23–25,28,41]. To address these challenges, this paper introduces advancements in structural condition assessment, enabling real-time evaluation through AR and cloud storage. It also integrates a web application for simultaneous visualization of current and historical data. Leveraging cloud storage and a real-time web application, this framework promotes seamless collaboration among inspection teams, facilitating quicker communication and decision-making.

## 3. Background of AR

The underlying system of AR applications blends software and hardware components, augmenting the real environment with virtual objects, and granting users the ability to interact with digital overlays. The software component utilizing specific markup languages acts based on the real-world coordinates and the input signals provided by the hardware component. These languages are used to define the layout and presentation of a scene Fombona-Pascual et al. [17]. They help the system understand the location of virtual objects and their appearance, access the properties of these objects, and handle events based on user inputs [22]. The hardware system in AR applications consists of three components: input devices, sensors, and output devices. The main objective of input devices is to enable users to interact with AR systems. For example, a user can employ input devices to move virtual objects around in the scene and trigger events. Inputs can be from the user's hand gestures, a holographic keyboard, a controller device such as the High Tech Computer (HTC) VIVE controller, or a haptic glove. AR devices leverage a diverse array of sensors to deliver tailored, immersive experiences to individual users [40]. Among these sensors, hand-tracking technology stands out as a pivotal component. This technology tracks the hands of the user, capturing data about the position and movements of the hand. This level of detail fosters a more intuitive and natural interaction between the user and virtual objects. Gaze-tracking sensors are also used to track the eye movement of users, which helps position virtual objects in the correct location with respect to the real environment and the user gaze. Output devices are the connecting component between the inputs of AR systems, sensors, and users. They display the holographic objects to the user based on input and sensor data. The camera of AR devices is the main output device that projects the AR scenes and integrates them with the real environment.

## 4. Proposed methodology

The proposed system represents an innovative solution designed to facilitate the instantaneous visualization of multiple 3D models and their SHM information for AR users in the inspection site. This solution is achieved by leveraging cloud storage capabilities, allowing users to view 3D models and corresponding SHM information in AR scenes in real-time. Utilizing cloud storage provides remote collaboration across multiple AR users on-site, and web users off-site users via a user-friendly web application. Before discussing the detailed methodology, the schematic overview of the proposed framework is shown in Fig. 1.

Initiating the process, AR users within a construction site scan a QR code attached to the structure, containing a URL link to cloud storage housing the 3D model and damage data corresponding to the observed structure. The utilization of distinct QR codes in combination with the cloud database enables the dynamic examination of various 3D models. Upon scanning, the AR system interfaces with a cloud rendering service, responsible for storing and streaming the 3D model. Simultaneously, the AR system connects to a database that provides the damage information of the different locations associated with the 3D model. The user can select a specific damage location using a holographic keyboard input. Subsequent to data retrieval, users can employ a measurement mechanism to gauge the severity of damages. These measurements are promptly stored and updated in the database, ensuring real-time structural condition assessment.

At the same time, a real-time maintenance web application that is available for off-site users enables remote data access by continuously retrieving stored SHM information from the database, generating plots of damage information over time. This feature aids inspectors in analyzing the progression of damages over time. Additionally, the web application facilitates remote access to real-time data, enabling users not physically present on the construction site to collaborate with on-site inspection teams. This capability expedites assessments of structures, ensuring swift and informed decision-making. The real-time nature of this system requires efficient data transfer between the AR and the cloud/database storage, which necessitates the adoption of cutting-edge technologies such as 5G networks to ensure fast data transfer. The higher data transfer speeds of 5G enable seamless exchanges, crucial for HD streaming of 3D models. The performance of this system is tested on 4G and 5G networks to examine how advanced networks aid in achieving a reliable real-time collaborative inspection process. The following subsections explain the integration of dynamic 3D models and their corresponding damage information in AR, the AR measurement process, and the real-time structural condition assessment approach using the web application.

### *4.1. AR with dynamic 3D models*

The first component of the system is the visualization of dynamic 3D models and damage information via cloud services and database storage. Both the 3D model and the damage information are displayed to the user simultaneously to provide an in-depth view of both. Fig. 2

illustrates an AR view of the system displaying a 3D BIM model of a bridge using AR.

*4.1.1. Remote access to a 3D model*

The remote access to the 3D model establishes connectivity and retrieves models from the rendering cloud service. This step initiates a connection, fetches the 3D model from the cloud, and subsequently positions it within the AR scene relative to the AR camera. Fig. 3 provides a visual illustration of the step-by-step workflow for accessing 3D models. This approach enables users to scan multiple QR codes in the same session, and the process begins by initializing the rendering service when the user starts the AR application, which helps the system identify which camera is used for rendering the scene. After that, the system retrieves information on the requested storage from the QR code and checks if the requested storage exists, if it does not exist it cancels the connection, otherwise it starts the session.

Once the system connects to a session, it fetches the URL retrieved from the QR code and checks if the corresponding model exists on the cloud. If the model does not exist, it alerts the user and prompts them to scan another QR code. If the model exists, it starts by creating an entity for the 3D model and loads it on AR. Before displaying the model, the system retrieves the camera position and window frame and then checks whether the 3D model dimensions are big. If the dimensions are big, it scales the model to project it to the AR scene. The scaling equation is shown in Algorithm 1. Once the model is scaled, it is then placed in the middle of the AR scene.

expanding this information to incorporate additional details is easily achievable.

The NoSQL database of the proposed framework allows for flexible and dynamic storage of structural parameters over time. In terms of database design, the NoSQL models accommodate timestamped entries for various structural metrics, including area, perimeter, and length. The model flexibility allows for incorporating updated parameter values, catering to the evolving nature of structural condition data. The system prompts the user to select from several pre-defined locations, for the specific location to be analyzed. After that, the system loads and displays the information to the user and repeats this process whenever the user provides new input. On the server, the system establishes a connection to the database and then accesses the URL, from the previously scanned QR code, which contains the name of the model and the location identifier to retrieve the corresponding data. Similarly, for saving data, the server constructs the appropriate URL using the database link, the location identifier, and the last update identifier to save the new data to the database. When saving new data, the system does not override existing data but keeps track of information history. The AR module handles various UI elements, including holographic text. This text displays information such as the area, perimeter, length of damage, and last update date, which are retrieved from the database. This AR module creates a holographic panel that displays this information once loaded, while also initiating a holographic keyboard to continuously handle user inputs. Allowing users to load information for multiple locations enhances the flexibility of the application and permits users to facilitate a comparative analysis of various parameters to understand how different locations evolve.

**Algorithm 1** 3D model scaling

**Input**
$Q$: Original Model Object
**Output**
$P$: Scaled Model Coordinates

$BB \leftarrow Q.bb$ ▷ Retrieve Original Model Bounding Box Coordinates
$ModelSize \leftarrow MagnitudeOf(BB.max - BB.min)$ ▷ Calculate Model Size from Bounding Box
$C \leftarrow getCameraFrame()$ ▷ Calculate camera window frame
$R \leftarrow 0.7$ ▷ Reduction Factor

*if* **ModelSize** *greater than* **C** ▷ Check model dimensions
    $S \leftarrow (C/ModelSize) \cdot R$ ▷ Compute scaling factor
    $P \leftarrow ModelSize \cdot S$ ▷ Compute scaled dimensions

**return** $P$

.

*4.1.2. Integration of real-time SHM information*

The integration of the structural condition information into the AR scene serves the objective of enabling a thorough analysis of the structure's condition. The integration of the SHM information (i.e., length and area of damage and type of damage) relies on two components, the server which hosts the database with the damage information, and the AR module which is responsible for reading user input and displaying damage information. Fig. 4 shows the behavior of SHM information integration. When the system connects to the database, the users are prompted to choose a specific damage location using the holographic keyboard. Once the user specifies a location, the system reads the user input from the keyboard and retrieves the damage information related to that specific location. Finally, the system displays the damage information of the specific location on a holographic panel for the user to view. In the experiments, the damage information includes the area, perimeter, length, and the date of the last update. Furthermore,

*4.2. Advanced immersive AR measurement process*

This component integrates and advances the approach proposed by Awadallah and Sadhu [5], where the inspector, equipped with an AR headset, can efficiently quantify segmented damage in real-time. Utilizing the AR application, the inspector places segmentation points around the damage, projecting these points in 3D real-world coordinates, and leveraging the coordinates to calculate the length, area, and perimeter of the damage. Building on this foundation, the current approach introduces additional features to enhance SHM information. The database storage capability is added to the measurement technique to keep track of these measurements over time. The load and save operations in this approach follow the same principle as in section 3.1.2, which connects to the database and performs data transfer between AR and the database. The recorded damage is linked to a pre-defined


**Fig. 2.** A typical view of a 3D BIM model of a real structure and its related information in AR.

location, by storing the damage measurements under the corresponding location identifier in the database. Once the location is specified, the most recent measurement data associated with the damage at the specified location is loaded and displayed to the inspector in the AR environment. The inspector is then able to take new measurements for that damage, and the results are saved to the database once the computation is complete. Fig. 5 shows the area measurement process of surface damage before and after taking a new measurement, where the information is updated immediately. Using a holographic button, the inspector can toggle between different damage locations which are known to them.

### 4.3. Real-time structural condition assessment

Once the damage information is updated by the AR user, the system incorporates a web visualization tool to analyze the information. In the context of SHM, visualizing data is crucial for inspectors to swiftly identify anomalies. Web-accessible visualization tools aid off-site users in quickly assessing trends and potential issues, enabling timely decisions and proactive maintenance for infrastructure safety and longevity. The system integration is facilitated through the communication between the NoSQL database, plotting engine, and user interface. NoSQL databases embrace a flexible approach, allowing scalability with large amounts of data and high user loads. This communication controls the flow of data, managing requests and responses. Fig. 6 displays the system architecture of the web application. The system collects data from the on-site AR user and sends it to the database server. After that, the web server retrieves SHM information from the database and retrieves the webpage files that contain the page structure and design. On the webpage module, when the off-site user opens the webpage, the webpage sends a request to the server to collect data, and the server responds with the SHM information. Finally, the webpage displays the information to the off-site and on-site users.

The web application described in this paper reads data from the same NoSQL database that stores the structural condition information. Data retrieval mechanisms leverage queries tailored for NoSQL databases and the REST (Representational State Transfer) API that acts as an interface between the web application and the database. Upon retrieving data from the NoSQL database, the information is organized and stored in key-list pairs. The systematic storage of data in this format facilitates the transfer to the webpage module, enabling the user interface to dynamically display the structural information in a comprehensible manner on the webpage. After the data is saved, the real-time plotting engine, driven by a graphing library, dynamically generates line plots illustrating temporal trends of structural parameters against timestamps. The algorithmic approach prioritizes real-time responsiveness, harnessing the inherent scalability of NoSQL databases to handle dynamic data updates. This ensures inspectors can observe and analyze structural changes with the precision required for scientific reliability. The user interface is developed as an interactive dashboard, providing advanced controls for exploration. Interactive elements, such as zoom and pan functionalities, enhance the user experience in exploring the real-time

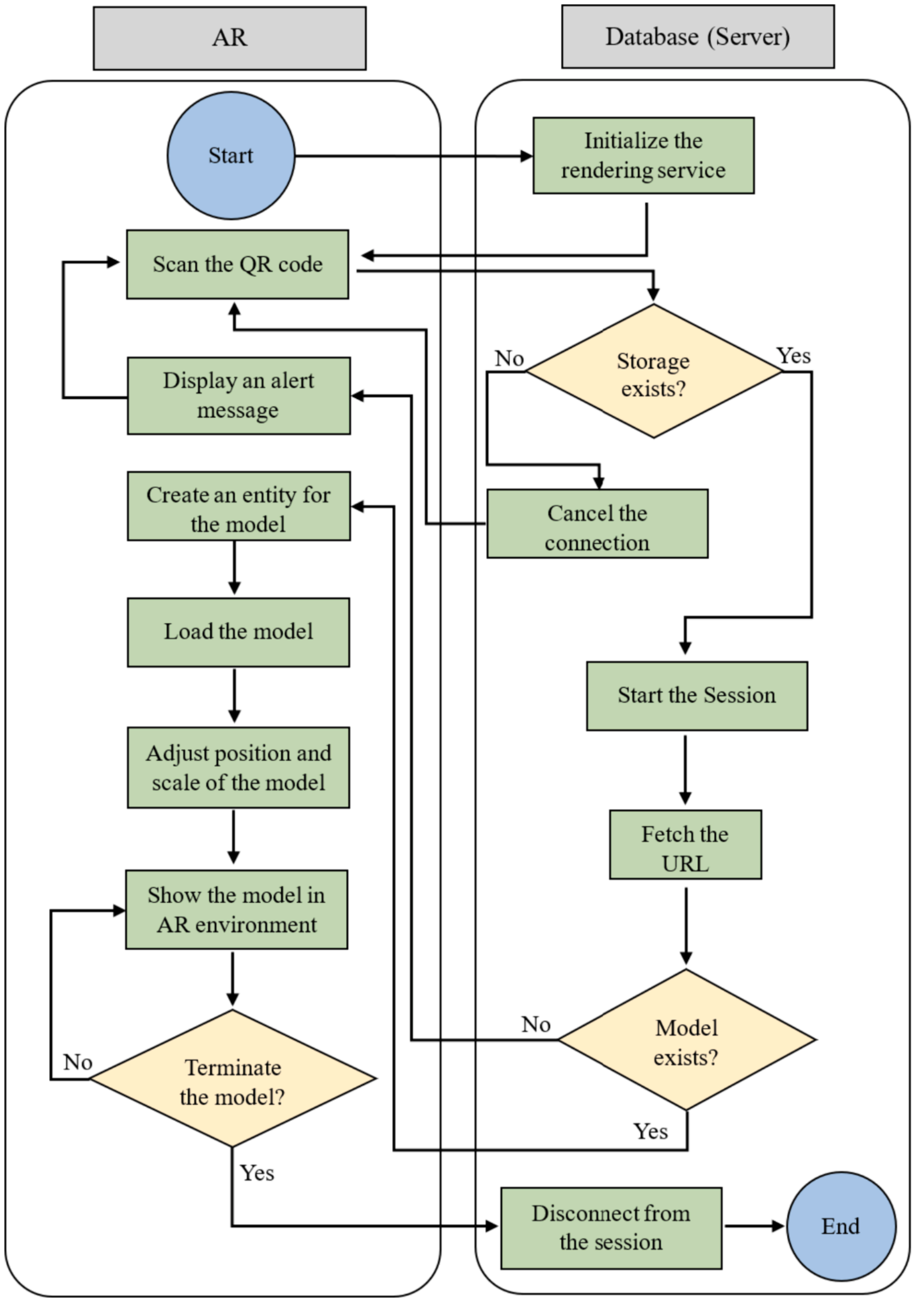



**Fig. 3.** Flowchart of 3D model access.

plots. Fig. 7 shows the dashboard on a webpage containing plots for two locations.

## 5. Experimental validation

This section explains the test setup employed in two practical use cases, a lab-scale experimental beam and a full-scale bridge, to evaluate the performance of the proposed framework. The damage maintenance is evaluated by scanning the QR code, loading the 3D model and damage information, and conducting multiple damage measurements over time. The study also aims to assess network efficiency when working with real-time AR systems using 4G and 5G networks, specifically focusing on load times for 3D structural models and the load and save times for their associated damage information. To establish network connections and facilitate HL-to-cloud storage and database communication, a Google Pixel phone is used. The Google Pixel acts as a gateway, enabling the HL2 to connect to 4G and 5G networks, it is used to provide a 5G connection through the phone network data which did not require any application development for the phone. This setup ensures that the network tests are conducted in a real-world context, simulating typical usage scenarios where mobile devices serve as intermediaries between AR headsets and cloud resources. The choice of these networks is justified by the growing demand for high-speed, low-latency connectivity in real-time AR applications to understand their capabilities and limitations.

To assess system performance with respect to 3D model sizes, load time comparisons are conducted for two distinct 3D models, the first model is the reinforced concrete beam (~154 MB), and the second model is from a use case conducted on a full-scale bridge (~430 MB). Every 3D model is loaded and displayed on the HL2, with a series of five trials conducted for each network, resulting in a total of 15 trials for each model. The average processing times across these 5 trials for each

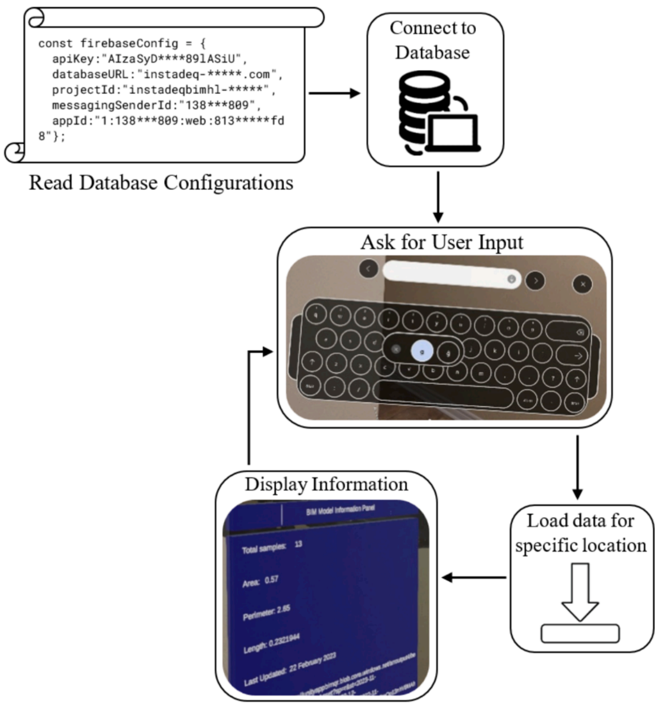



**Fig. 4.** SHM information integration into the proposed framework.

network and model are recorded. This approach enables a comprehensive assessment of how each network handles the loading of diverse 3D models. In addition to 3D model loading, the study investigates the efficiency of the tested networks in handling load and saving operations for the SHM information in the system. This information represents critical data that is transmitted and stored in real-time and is analyzed by measuring the processing times for load and save operations. For precise measurement of processing times, a profiling algorithm is implemented using the HL2 internal clock. The processing times for load and save operations are recorded, and the results are saved to a CSV file for subsequent analysis. This profiling approach ensures the reliability and consistency of performance data, enabling rigorous analysis and comparisons.

### *5.1. AR system and software frameworks*

This study utilizes the Microsoft HoloLens 2 (HL2) headset for real-time structural inspection, offering exceptional portability, high-resolution image sensing, and a broad field of view. The HL2's depth sensor enables the projection of virtual objects in real-world coordinates. Fig. 8 shows the HL2 device used in this research.

The developed system harnessed the capabilities of various frameworks to achieve its objectives. Table 1 summarizes the key frameworks employed in the system.

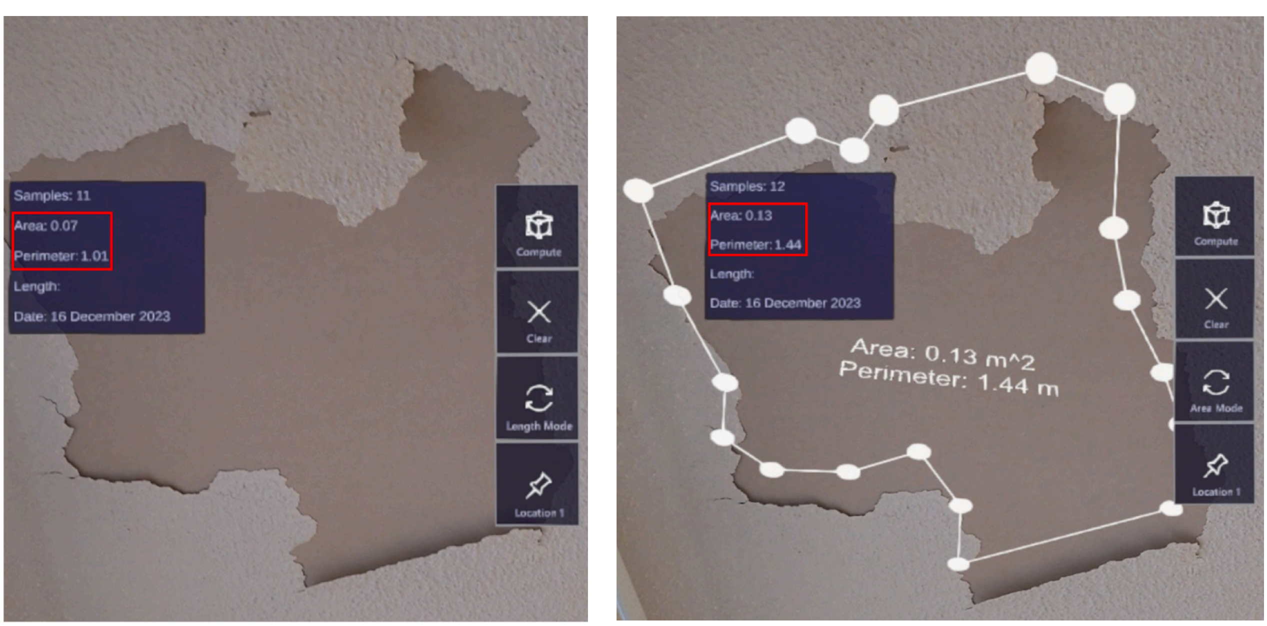
### *5.2. Lab-scale experimental beam model*

#### *5.2.1. Details of the testbed*

To test the performance of the developed system, a reinforced concrete (RC) beam, as shown in Fig. 9, is used as a use case. RC beams are made of concrete and are reinforced with steel bars to increase their flexibility and tensile strength. Because of its capacity to endure external forces, reinforced structures serve as excellent test subjects for evaluating the performance of the system. These structures can develop cracks and damages under applied loads without catastrophic failure, enabling testing of the data transfer using the proposed system.

The 3D model is tested on the RC beam by generating a 3D scan of the structure. The ZED 2i depth camera, shown in Fig. 10(a), and the ZED software development kit (SDK) are used to take a live video capture of the whole structure and process it to generate the 3D model. Fig. 10(b) and (c) show the ZED SDK generating the 3D model of the RC beam from live video capture.

Finally, the 3D scan is exported in *glb* file format, which is a file format used to share 3D data. The 3D file is then processed and uploaded to the Azure Remote Rendering (ARR) cloud service using the ARR toolkit that processes the 3D file in *glb* format and converts it to Azure *arrt* format for rendering. Once the 3D file is stored in the cloud, it is linked to a QR code, which is created by encoding the cloud storage URL using an open-source QR code generator. The user then scans the QR code using the AR headset which retrieves the URL of the RC beam




(a) (b)

**Fig. 5.** AR view (a) before taking new measurements and (b) after taking new measurements.

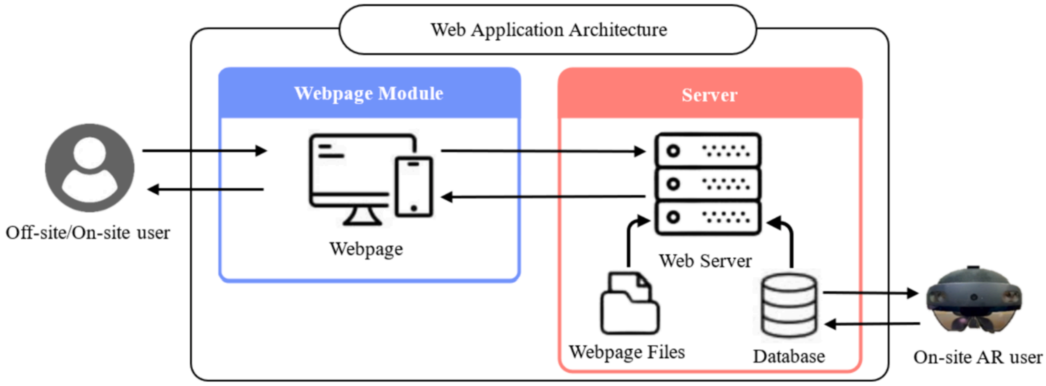



**Fig. 6.** System architecture for the web application.


**Fig. 7.** Real-time web dashboard of the proposed framework.

**Fig. 8.** HL2 Headset.

**Table 1**
Summary of the software framework implemented.

| Framework Name | Purpose in the System |
|---|---|
| ZXing (Zebra Crossing) Library | QR code scanning and decoding |
| Python Flask Framework | Web application backend development |
| Python Language | Data plots generation web application |
| HTML/CSS | Frontend web page development |
| Unity | Platform application development for HL |
| Google Firebase | Database to store damage information |
| Azure Remote Rendering | Cloud storage to store 3D models |

storage from the QR code and connects to the cloud storage using the URL. Next, the system loads the beam model from the cloud and superimposes it in front of the user in the AR scene. Fig. 11(a) shows the conversion of the beam to a 3D model using the ARR service, and Fig. 11 (b) shows the QR code and the loaded 3D model in an AR environment.

### 5.2.2. *Results and discussions*

To test the damage maintenance in an AR environment, the user scans the QR code for the structure by positioning the HL camera in front of the QR code. The system reads the URL endpoint from the QR code and connects to the cloud storage and database to load the 3D model and read the corresponding damage information. Once the damage data (i.e.,

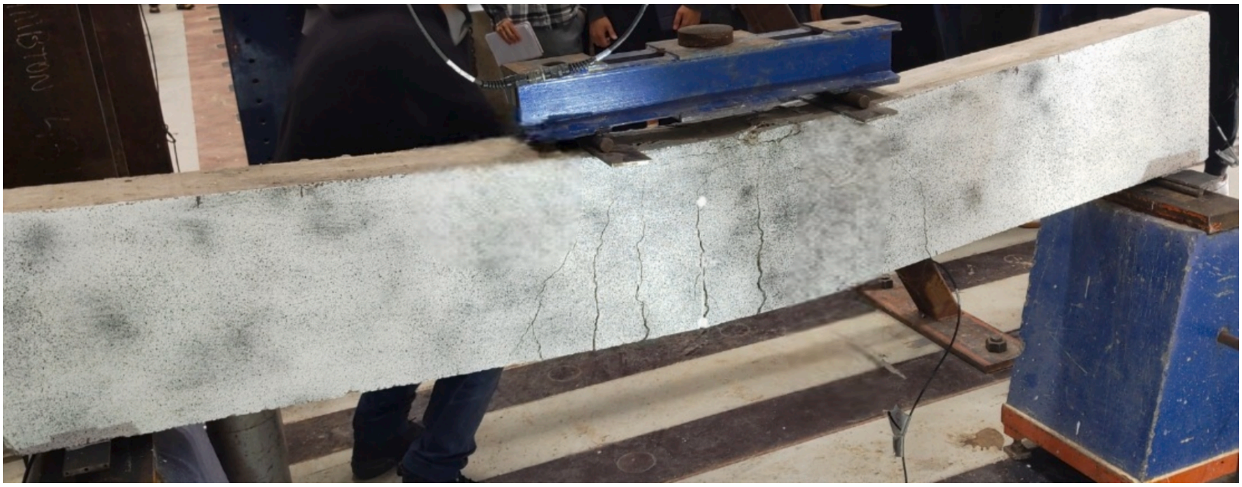
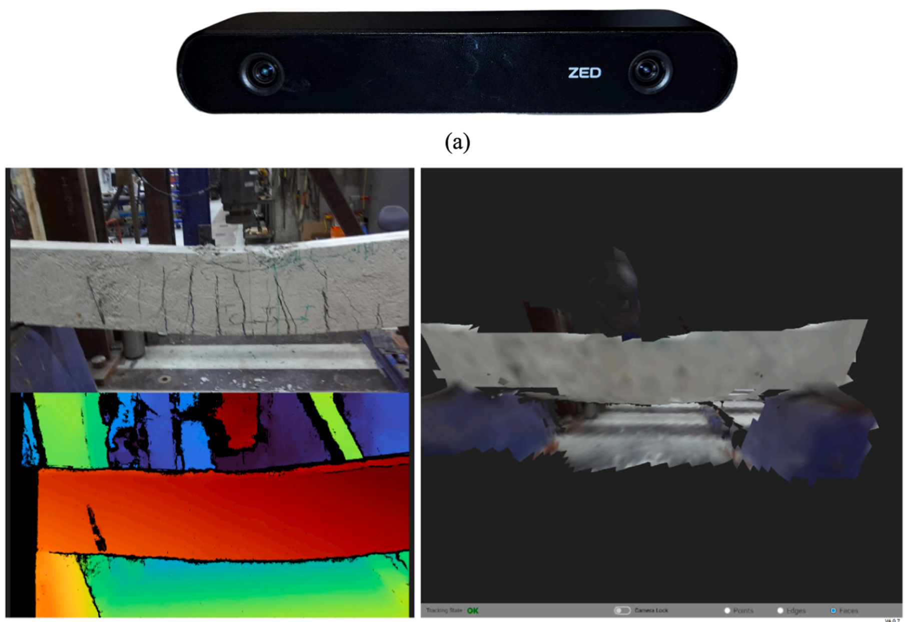


**Fig. 9.** RC beam subjected to progressive loads.




(a)

(b) (c)

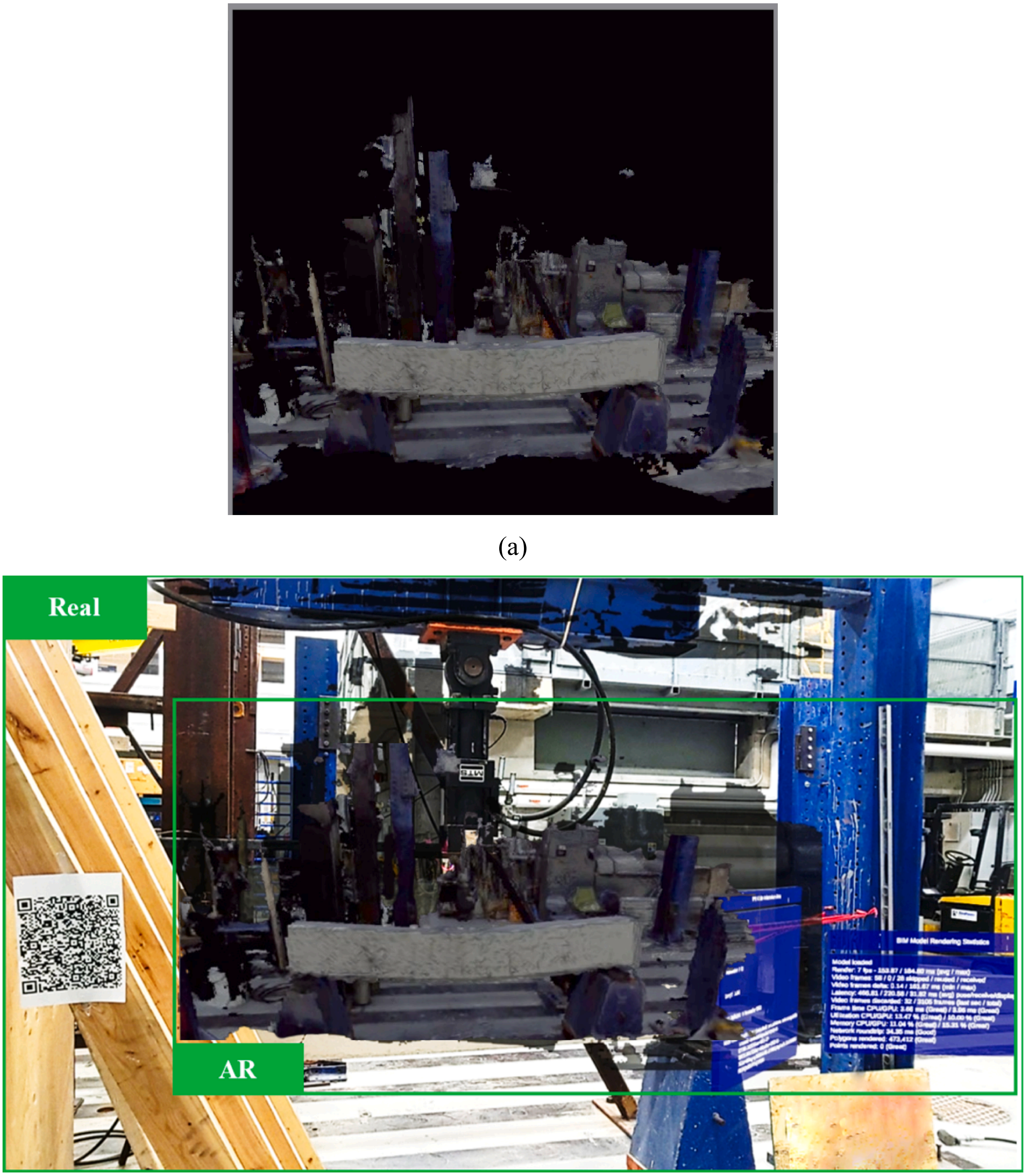
**Fig. 10.** (a) ZED 2i depth camera (b) live capture (c) 3D scan.

crack length) are retrieved from the database, the user is prompted to choose a damaged location using the holographic keyboard, as seen in Fig. 12, location 1 is selected for this use case.

Existing damage data is loaded for Location 1, then multiple length measurements are taken over four timestamps, as cracks form when a load is applied on the RC beam, and the new data is saved to the database. The crack length over time is displayed in front of the AR user once the new measurements are saved. Fig. 13 shows the successful projection of data for Location 1 over time for the AR user in the holographic panel and the web application respectively.

To validate the performance of the system on different networks, the first step is to load the 3D model for the beam by scanning the QR code, this records the total time to load the models. The next step is to load the damage information corresponding to the loaded model using the holographic keyboard, this records the total time it takes to load the data, and then the system updates the existing information when the user conducts new measurements, this records the total time it takes to save the data. The 3D model of the RC beam (~154 MB) and its corresponding information were successfully loaded without connection issues. The total time in seconds to load the 3D model for the reinforced beam is shown in Fig. 14(a). The findings indicate a notable speed advantage for the 5G network over 4G, with the 3D model loading in approximately half the time. In the next step, the load times in milliseconds for the model's corresponding damage information are analyzed. These findings can be visualized in the box plot in Fig. 14(b). The box plot shows consistently smaller processing times for 5G compared to 4G, with the majority of 5G data indicating faster loading times, as evidenced by the lower quartile positioning of the median line.

Finally, the times in milliseconds to save new damage information and update the database are recorded. Fig. 15 shows the box plot for the save operation of both networks. It is notable that the 5G connection is faster during save operations as the median of processing time is less than the median of the 4G connection, and the outliers of the 5G connection are less severe.




(a)

(b)

**Fig. 11.** (a) Conversion of 3D model file, (b) 3D model of the RC beam in HL2.

### 5.3. Full-scale bridge

#### 5.3.1. Details of the bridge

The bridge used in this use case is an RC bridge located in London, Ontario, Canada, shown in Fig. 16(a). Due to the large size of the bridge, generating a 3D model of the bridge using the depth camera is not feasible. Therefore, a drone is used to scan the bridge and generate four 3D mesh segments of the bridge. These 3D components are integrated using 3D modeling software, shown in Fig. 16(b), to create the 3D model.

After the model is generated, it is exported into the appropriate *glb* format for conversion to Azure *arrt* format and uploaded to the cloud storage using the ARR toolkit.

#### 5.3.2. Results and discussions

Similar to the first RC beam test, multiple area measurements are taken weekly of the full-scale bridge to test the maintenance of damage data progression in the AR environment, the progression of this data is projected to the HL user as shown in Fig. 17. The results show that the data is immediately updated both on the holographic panel available for


**Fig. 12.** Holographic keyboard input for location 1.

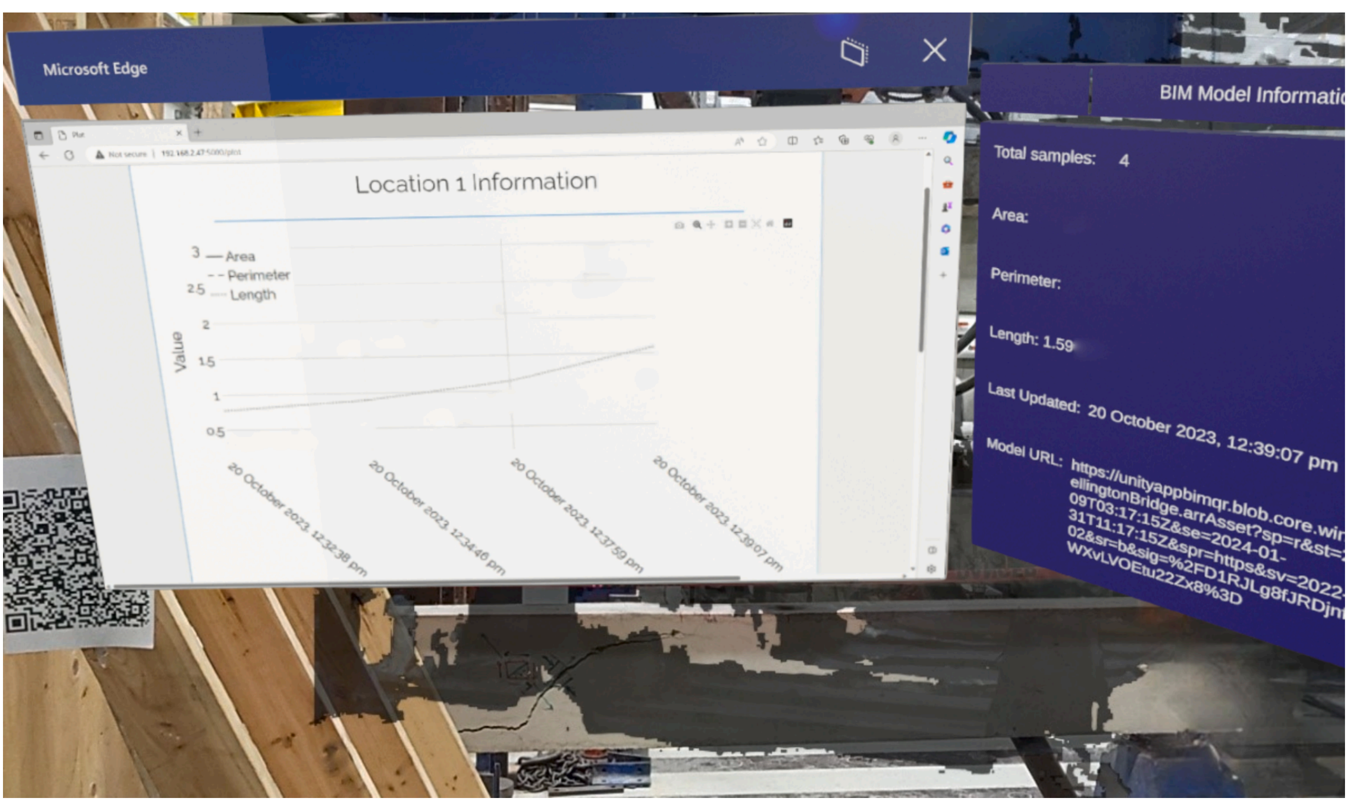



**Fig. 13.** Progression of crack length information over time for Location 1 in AR view.

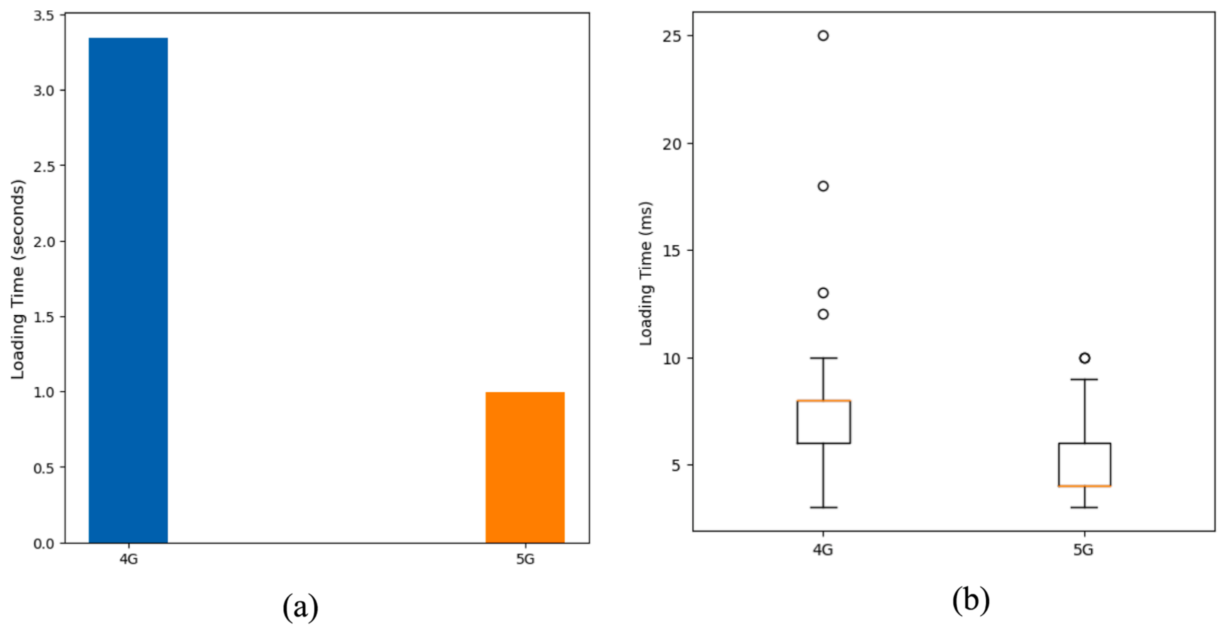



**Fig. 14.** (a) Load operation times for a 3D RC beam model (b) Box plot of data loading time.

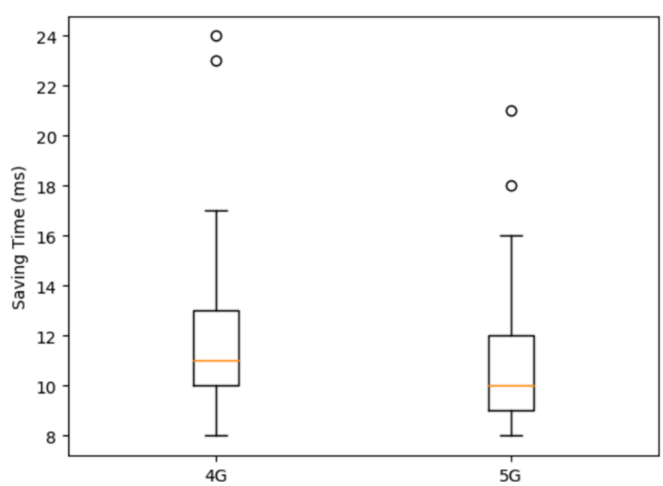



**Fig. 15.** Box plot of data save times for 4G and 5G.

the on-site user and the web application available for both on-site and off-site users. This demonstrates the effectiveness of real-time updates and how inspection teams can monitor conditions as they occur for faster collaboration.

The 3D model of the city bridge (∼430 MB) was loaded and displayed in front of the AR user. Fig. 18(a) shows the loading times in seconds for the 3D model. The results indicate a higher loading speed on the 5G network as compared to the 4G network, this matches the result of the first use case. However, the load times for the city bridge model, which is larger in size than the beam model, have increased on both 4G and 5G networks, with load times of about 4.25 s and 2 s respectively. Inspecting the box plot for the load times in Fig. 18(b) shows again that the loading times in 5G range between smaller processing times than 4G. The median line for 4G is still at the upper quantile where most values are shifted towards slower load times as opposed to the median line for 5G.

Finally, the analysis of saving times in Fig. 19 reveals that the 5G connection exhibits a marginally swifter performance during save operations, evidenced by its median processing time being lower than that of the 4G connection. Examining the delays in the box plot, the 5G network has one delay only with more substantial delays for the 4G network.

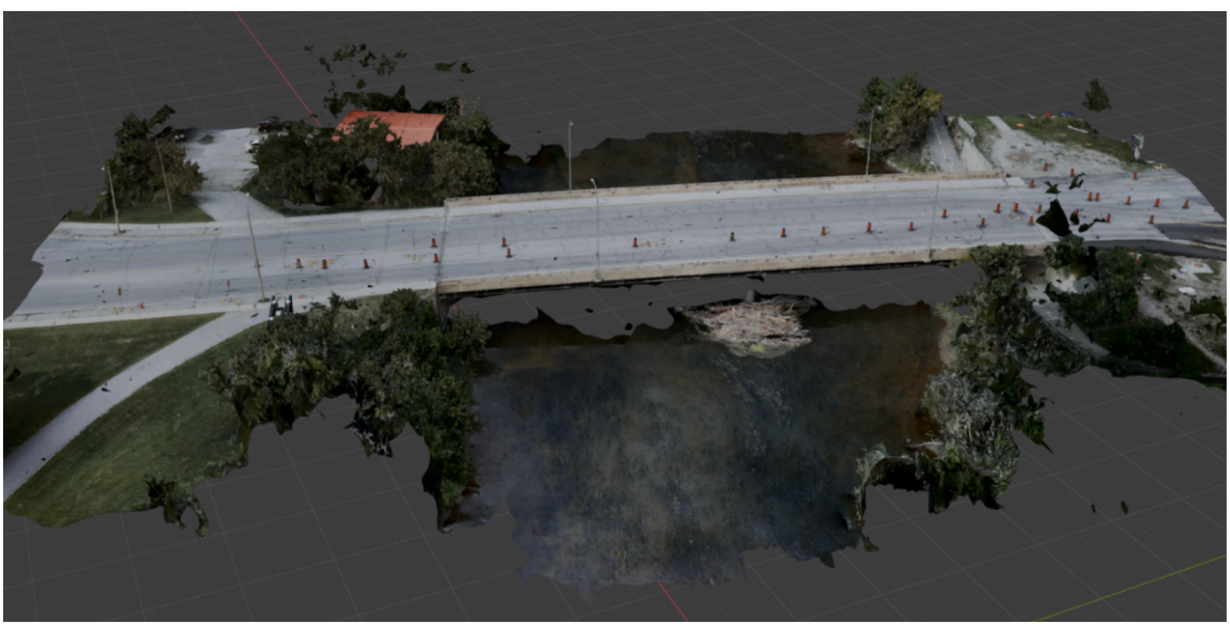
In summary, the system successfully demonstrates real-time collaboration between on-site and off-site users as both teams can collaborate by monitoring data during the inspection and visualizing data updates as they occur, facilitating quick decision making. On the other hand, the 5G network proved to be more reliable than 4G as it is faster and more stable.

## 6. Conclusions

In this paper, a framework for remote collaborative real-time structural condition assessment using AR was proposed. The framework is developed to work with the HL2 headset as the main AR device. The proposed framework consisted of three components, visualization of 3D models of civil structures and damage data updates, damage measurement tool, and remote access to data via a web application. The first step prompted AR users to scan a QR code to retrieve a specific URL endpoint. Once the QR was scanned, the URL was used by the system to connect to a cloud storage and a database to load a 3D BIM model alongside its corresponding damage information in an AR environment. After the data was loaded, the user was able to use an interactive measurement tool to measure the length, area, and perimeter of damages in different locations of the structure. When measurements are taken, changes are saved instantly in real-time to the database and are reflected in front of the AR user. Simultaneously, a web application updates regularly as new measurements are taken and generates plots of damage information over time. To test the system functionality, two use cases were conducted on an RC beam in a lab and on a full-scale city bridge, where different damage measurements were taken over different timestamps. The performance of the system was also tested on 4G and 5G networks to examine its efficiency. Based on the results of this research, the following conclusions were made:

1. The system projects 3D structural models and their corresponding damage information in the AR environment to the on-site users. The AR on-site users can instantly measure damage length, area and perimeter in real-time to be saved for remote access within 5 s or less.
2. The remote access functionality updates damage information as measurements are taken and changes are reflected in real-time and presented in the form of plots for off-site users to analyze and collaborate with on-site users to make timely decisions.

(a)



(b)

**Fig. 16.** (a) Full-scale bridge and (b) its 3D model.

3. It was observed that the computational performance of the system is more efficient on the 5G network than 4G network. The 3D model load times for both use cases on the 5G network were around 2.5 s faster than the 4G network. The load and save times for the damage data for both use cases on the 5G network were faster and more stable than on the 4G network.

This study shows how AR and 5G technology can be utilized to improve structural condition assessment methods to make structural inspections faster through remote collaboration. The work done in this paper enhanced existing research findings by including visualization of 3D BIM models and maintenance of data over time via AR and a web application. This improved timely decision-making during the inspection process through remote collaboration between on-site and off-site users. While the findings of this study are promising, further research could be conducted to improve the inspection process and remote collaboration. Currently, the study does not consider the creation of 3D models as it uses pre-made models, also off-site users are unable to see what on-site users see; they are limited to visualizing data through real-time plots. On the other hand, the inspection process is limited to surface-level damages. Future research could include the real-time creation of 3D models, the incorporation of visual data such as pictures or videos for visual collaboration, and the inspection of below-the-surface damages for inner structures assessments.

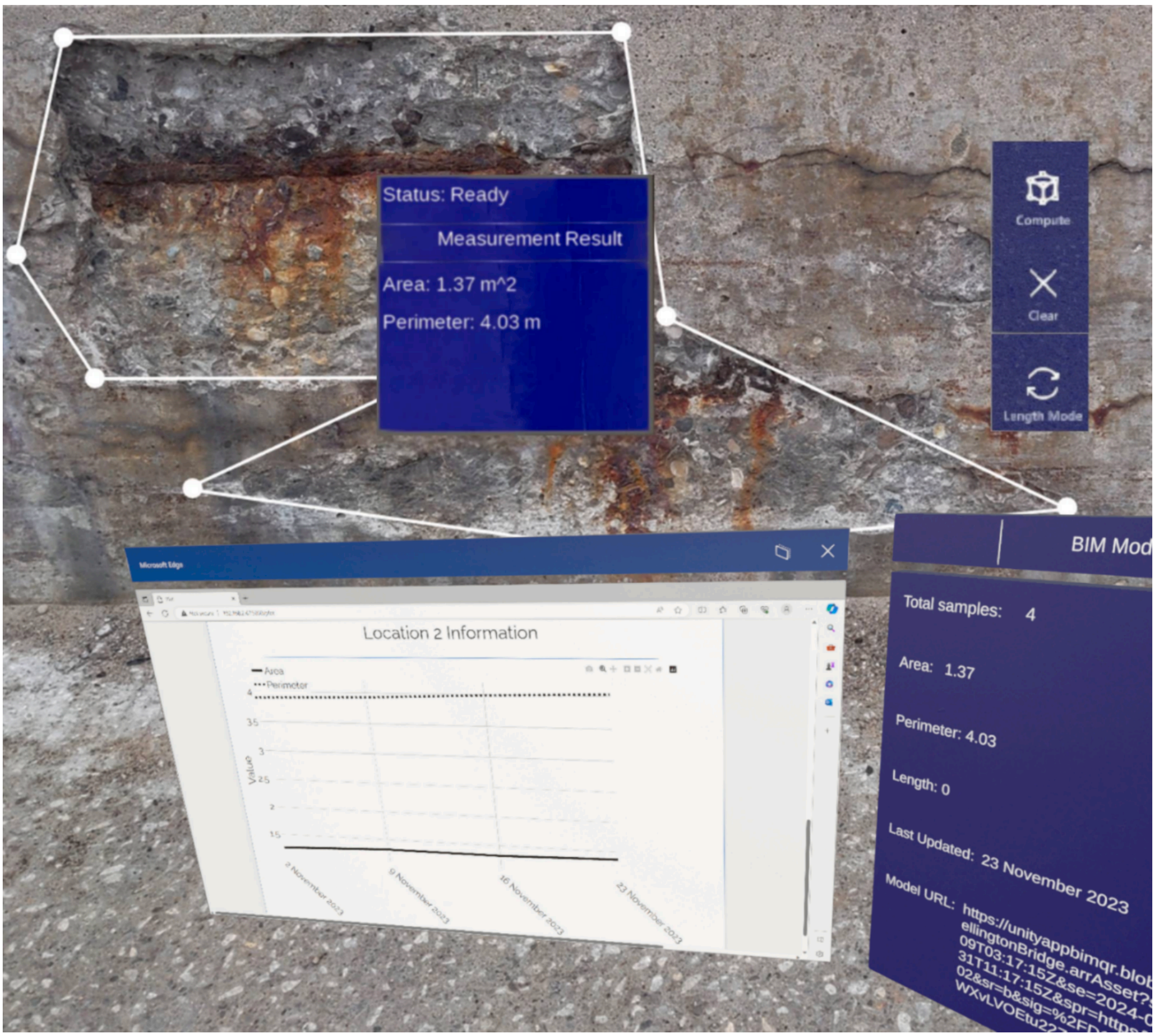
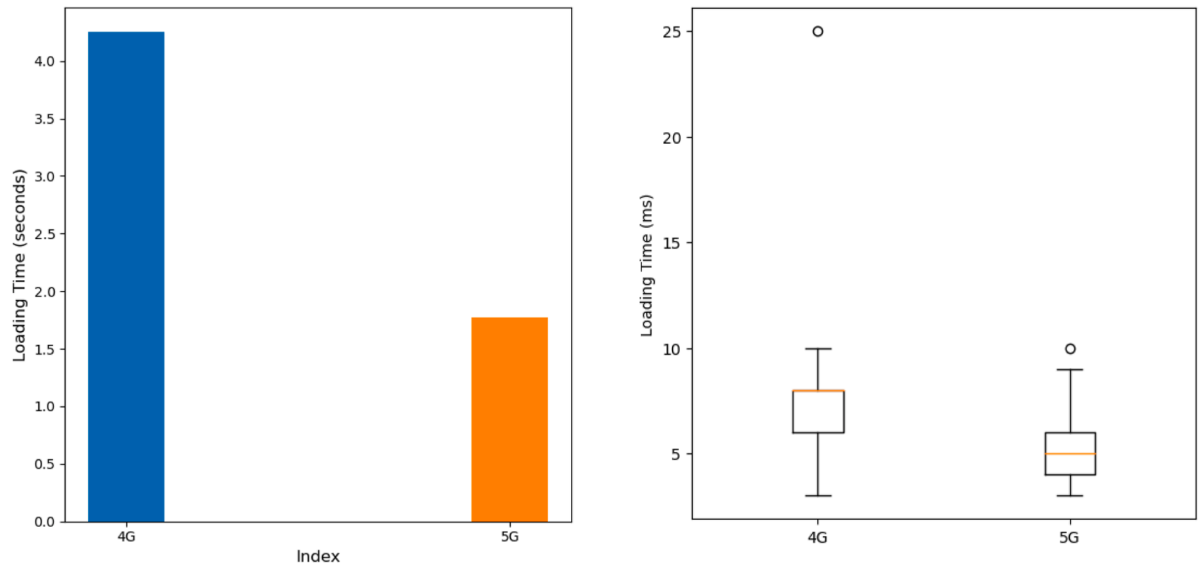



Fig. 17. Progression of damage area and perimeter over time in AR view.




(a) (b)

**Fig. 18.** (a) Load operation times for 3D bridge model (b) Box plot of data load times.

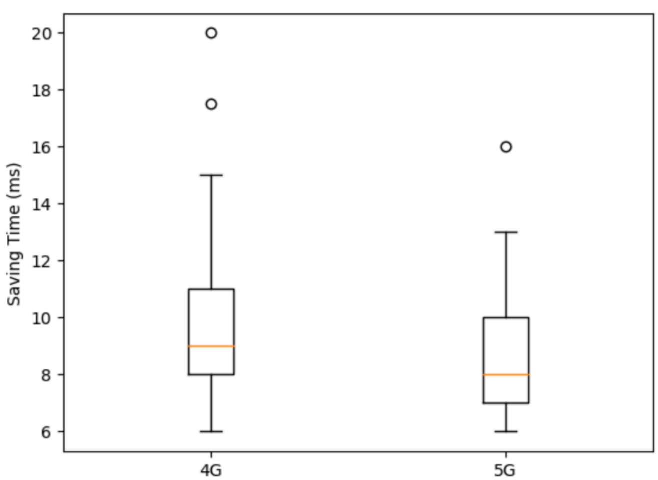



**Fig. 19.** Box plot of data save times for 4G and 5G.

## CRediT authorship contribution statement

**Omar Awadallah:** Writing – original draft, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Katarina Grolinger:** Writing – review & editing, Supervision, Investigation, Funding acquisition. **Ayan Sadhu:** Writing – review & editing, Supervision, Funding acquisition.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data will be made available on request.

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