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Virtual reality visualisation of automatic crack detection for bridge inspection from 3D digital twin generated by UAV photogrammetry

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A R T I C L E I N F O

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A B S T R A C T

This research develops a UAV photogrammetry methodology to generate 3D digital twins (DT) of the Elvanlı Bridge in Mersin, Turkey. These DTs are then analyzed using advanced image processing algorithms for automatic crack detection. The identified cracks were incorporated into the 3D model, creating a DT to damage-augmented digital twins (DADT). Subsequently, the DADT was rendered in virtual reality, offering an interactive alternative solution with remote access to on-site structural visual inspections in a digital environment. This approach has increased the objectivity and efficiency of inspections in the digital environment. The results demonstrate the potential of this integrated approach to enhance the accuracy and reliability of bridge inspections, reduce operational costs, and provide a comprehensive platform for structural health monitoring through non-invasive methods. The study transformative impact of combining emerging technologies such as UAV photogrammetry and VR in civil engineering, paving the way for more systematic and precise infrastructure assessments.

1. Introduction

Infrastructural artifacts are employed in transport systems to overcome difficulties in topography. Countries with challenging topography have a substantial infrastructure heritage in bridges, viaducts, and overpasses [1]. One of the principal challenges in developing and underdeveloped countries with a substantial infrastructure heritage is the identification and rehabilitation of aging infrastructure. The normal aging of structures presents numerous problems. To control safety and ensure adequate performance over time, it is necessary to implement a continuous cognitive process and apply methods and techniques that periodically monitor and control structures.

Infrastructure and superstructure systems are visually inspected on-site by engineers in charge according to the structural code regularly or immediately after a natural disaster [2]. During an inspection, engineers attempt to visually identify damage to structural components and determine whether the structure is fit for service, requires additional analysis and strengthening, or needs demolishment [3]. Cracks are the most frequently observed form of damage during the inspection of fragile structures such as concrete or masonry, which makes them a crucial aspect of structural inspection [4]. Therefore, cracks must be inspected continuously, a process carried out by traditional methods for many years. However, traditional structural inspections have significant limitations. In particular, the most prominent limitations are the lack of objectivity, lengthy application time, significant costs, and difficulty documenting damages. Due to these limitations in traditional inspection systems, bridge inspection and diagnosis based on artificial intelligence technologies should be widely investigated with applications for non-destructive testing, damage detection and diagnosis, crack detection, bridge dynamics, and static load assessments.

Infrastructure such as bridges exposes varying safety risks from decay and deterioration as service life increases. Regular inspection is therefore required to determine and maintain the safety of such infrastructure. Structures must be efficiently inspected and maintained to interpret and prevent future deformation and displacements. Given that current procedures for rapid inspection of structures are subjective, time-consuming, and cumbersome to document, it is recommended that new technologies be used to automate the process and eliminate shortcomings [5]. Recent advances in artificial intelligence, such as image and range-based data collection methods and computer vision, have not yet been extensively integrated into building and infrastructure applications. However, the necessary work has accelerated, and positive

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contributions are being made [6]. The most recent technology available for damage assessment is virtual reality (VR) supported digital twin (DT) technology. Kritzinger et al. [7] defined DT as the complete integration of data flow between an existing physical object and a digital object based on the definitions of digital model and digital shadow. In such a combination, the digital object can also act as a controlling instance of the physical object [8]. This implies that a change in the state of the physical object directly leads to a change in the state of the digital object and vice versa [7]. This technology uses image data with computer vision techniques [8], including deep learning and photogrammetry (image-based) methods. The most significant advantage of these technologies is that they reduce the subjectivity, cost, and operation time associated with traditional inspections. The primary objective of the process is to produce a complete and accurate three-dimensional (3D) model as rapidly and accurately as possible. At this juncture, photogrammetry, one of the image-based methods, is the most prevalent approach for producing 3D models [9]. The advancement of technology has enabled the use of Structure from Motion (SfM) and Multi-View Stereo (MVS) in photogrammetry, which can rapidly generate detailed models in the form of textured meshes to create high-quality photorealistic 3D scenes of an object [10]. Although the models produced by this method offer high accuracy, the resulting data size is considerable, which can impede the modeling of many entities [11]. For structures, existing damage can create an end-to-end solution with VR-supported DT, which includes geometric information and data on damage conditions and characterizations [12,13].

As previously stated, the initial step in utilizing image-based methodologies, such as photogrammetry, which may be employed as an alternative to on-site inspections, is to capture images of the structure in question. The quality and resolution of the images taken will influence the quality of the Model to be obtained and, consequently, the accuracy of the final product. Although there are many advantages to collecting image data about the structure, manual image acquisition is challenging, especially in areas with difficult access and traffic obstacles, such as bridges [14]. To overcome these challenges, countries worldwide have recognized that for bridges with high abutments and bridges over rivers that are difficult to approach, professionals must use equipment such as large bridge inspection vehicles with lifting platforms, boats, and ladders to perform detailed inspections. Such inspections are technically complex and difficult, increasing occupational risks for professionals [15,16].

Furthermore, for very high or wide bridges, bridge inspection vehicles are unsuitable for structural inspections. During traditional bridge inspection operations, inspectors must use a ruler to measure the length and width of the bridge crack. However, this can result in a lack of clarity as the distance increases [17]. If the distance between the inspector and the inspected surface exceeds this, the inspector cannot measure the bridge crack; they can only take an image of the crack. If the distance is more than 6 m, it is not easy to obtain a clear image and recognize it with the human eye [18,19]. This reduces the completeness and accuracy of the data obtained from bridge inspections [20,21]. Although visual inspections are necessary for bridge planning-related tasks that ensure the availability and safety of the bridge, these inspections have many disadvantages [22,23]. Therefore, following the development of unmanned aerial vehicles (UAVs), researchers and professionals have investigated the feasibility of combining UAVs with digital image processing technology to overcome the problems related to the visual inspection of concrete cracks [24]. Using UAVs allows for capturing images of surface cracks in structures at a closer distance, enabling personnel with the relevant expertise to detect cracks more accurately [21]. Using UAVs for bridge inspection offers several advantages over traditional methods, including cost-effectiveness, enhanced safety, and flexibility in collecting data [25].

Although the images obtained from UAVs and photogrammetric products offer advantages in bridge inspection, the results should be updated regularly, and the inspections should be diversified. To diversify the inspections, photogrammetric 3D models produced with images obtained from UAVs and 3D models created to detect cracks are used as a basis for DTs to monitor structural health. Furthermore, the delivery of DT models to different inspectors, particularly in conjunction with platforms such as VR, facilitates the rapid acquisition of diverse expert opinions in structural health monitoring.

The objective of VR-assisted structural analyses with photogrammetry-generated DTs is to automate damage assessments to monitor an asset throughout its service life. It is established that this methodology will more efficiently document the information collected during an inspection, increase objectivity, and reduce operation time [26]. Integrating a 3D model produced by photogrammetry and automatically detecting damages, known as damage-augmented digital twins (DADT), can be helpful for more in-depth damage assessment activities such as mechanical analysis using numerical methods [27–29]. The advantages of integrating the 3D reconstructed geometry of a building asset with cracks and their characterization, supported by VR, provide significant advantages as an alternative to on-site building inspections. The advent of advanced image acquisition hardware and artificial intelligence, encompassing deep learning and machine learning, as well as computer vision, has enabled the automation of this pipeline, which previously relied solely on the actual image of the structure [30–32]. While existing damage assessment methodologies leverage techniques from these domains, they are constrained to tasks that may necessitate manual intervention, such as damage detection or creating a digital twin for a specific asset. To achieve this, several methodologies must be combined to create 3D building models and to segment and characterize cracks from images semantically.

In contrast to most existing studies, which detect cracks in two-dimensional images, the proposed approach employs machine learning and deep learning techniques to identify cracks in 3D models. This constitutes a notable advancement in the field of structural damage detection. Additionally, developing a DADT represents a novel approach to structural damage detection. This tool employs photogrammetry to identify cracks and damages within a 3D model, facilitating a more comprehensive and interactive method for monitoring and analyzing structural health. This integration provides a more objective and efficient alternative to traditional structural inspections. This approach is a relatively novel one in civil engineering and has the potential to enhance the precision and dependability of bridge inspections markedly. Creating a DADT is a far more comprehensive process than undertaking a single inspection, thereby allowing the health of a given structure to be continuously monitored and analyzed. The final stage of the study, which involves visualizing the DADT through VR, permits several experts to inspect and analyze structures remotely, thereby facilitating collaboration by removing the necessity for their physical presence on site. The utilization of VR for collaborative and remote structural inspections of bridges represents a relatively under-explored area of research that has not been adequately addressed in the existing literature. However, it offers significant potential for advancement. This study addresses this gap by demonstrating how VR can be employed as a supplementary tool in structural inspections and how it can enhance the inspection process. This study attempts to address a gap in the literature by proposing a holistic structural health monitoring approach.

In the study context, a bridge with numerous cracks was selected to simulate an automatic structural inspection. Initially, UAV images of the bridge were taken, generating a 3D model through the photogrammetry method. Subsequently, the cracks were automatically detected. Subsequently, the detected cracks and the 3D Model were integrated to produce a damage-augmented DT. This process involved significant contributions to the analysis and representation, with the produced DT being transferred to the user with visualization tools such as VR. As a result, the obtained structural 3D models were inspected and analyzed, transferred with various visualization tools, and presented to different users. The study's findings will contribute to the development of optimal representation scenarios in future DT studies, as well as to the inspection and analysis of 3D models and the presentation of these models on various platforms. Furthermore, the study's findings will be the basis for a more extensive structural inspection study.

2. Literature review

As indicated in the 2021 report published by the American Society of Civil Engineering, bridges require rehabilitation and maintenance at some point during their operational lifespan. They are among the most crucial structural components [33]. Notably, in most developed and developing countries, bridges have been in use for a considerable time or are required to be used. For instance, the report indicates that approximately 40 % of American bridges are over 50 years old, with 13.6 % still operational [33]. Concurrently, globally, in Australia, the United Kingdom, Norway, and most European countries, bridges have been in use for an extended period, underscoring the significance of bridge inspections [34]. In developing countries such as Turkey, the high cost of constructing infrastructure services necessitates the utilization of these structures for extended periods. Therefore, It is necessary to develop alternative methods for inspecting newly constructed modern bridges in Turkey. As documented in the literature, the construction sector is the least digitized and is slow in adopting new technologies, mainly digital technologies [35]. Cracks represent a significant issue in all structural types, posing a considerable threat to overall structural integrity. It is, therefore, imperative that crack detection and monitoring are employed in various structures, as this can assist in maintaining the safety and integrity of buildings, bridges, dams, tunnels, and other infrastructure components [36]. The early detection of cracks allows for implementing cost-effective repair strategies, thereby preventing significant structural deterioration and reducing the expenditure of time and resources.

Munawar et al. [37] asserted that the maintenance of most damaged infrastructure is typically conducted through visual inspection to ensure their continued functional and physical integrity. It was reported that significant financial resources are allocated annually to detect defects in infrastructure. Crack detection is inherently laborious when conducted through manual visual inspection. It was proposed that a regular inspection schedule be implemented for infrastructure components using contemporary methodologies. In their study, they conducted a comprehensive investigation into image-based methods for crack detection in infrastructure. In this study, the authors compare the performance, data sets, and application areas of image processing and machine learning techniques developed over the past decade. The authors present an overview of the advantages and limitations of these methods, summarize the current state of the art in the field of crack detection, and suggest future research directions. This review comprehensively assesses the application areas, efficiencies, and challenges associated with the methods under consideration [37].

Ali et al. [38] emphasized the significance of structural health monitoring systems and the role of crack detection in such systems. Cracks are regarded as a crucial indicator of the safety and maintenance of civil infrastructure. The study examines manual and conventional image processing techniques and elucidates the limitations of these methods. Furthermore, the study delves into utilizing a Deep Convolutional Neural Network (DCNN) to identify cracks in civil infrastructure. The study elucidates the shortcomings of manual detection, conventional image processing techniques, and machine learning methods while underscoring the exceptional accuracy and efficacy of DCNN for crack detection. This comprehensive review illustrates the benefits of deep learning techniques, focusing on the datasets, hardware requirements, and evaluation metrics employed for crack detection. The paper posits that DCNN represents the most successful and widely utilized deep learning architecture in the domain of crack detection. The advantages of DCNN include its high accuracy on various datasets and superior performance compared to other machine learning methods. The paper underscores the fact that the potential of deep learning in crack detection remains untapped mainly and that further research is necessary in this field. In particular, developing more robust algorithms is required to achieve high accuracy in different environmental conditions. For instance, low contrast, noise, and complex backgrounds represent a significant challenge in the crack detection process [38].

Ai et al. [39] emphasized that construction infrastructure inevitably deteriorates physically and functionally over time. They further emphasized the necessity for timely and accurate inspection and evaluation of such infrastructure. In their study, the authors highlighted the significance of cracks, a prevalent issue, as they indicate severe structural integrity concerns that could compromise the safety of the structure and the surrounding individuals. The accurate, rapid, and automated detection of cracks on building surfaces is becoming increasingly crucial, as it is a crucial aspect of ensuring the structural integrity of the structure. Furthermore, they indicated that advances in hardware data acquisition systems have considerably improved the automated detection and quantification of cracks in recent years. They also comprehensively investigated computer vision-based methods for crack detection in civil infrastructures. The study evaluated data collection techniques, available datasets, and detection algorithms for crack detection in different materials, including asphalt, concrete, and metal.

Additionally, the authors highlighted the significant progress made by deep learning techniques in this field and discussed the challenges and future research directions in crack detection. This review provides an essential reference source for the condition assessment of civil infrastructures. This article systematically categorizes existing work in the field of crack detection and identifies gaps and challenges in this area [39].

Deng et al. [40] asserted that the precise extraction of minute cracks discerned in high-resolution images represents a crucial yet demanding stage. Consequently, they devised an innovative deep learning-based method, designated the "crack-boundary refinement framework" (CBRF), to precisely segment concrete cracks from high-resolution images. This study employs multiscale cascaded operations and active boundary loss functions to enhance the accuracy of miniature crack detection in high-resolution images. Moreover, the study presents a case study that enhances the precision of bridge inspections conducted using UAVs. The results demonstrated enhanced accuracy and efficiency compared to conventional deep learning techniques. This method contributes significantly to the literature, particularly segmenting high-resolution crack images. Ultimately, the study underscores that, compared to conventional inspections, UAV-based bridge crack inspection provides a more dependable and efficacious solution, mainly due to the benefit of high-resolution images. Furthermore, implementing the proposed CBRF enabled the UAV to inspect the crack at 1.5 m from a structural surface. This results in a safer inspection process, and the larger field of view enabled by the more significant capture distance allows for the inspection to be completed in half the time [40].

Chu and Chun [41] observed that cracks are pivotal indicators in concrete performance testing and represent a fundamental aspect of bridge health assessments. In the context of concrete bridge structures, the presence of cracks can accelerate the shedding of protective layers and cause reinforcement corrosion, thereby reducing structural durability and directly affecting the strength and stability of the concrete structure. Consequently, they developed a deep learning model, designated the "HR crack segmentation framework" (HRCSF), for segmenting fine cracks in high-resolution images. This model has been optimized for the specific purpose of detecting cracks in bridges using UAVs. The methodology was validated through field trials to detect bridge cracks using UAVs. The tests substantiate the model's high degree of accuracy and practicality. The study attains exact segmentation by integrating multi-scale feature extraction and physical cascade operations while effectively balancing memory usage and performance. The method has demonstrated superior performance in field tests on large datasets [41].

The studies tend to underscore the necessity of employing contemporary methodologies to monitor structural integrity and inspect bridges to supplant the conventional techniques that have been utilized. These studies underscore the utility of high-resolution images in the detection of cracks. The utility of machine learning and deep learning algorithms in identifying cracks from high-resolution images captured by UAVs has been a recurring theme in the studies. While most studies employ machine and deep learning algorithms, detecting cracks is constrained to two dimensions. However, with the advent of new technology and the digital twin, the importance of 3D detection is becoming increasingly evident in the digital environment.

Consequently, some scientists have utilized distance-finding equipment to directly ascertain the photographic shooting distances. For instance, Zhong et al. [42] employed a laser rangefinder attached to the UAV camera to measure object distances and pixel resolutions on a UAV for bridge inspection [42]. Tian et al. [43] developed a data acquisition system comprising a camera and a laser range finder, which they employed to conduct laboratory tests on cracked concrete beams. The captured images were initially analyzed to identify the cracks, after which the object distance method was employed to calculate the crack size in metric units. This method is based on the optical triangle similarity theory and involves the conversion of pixel size into metric units. The results demonstrated the system's precision in measuring cracks with a width greater than 0.1 mm, with an accuracy of 92 % in crack length measurement [43]. While these approaches yielded favorable results, using a single distance sensor to obtain the photographic distance introduces a potential for measurement error when the cameras are not perpendicular to the targets, particularly in the case of tilted cracks, limiting the practicality of the approach.

The objective of the study conducted by Shim et al. [44] is to develop a bridge maintenance system based on the concept of a 3D DT model to optimize the maintenance process of prestressed concrete bridges. The authors assert that the current maintenance practices for existing bridges are inadequate and that a novel approach is necessary. The study proposes a parallel solution comprising data management and photo processing systems. Shim et al. [44] reported that using DTs for bridges facilitates comprehensive information management throughout the entire lifecycle, ensuring continuous data exchange and updates during the design, construction, operation, and maintenance phases. Ultimately, the study demonstrates that utilizing the DT model in maintaining prestressed concrete bridges confers a substantial advantage in formulating strategies and assuring structural sustainability. This approach presents an efficacious solution to diminish maintenance expenditures and enhance the long-term security of existing bridges. In a recent study, Ayele et al. [45] explored the potential of using UAVs for automated crack segmentation in structural inspection. Given the time-consuming and costly nature of traditional structural inspection methods, the study highlights the advantages of using UAVs in terms of time and cost. The study underscores the necessity of employing big data analytics to assess the current condition of structures and the importance of developing 3D models to maintain a permanent geometric record of structural elements with this data [45].

In a recent publication, Yoon et al. [46] presented a novel deep learning-based geometric framework for the structural health monitoring of bridges. The study's initial focus was to ascertain the most effective means of integrating 3D modeling and DT technologies to enhance the safety and durability of bridges. The study examines the potential applications of machine learning algorithms and deep learning models in the context of structural health monitoring of bridges. Additionally, the study presents various methods for the segmentation of 3D data and the automatic identification of components. In conclusion, this study demonstrates that integrating DTs and deep learning techniques represents an innovative and practical approach to structural health monitoring of bridges. These methods may be employed in future studies to enhance the safety of bridges and optimize maintenance processes [46].

Moreover, following the 2022 earthquakes in Zagreb and Petrinja, Stepinac et al. [47] demonstrated the pivotal role of DT in damage assessments following natural disasters and structural maintenance with emerging technologies such as photogrammetry and laser scanning [47]. To monitor and identify structural maintenance, Rainieri et al. [48] presented the use of DT as building information modeling [48]. Levine and Spencer [49] proposed a DT framework for post-earthquake building assessment with UAV imagery, component identification, and damage assessment [49].

3. Material and method

3.1. Study area

The Elvanlı bridge, situated 10 km from the center of Mersin/Erdemli (Turkey) and constructed in 2018, was the subject of this study (Fig. 1). The bridge was built in 2018 on the road connecting Erdemli district, a coastal city developed in the south-north direction, to the highlands. The bridge is situated at approximately 36°42′40.82″ N and 34°20′53.06″ E. The bridge is a modern structure with a total length of 30 m and a width of 10 m, consisting of two spans supported by beams, with a nominal life span of approximately 50 years. The columns are reinforced concrete members with a rectangular cross-section comprising vertical and horizontal reinforcement to enhance structural stability. Although the topography of the structure is generally flat, its height varies in some parts. The base columns of the bridge are located on firm ground in a rehabilitated stream bed. An on-site visual inspection of the entire structure and the formation of degradation forms enabled the selection and measurement of this structure despite the structure being relatively new. The primary factor for selecting this structure is the presence of subtle pathologies (cracks), such as fine cracks, which are challenging to detect due to their minimal width, irregular patterns, and the potential for being obscured by surface texture or environmental factors.

3.2. UAV photogrammetry and SfM algorithm

Photogrammetry is a discipline that records, surveys, measures, and analyzes visual representations and the propagation of electromagnetic waves to obtain reliable information about the qualities of tangible assets and their adjacent environments [50–52]. Geoscientists widely use photogrammetry due to its efficiency and practicality. This technique facilitates a comprehensive understanding of the natural environment's spatial characteristics and helps detect gradual surface or topography changes over time [53]. Additionally, photogrammetry is a scientific discipline that enables the collection of precise data by creating a 3D model from 2D images and providing a digital 3D archive of objects [54]. Photogrammetry is an effective technique for digital documentation, facilitating the study of structures with limited or complex access points and the creation of 3D models of components [12].

The photogrammetry technique, which has been employed for years, is essentially divided into aerial photogrammetry and terrestrial photogrammetry according to the location of the image. Aerial photogrammetry is typically preferred for topographic mapping of extensive areas, whereas terrestrial photogrammetry is predominantly utilized for 3D modeling of objects. Over time, alternative data collection techniques have been employed to address aerial and terrestrial photogrammetry limitations [55]. This has accelerated the adaptation process of UAVs, which offer advantages in terms of time and cost, to photogrammetry. Consequently, UAV photogrammetry has begun to emerge in the literature [50]. UAV photogrammetry describes the photogrammetric process whereby images are taken with a camera integrated into an autonomous or manually controlled aerial vehicle without a human operator. In this context, UAV photogrammetry, particularly the newly developed image processing techniques, has become a popular subject of study in several disciplines. In addition to the evolving data collection methodologies, bespoke algorithms such as SfM, which have begun to be incorporated into numerous photogrammetric software packages with

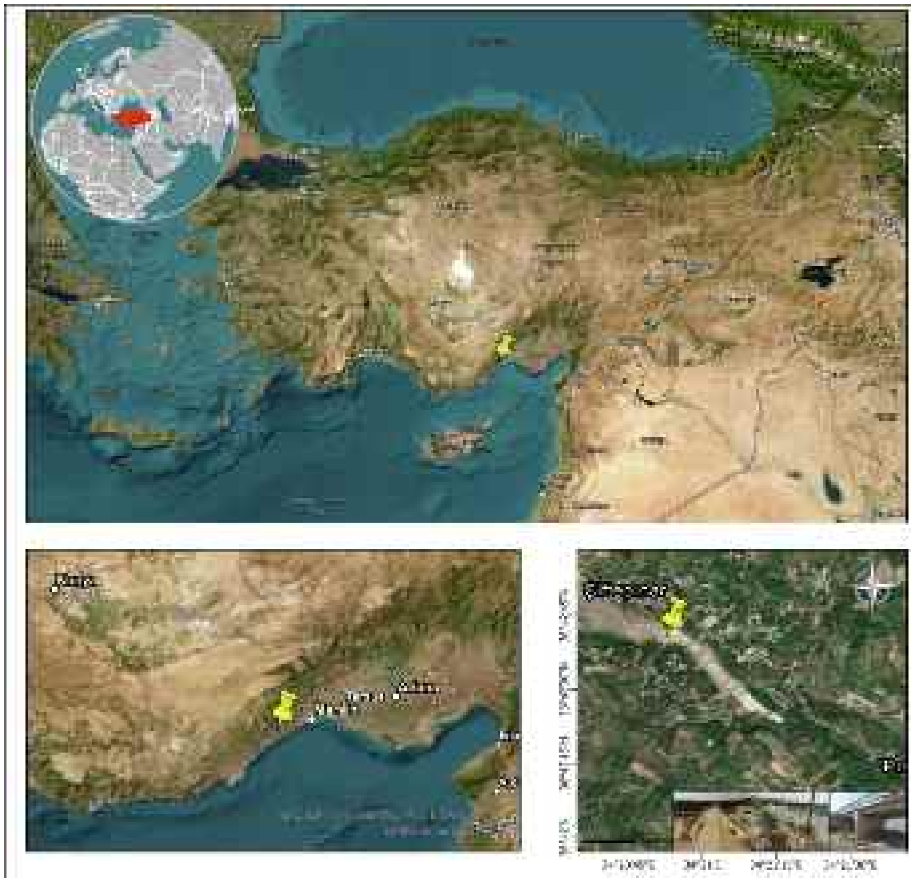

Fig. 1. Elvanli Bridge (study area) location.

the advent of digitalization, have made a significant contribution to the generation of fast, practical, and high-precision outcomes in the utilization of images obtained from UAVs in photogrammetry [56].

The SfM approach has enabled the generation of high-resolution data using images captured with metric or non-metric cameras. This technique reconstructs a 3D model of an object in focus by matching a series of two-dimensional images or images of the object, thus obviating the need for costly software for standard use [11]. This technique combines photogrammetric principles with computer vision algorithms for feature detection and matching. In contrast to traditional photogrammetry, SfM has dramatically accelerated the process, allowing point cloud generation without prior knowledge of camera orientations or ground control points. Although UAV photogrammetry adopts the basic photogrammetric approach, it has emerged as an alternative to aerial photogrammetry. UAV photogrammetry, which has found its place in aerial image collection and map production stages for mapping partially large areas such as areas where aerial photogrammetry is used, has been increasing in popularity in recent years with the photogrammetric workflow carried out in software using the SfM algorithm. In photogrammetry, the 3D coordinates of points on the surface of an object are obtained from the camera positions and external orientation parameters of overlapping images. The external orientation parameters can be calculated using at least three control points in the overlapping images. This technique usually requires prior knowledge of the internal orientation parameters and camera calibration values. However, applying advanced algorithms such as SfM eliminates the need for calibration [57]. SfM has significantly simplified the creation of 3D models and the reconstruction of surfaces from images captured with traditional cameras [58]. This technique creates 3D structures by identifying and aligning standard features in overlapping images. SfM is based on ideas like those used in stereoscopic photogrammetry [59]. SfM differs from stereoscopic photogrammetry in that it automates the calculation of the exact coordinates of points in 3D space.

Unlike stereoscopic photogrammetry, SfM does not require a camera setup [60]. Software using SfM is based on methods that automatically extract common points from many images and create a sparse point cloud [61]. The SIFT technique, which utilizes radiometric pixel values, is a widely employed primary algorithm in this process [62]. After generating a sparse point cloud, a dense point cloud is created as an additional step in the SfM process. At this stage, the Dense MVS technique is applied [63]. Here, the mapped pixels and their corresponding 3D coordinates are converted into point clouds, which are then used to create a network model. Finally, the 3D Model is obtained by overlaying natural textures from the images. For a more comprehensive review of SfM, see Michele et al. [64].

3.3. Data acquisition

Due to their low-altitude flight capability and advanced technical imaging systems, UAVs offer significantly higher resolution and more detailed information than satellite imagery and manned aircraft. However, the advent of different UAV models has brought a new perspective to this sector [65]. A comprehensive system has been developed for existing UAV platforms that include a camera, automatic image capture, a global navigation satellite system (GNSS), an inertial measurement unit (IMU), and real-time kinematics (RTK) [1]. Images captured using GNSS, IMU, and RTK modules can rapidly obtain geographic coordinates, including latitude, longitude, and ellipsoidal height [66]. This feature confers a distinct advantage upon photogrammetric processing. The utilization of UAVs is becoming increasingly prevalent in capturing imagery to investigate the sustainability of structural assets. This is a consequence of improvements in spatial resolution and a reduction in the associated costs [67]. The technology offers a significant advantage over traditional methods in mapping, documenting, and surveying large and complex architectural structures using UAV photogrammetry methodology to create 3D digital models and maps. The UAV platform has recently developed significantly, especially as an image capture tool in photogrammetry. This approach enables the advantageous collection of image data. The resolution and detail of UAV data are significantly superior to that of satellite imagery and manned aircraft. This is due to the UAV's ability to fly at low altitudes and utilize advanced technological imaging systems [68]. The collection of photogrammetric data with UAVs can be divided into three main field activities: (1) flight mission design, (2) ground control point (GCP) placement and measurement, and finally (3) flight operation and aerial imagery collection. There are two types of flights in aerial images with UAVs. The first is the flight with the height profile created according to the terrain model, and the second is the conventional flight from a certain height.

It is necessary to set specific parameters in the flight mission design. The photogrammetry technique employs the basic stereoscopic vision technique. Therefore, at least two images must be taken from different angles and positions and have a common overlapping area (Fig. 2). The UAV photogrammetric flight mission generally performs 85 % forward (front) overlay and 60 % side overlap. Furthermore, although the significance of flight altitudes remains unchanged in the context of digital photogrammetry and the SfM algorithm, the more crucial parameter is ground sample distance (GSD). As illustrated in Fig. 2, the GSD represents the mean distance between two neighboring pixels in the image, which has been adjusted for errors resulting from internal orientation in the photogrammetric process. As this parameter is primarily contingent upon the sensor's resolution that captured the image, it is arguably one of the most significant parameters influencing the flight altitude, precisely the distance between the centroid projection and the target object (Hamal et al. 2022).

The data were collected between 8 and 11 a.m. when cloud cover was below 15 %. In order to avoid solar hotspots and high temperatures (>30 °C), the sun angle was considered. Another crucial aspect of UAV photogrammetry is flight planning. Flight planning is typically conducted in two distinct ways, with alternative plans employed for different purposes (Fig. 3).

The fundamental automated flight plans for map production are designated as grid and double grid. While fully automated planning can be accomplished with these two plans, grid-type flight is typically employed for 2D mapping and non-precision studies to expedite the process, whereas double grid flight type is recommended for numerous 3D photogrammetric studies. Finally, the angle at which the images are captured is essential in data collection. In UAV photogrammetry, while nadir images are typically captured, oblique images can be taken for specific purposes. With recent advancements, highly equipped UAVs can capture oblique images in addition to nadir images. In this mission, it is crucial to utilize a high-resolution 3D model generated through UAV photogrammetry to facilitate the identification and analysis of cracks. Therefore, it is of paramount importance to obtain precise data.

This study devised two distinct flight strategies for collecting aerial imagery. The first strategy is a fully automated double grid approach, which is employed to gather data on the side and top facades. The second strategy is a free flight planning methodology utilized to obtain data from the lower portions of the bridge. (Fig. 4).

Firstly, a plan was devised for the side and top façade data, and the initial flight design was created for the top façade data, which is relatively straightforward to plan. The double-grid flight planning method was selected, with an approximate grid length of 12 m. In the initial flight planning phase, 72 aerial images were captured in approximately eight minutes at a ground sample distance (GSD) of approximately 0.71 cm/pixel from 20 m above the ground at a nadir position. As the side elevations were deemed unsuitable for regular aerial photogrammetry planning, oblique images were taken instead of nadir (approximately 90 degrees). To achieve the desired result, oblique images were taken at an angle of approximately 45 degrees. These images were taken along a block grid approximately 5 m from the bridge (about 0.21 cm/pixel GSD). To achieve the desired output, a flight strategy that differs from the traditional standard method of air travel was formulated instead of opting for gradually increasing altitude. To clarify, the images were taken from a vertical distance of 5 m relative to the intended direction and obstacle. One hundred and four oblique aerial images were obtained from three heights, 5, 10, and 15 m, respectively, precisely above the ground. These images were taken at the same angles and block direction. For the top and side facades, a fully autonomous flight strategy was employed, resulting in a total of 176 aerial images being taken. There are two principal reasons why GSD values diverge in the context of flight planning. At this juncture, it is imperative to emphasise that the GSD value should be of superior quality to a 1 cm/pixel value. Because the methodology used this study employed in the study should utilize a superior value to that of 1 cm/pixel. The second point of consideration is the enhancement of the level of detail in the vicinity of the object, achieved through the maximisation of overlap ratios in the context of automatic flights on the upper facades. This corresponded to an altitude of approximately 20 m (0.71 cm/pixel). On the lower facades, i.e., beneath the bridge, manual flight planning was conducted in a narrow area, resulting in data acquisition in closer proximity to the object and a lower GSD value. This was calculated to be approximately 0.21 cm/pixel for our study. These flight strategies' front and side overlap ratios were

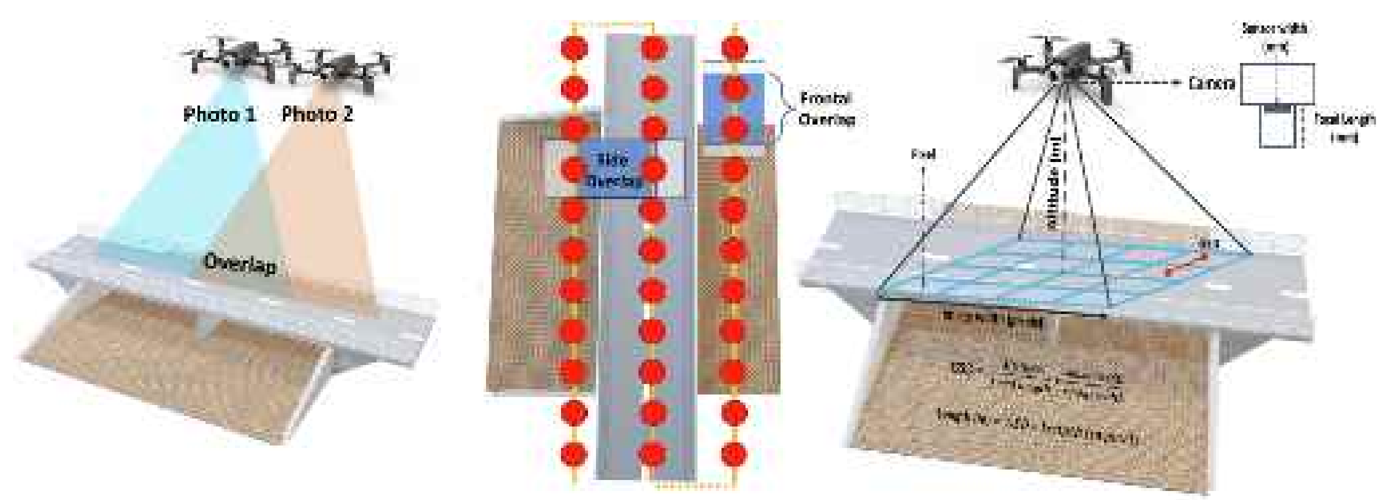

Fig. 2. Flight parameters that need to be set (Overlap and GSD).

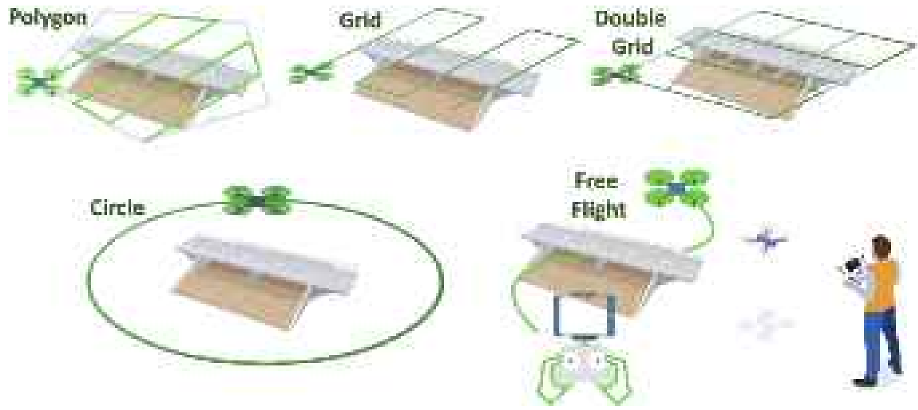

Fig. 3. Alternative flight planning with UAV during bridge inspection.

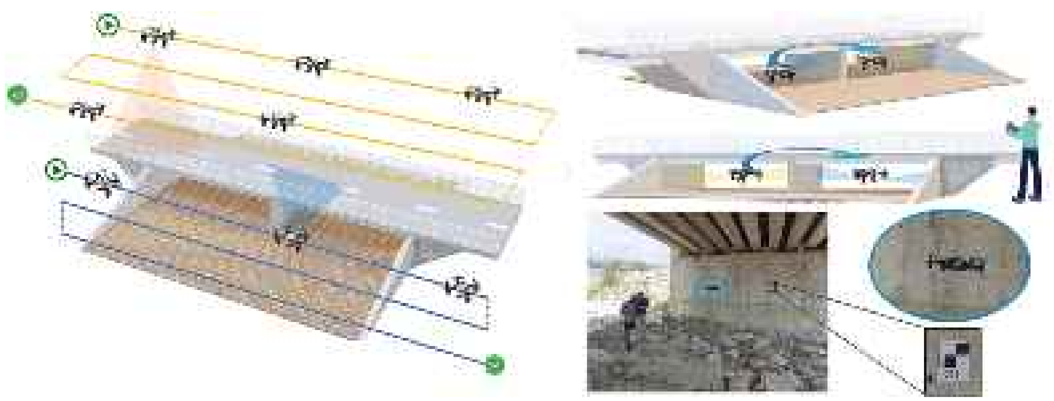

Fig. 4. Flight planning was used in the study (double grid and free flight plan).

planned at 80 % and 70 %, respectively. The Anafi Parrot drone was employed to collect aerial imagery, which was used to generate 3D data on the study area. Table 1 presents the technical specifications of the Anafi Parrot.

The Parrot ANAFI drone's camera, featuring a 1/2.4-inch CMOS sensor with a focal length of 23–69 mm for photos and 26–78 mm for videos, is crucial in capturing high-quality images for 3D modeling [70]. The f/2.4 aperture allows sufficient light for clear images, but care must be taken to focus on critical areas to ensure model accuracy. The shutter speed (up to 1/10000 s) minimizes motion blur, which is essential for sharp imagery during flight [71]. The ISO range (100–3200) adapts to light conditions, though a higher ISO may introduce noise (Parrot Anafi 2024). Properly balancing these settings is vital for producing accurate and detailed 3D models. In summary, the camera settings on the Parrot ANAFI drone, including focal length, aperture, shutter speed, and ISO, play a crucial role in the quality of the images captured and, consequently, the accuracy of the 3D models generated. Proper adjustment of these settings based on the specific conditions of the inspection site ensures that the generated models are accurate and detailed.

This study employs the fundamental techniques of photogrammetry and SfM algorithms. Automated photogrammetry software utilizing the SfM algorithm can generate models without georeferencing input. However, the generated Model and digital products are in an arbitrary coordinate system, rendering them unscaled and of limited value for research purposes. Advanced UAV platforms are equipped with a global satellite positioning system (GPS) and the Globalnaya Navigatsionnaya Sputnikovaya System (GLONASS), which enables recording latitude, longitude, and altitude information on captured images. While this contributes to producing a model in the desired coordinate system and approximate scale without georeferencing input, exact results cannot be obtained in the desired coordinate system or measurement value. To create a complete and accurate model, GCP and Check Point (ChP) should be placed in the study area with precision measuring devices (total station, GNSS receiver) and georeferencing of the Model with these points, as shown in Fig. 5. The bridge under study is located on a highway with a length of approximately 26 m and a height of approximately 12 m. As previously stated, the flight planning was performed from the bottom up. At least three references are needed to bring a space model to the same system as the ground center. The number of required references depends on the workspace and should be optimal.

For this reason, ten control points were placed on the road lines at 3-meter intervals, and 26 control points were placed on all sides of the bridge, with at least two control points in a horizontal position and different height increments. These points are also employed to assess the accuracy of the 3D products generated from the UAV data. To ascertain

Table 1
Main technical specifications from the official datasheets of the UAV [69].

Specifications	Value
Dimensions	17,5 × 23,8 × 6,3 cm
Weight	320 g
Maximum horizontal-vertical speed	15.2 m/s – 4 m/s
Maximum wind resistance	50 km/h
Maximum distance	4000 *m*
GPS with RTK	No
Satellite Positioning Systems	GPS & GLONASS
Camera model	Factory mounted camera
Sensor	Sony Sensor® 1/2.4″ 21MP (5344 × 4016) CMOS
Pixel size	1.3 µm (0.00134424 mm)
Focal length	4 mm
Rotation	180°, i.e. a rotation from –90° (nadir) to + 90° (zenith)

Fig. 5. Measurement of GCP and ChP during fieldwork.

the positions and heights of these points, measurements must be taken with a precision measuring device (total station) (Fig. 5).

3.4. Crack detection

To achieve partial automation, this study proposed a vision in which the tasks of damage inspection in structures are not treated separately, but instead, a single method generates a complete 3D model containing damage information in the form of a DT at a given level of detail. To achieve this, 3D models that contain in-depth data about the geometry of a physical part of the structure were analyzed with a DT that contains geometric information. The photogrammetric 3D Model with geometric information is combined with damage data obtained from images to produce DADT. The first step is to produce a high-quality 3D model with detailed geometric information of the structure by photogrammetric method, overlaid with natural texture. This is followed by calculating the positions of the cracks detected from the 3D Model and their automatic vectorization, which saves time and cost. The comprehensive information provided by this representation will assist in preparing future actions and decisions. The intended DADT output can combine the geometric information provided by the detail-level Model with the mapped and characterized damages and can be analyzed. This represents an alternative method to on-site inspections. In this study, the automatic detection of cracks was performed using machine learning and deep learning algorithms developed by Bentley [72,73].

The process begins with generating a detailed 3D model from UAV-captured images using the SfM algorithm. The resulting 3D model is represented as a dense point cloud, which is then analyzed for surface differences using Curvature Estimation and Neighborhood Aggregation algorithms. These algorithms, integrated into Bentley's Insight Detector tools, utilize pre-trained machine learning models to identify points with significant curvature variations indicative of cracks. Machine learning and deep learning algorithms detect cracks by analyzing surface differences in the 3D model. In general, the algorithm functions based on the digital products produced. The 3D model, which is the fundamental input of the algorithm, is represented as a series of point clouds. Subsequently, the point cloud is analyzed to determine the surface differences of the Model. Cracks are identified due to the differences in the analyzed surfaces. The features employed for 3D object detection in classical photogrammetric models include the minimum value of the surface differences to be considered as cracks, the direction and minimum length of the cracks, the minimum width of the cracks, and the smoothing value of the surface differences [74–76].

Object detection tools utilize both machine learning and deep learning. These tools primarily use Neighborhood Aggregation and Curvature Estimation algorithms based on machine learning [76]. These algorithms use pre-existing models to analyze variations in a 3D surface. The algorithm used to detect cracks is based on artificial intelligence algorithms. This mechanism compares the curvature value and a predetermined threshold value. This procedure is analogous to how the human brain detects cracks [77]. The Neighborhood Aggregation algorithm identifies the neighboring points of each point in the point cloud using a pre-trained model to represent surface differences in the 3D Model [77,78]. The Neighborhood Aggregation algorithm employs Eq. (1) to identify the neighbors of each point.

$$n(p) = \{q \in P| ||p - q|| < r\} \tag{1}$$

In this Equation,

$n(p)$: represents the set of all points within a given radius r around a point p (p: point set).

q: neighbor of point p

P: Point cloud

r: Neighborhood distance

The Curvature Estimation algorithm is used to calculate point curvatures. This algorithm uses a pre-existing model that learns how to approximate the curvature of the point cloud. The Curvature Estimation algorithm uses Eq. (2) to calculate the curvature of the points.

$$K(p) = \frac{k_1(p) + k_2(p)}{2} \tag{2}$$

In this Equation,

K(p): curvature of point p

k1(p): primary curvature of point p

k2(p): secondary curvature of point p

The Crack Detection algorithm identifies points with slopes that exceed a specific value [78,79]. The algorithm provides information about the detected cracks' size, depth, and location. The Crack Detection algorithm uses Eq. (3) to identify points with a curvature more significant than a specific value as cracks.

$$c(p) = 1 if |K(p)| > t else 0 \tag{3}$$

In this Equation,

c(p): whether point p is cracked or not

|K(p)|: absolute value of the curvature of point p

t: Threshold value

These formulae form the basis of the mathematical Model of the Detector tools. These formulas analyze surface differences in the 3D Model and detect cracks. As a result, with these algorithms, automatic crack detection is performed from images positioned on the 3D Model rather than 2D images. By combining the 3D Model and the detected cracks (3D Model + crack), damage-augmented DTs can be produced at different levels of detail.

3.5. Accuracy analysis

Two accuracy analyses were conducted in the study. The first analysis evaluated the spatial and geometric accuracy of the 3D Model created by photogrammetry. This analysis involved assessing the accuracy of the Model coordinates concerning the control points. The reference data were compared with the coordinates of the 3D Model, and any discrepancy was calculated as an error. Natural target signals measured with total station were used as reference measurements, and the analysis was performed using Equation (4). In the test run, 14 out of 36 target points (approximately 40 % of the total target points) were used for the accuracy analysis. The difference between the reference data and the data obtained from the DT model indicates the distance between the model position and the reference point. The Root Mean Squared Error (RMSE) was calculated to quantify this error, demonstrating the Model's accuracy. The accuracy of the Model is proportional to the reduction of the error value. As a second analysis, an accuracy analysis was performed to assess the reliability of cracks found on the surface through automatic detection. Manual measurements from the surface were compared with the lengths of vector data obtained from automatic detection. An expert manually performed the reference data collection for the cracks on the bridge using measurement tools. The expert operator could not reach the points analyzed from the images. Eq. (4) was employed to perform the accuracy analysis, calculating an RMSE value.

$$RMSE = \sqrt{\frac{\sum (x-y)^2}{n}} \tag{4}$$

where

x: coordinates of the control point/manual crack lengths.

y: Coordinates taken from the 3D model/Automatic crack lengths.

n: Represents the number of control points/number of cracks.

4. Results and Discussion

4.1. Data analysis and creating 3D model

The accuracy of 3D models generated through SfM/MVS algorithm-based photogrammetry is contingent upon the quality of the image data. A significant technical challenge in applications utilizing these algorithms is the acquisition of the images. The outcomes of SfM/MVS are contingent upon the quality of the images captured, with inadequate coverage of the focal object or substandard images having the potential to significantly diminish the precision of a 3D model. One of the most crucial parameters in UAV photogrammetry is the ground sample distance (GSD) value. A detailed explanation of the significance of GSD can be found in the Data Acquisition section.

Since automated crack detection will be conducted in the study, collecting data for this is essential. The image resolution should be approximately 1 cm/pixel at this stage to ensure the library and detectors function optimally. Consequently, the planned flight strategy accommodates the desired image resolution. As a result, the image data were collected at the specified resolution, as illustrated in Fig. 4. The image data are presented in Table 2. Image quality is of paramount importance, necessitating the acquisition of high-quality images. Although the fundamental specifications of the UAV utilized in the study are presented in Table 1, the primary rationale for employing this UAV is its expansive camera rotation angle and the sensor's requisite resolution. Collecting data from the requisite distance with the UAV, which has a 21-megapixel resolution, enabled us to attain the desired GSD value. In UAV photogrammetry, the GSD value depends on the height or distance between the object and the sensor. In addition to flight altitude, other parameters that affect GSD include the pixel size and width of the sensor, the focal length of the camera, image resolution, and viewing angle. The flight planning described in the previous sections and data collection with gradual height allowed us to capture unique images of the bridge. The fact that the UAV has comprehensive angular camera rotation features, especially in the lower parts of the bridge, provided significant data collection advantages. In addition, it is advisable to take aerial images at appropriate times to avoid the shadow effect during the image data collection phase. At this point, the appropriate time zone was selected for taking aerial images.

Table 2
Flight parameters in aerial image collection with UAV.

Flight Mission	Flight Height/ Distance	Flight Time	Total Image	Overlap (Front/side)	GSD (cm/ pix)
Double Grid	20 *m*	~8 min	72	%80 / %70	0.75
Free	5—10- 15 *m*	~19 min	104	%80 / %70	0.21

The advent of technology has facilitated the automation of the digital photogrammetric process, which is typically executed through algorithms. In digital photogrammetry, the SfM algorithm calculates the internal and external orientations and generates the final products. SfM is a photogrammetric algorithm that automates the scene's geometry, camera positions, and orientation without needing a pre-defined target network with known 3D positions. The generation of 3D geometry necessitates using two or more overlapping images. The cross-correlation between two or more overlapping images of the same object allows for the determination of height information, provided that the orientation of the images is known. The process may be repeated for each image pixel, thereby creating a 3D point cloud. One advantage of using dense image matching over LiDAR when generating point cloud data is that color attributes are automatically stored within the points, thus directly providing a photorealistic representation of reality in terms of geometry and RGB values.

Furthermore, the SfM technique also offers the possibility of integrating images taken on the ground and from different aerial platforms, provided that specific working methods are followed. The principal distinction between conventional stereoscopic photogrammetry and SfM is that the calculations necessary to determine the precise position of a point in 3D space are entirely automated and do not necessitate precise camera positioning. The SfM algorithm, which has become a prevalent tool in scientific research due to its accessibility and cost-effectiveness, has had a transformative impact on earth science research due to its low cost, rapid results, and straightforward 3D measurement capabilities.

The process commences with estimating the 3D structure of the two images and the camera poses based on their respective poses. Subsequent camera poses are then incorporated sequentially, with the estimation of the new 3D structure occurring as new parts of the scene are observed. Block balancing is performed repeatedly as more cameras are added, ensuring high-quality reconstructions and avoiding drift. SfM follows a general procedure to filter out outliers and to estimate camera poses or structures from consecutive images. Although the performance of the SfM algorithm is significantly enhanced by camera self-calibration, there are instances when pre-calibration is still necessary to achieve optimal results. Currently, most digital photogrammetric software incorporates algorithms that automatically estimate the internal orientation parameters of the cameras through self-calibration. At this stage, the binary relative poses are determined by estimating the camera position and the absolute orientation of the cameras. In other words, triangulation in the structure calculates the 3D position of an image coordinate tracked through two or more images. All cameras with estimated camera pose are used to estimate the 3D point of a track, and by block balancing, the track of the tie points is adjusted after the initial estimate (keeping all camera parameters constant). To triangulate the features correctly, there should be a sufficient baseline concerning the point's depth between the cameras. Points with a depth that is too high and a baseline that is too small are highly inaccurate. For the estimation to be successful, at least one pair of cameras must have a sufficient field of view for the estimated track. The poses represent the calibrated poses of the two cameras, while the points correspond to the 2D image points of the matching features used to triangulate the 3D point. Triangulation is performed by determining the closest point between two rays.

In this case, the ray origins are the camera positions, while the ray directions are the directions of the features in 3D space. This method has been demonstrated to be less efficient than other triangulation methods in minimizing the reprojection error. However, it is approximately ten times faster. All cameras and 3D points are optimized for non-linear optimization to minimize the reprojection error. View pairs containing the relative poses between matching geometrically verified views and the previously estimated absolute orientations of the camera are computed. Camera positions are estimated from this information, with specific strategies and implementation determined by the derived classes. The primary objective is to sort the images and construct a preliminary model.

Following the orientation process, new workflows are defined for creating digital products such as dense point clouds and 3D models. In the pre-orientation stage, the highest setting is selected to obtain more accurate camera position estimates for all objects (lower accuracy settings can be employed to obtain coarse camera positions in less time). At the highest accuracy setting, the software operates with original-size images, while the medium setting causes the image to be downscaled by a factor of four (two times on each side). At low accuracy, the source files are downscaled by a factor of 16, and the lowest value means four times more downscaling. The highest accuracy setting, which was the focus of the study, resulted in an image being upscale by a factor of 4.

Since anchor point locations are estimated based on feature points in the source images, it may be beneficial to enlarge a source image to localize an anchor point accurately. However, the highest accuracy setting is only recommended for very sharp image data and is mainly used for research purposes, as the associated processing is quite time-consuming. Furthermore, the highest option matches the images with the lowest overlap ratio. As the other sub-options are selected, the images without a high overlap ratio are not matched, and no points can be generated from the unmatchable images. In photogrammetric evaluation, software settings are as important as the importance of the image.

The creation of photorealistic 3D models to create DTs was achieved using Context Capture software. The process begins with estimating the two images' 3D structure and camera poses. Subsequently, camera positions are added or calculated, and new scene components are observed to create the new 3D structure. Block balancing is performed at this stage while continuously analyzing the images provided as overlapping input. SfM employs a conventional procedure to eliminate inconsistencies and evaluate camera positions or formations from consecutive images. While the camera's self-calibration enhances the functionality of the SfM algorithm, pre-calibration is occasionally necessary to achieve satisfactory results. In this study, the Context Capture software automatically estimated the internal orientation parameters of the cameras. Subsequently, the absolute orientations of the cameras, as well as the camera position of the given images, were estimated to determine the binary relative poses. Subsequently, the 3D position of an image coordinate tracked over two or more images was calculated. Following the initial estimation, the track of the anchor points was adjusted by block balancing while maintaining all camera parameters constant. In creating dense point clouds, solid models and point clouds are generated by estimating the pixels that require mapping to one another and their virtual 3D positions. In the final stage, a photorealistic 3D model was obtained using the image to provide the Model with a realistic and natural surface (Figs. 6-7).

4.2. Automatic crack detection and DADT model

An automated crack detection system was used to identify a 3D model's cracks. The method employed for crack detection on the 3D Model necessitates the segmentation of the facade using machine and deep learning models that have been trained on the initial view image. During this stage, the corners of the identified apertures are moved from the initial to the second to identify the correct corners. The Insight Detector tools employed in this study can identify cracks in 3D models and evaluate their dimensions, extent, and position. The mathematical framework of Insight Detector tools consists of algorithms that analyze discrepancies on the surface of the 3D Model. The Insight Detector tools and the Neighborhood Merge and Curvature Estimation methods utilize deep learning algorithms. The pre-trained models were utilized to examine the surface irregularities of the provided 3D Model. The Neighborhood Aggregation and Curvature Estimation techniques utilize Convolutional Neural Networks to identify objects in images and videos. When trained with labeled data, supervised learning algorithms can detect surface distinctions. By implementing these structures, Insight Detector can accurately detect flaws in 3D models.

This study's most significant distinguishing feature is that the detected cracks are obtained from 3D models instead of 2D images. This was achieved through the utilization of artificial intelligence algorithms. The Bentley machine learning and deep learning detectors were employed to run the fundamental algorithms. The use of ready-made libraries and the design of the most suitable parameters for the study area were also employed. The compatibility of the data in the library used and the workspace will directly affect the accuracy. These tools detect cracks by analyzing surface differences in the 3D Model. The Insight Detector tools have different features, so a suitable tool should be selected according to the user's needs.

It should be noted that these tools may not always give perfect results. The working mechanism of Insight Detector tools starts by first representing the 3D Model as a series of point clouds. Then, the point

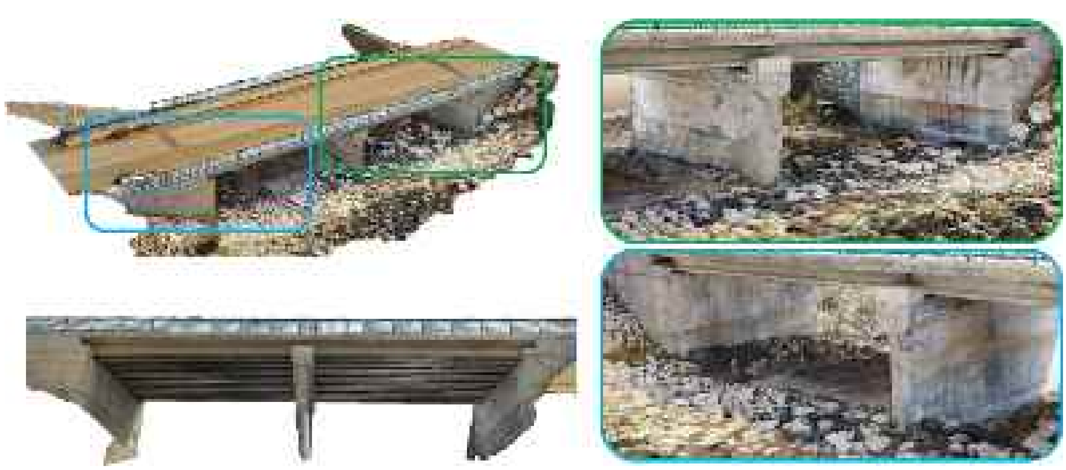

Fig. 6. 3D Model of the bridge (North Facade).

Fig. 7. 3D Model of the bridge (South Facade).

cloud is analyzed to identify surface differences. Finally, cracks are detected due to surface differences. The features and settings employed by Insight Detector tools for the detection of 3D objects in photogrammetric models are as follows:

- Threshold: Sets the minimum value of surface differences to be considered as cracks.
- Angle: Determines the direction of the cracks.
- Length: Sets the minimum length of the cracks.
- Width: Determines the minimum width of the cracks.
- Smoothing: It is a setting used to smooth surface differences.

The mathematical Model of the Neighborhood Aggregation and Curvature Estimation Insight Detector tools, described in detail in section 2.4, is comprised of a set of algorithms for analyzing surface differences in a 3D model. The Neighborhood Aggregation algorithm determines the neighbors of each point in the point cloud. The Curvature Estimation algorithm, when calculating the curvature of points, identifies points with a slope higher than a specific value as cracks. The neighborhood aggregation and curve estimation algorithms are based on machine learning. These algorithms utilize pre-existing models to analyze variations on a 3D surface. The Neighborhood Aggregation algorithm identifies the neighboring points of each point in the point cloud using a pre-trained model to represent surface variations in the 3D Model. The Curvature Estimation algorithm for calculating point curvatures uses a pre-existing model that learns how to approximate the curvature of the point cloud. The crack detection algorithm is based on artificial intelligence algorithms. This mechanism performs comparisons between the curvature value and a predetermined threshold value. The crack detection algorithm identifies points with curvatures exceeding a specific value. Some parts of the detected cracks of the bridge selected as the study object are presented in Figs. 8–10.

The Neighborhood Aggregation and Curvature Estimation algorithms are based on deep learning algorithms. These algorithms utilize pre-trained deep learning models to analyze surface differences in a 3D model. The Neighborhood Aggregation algorithm and the Curvature Estimation algorithm are based on convolutional neural networks (CNN) algorithms. CNN algorithms are deep learning algorithms that detect objects in images and videos. These algorithms are also based on supervised learning algorithms. Supervised learning algorithms are trained with labeled data, which enables them to learn to analyze surface differences in a 3D model. These algorithms are then utilized in Insight Detector tools, which can detect cracks in 3D models quite effectively. Insight Detector tools use various architectures, including the Neighborhood Aggregation algorithm, which uses the PointNet++ algorithm. The PointNet++ algorithm is a deep learning algorithm for detecting objects in 3D point clouds. The Curvature Estimation algorithm utilizes the PointNet algorithm. The PointNet algorithm is a deep learning algorithm that detects objects in 3D point clouds. Finally, the Crack Detection algorithm compares the curvature value to a specified threshold value. This process is like the way the human brain detects cracks. Insight Detector tools are constantly being improved.

Fig. 8. Cracks in the columns and upper support of the bridge were automatically detected.

Fig. 9. Automatically detected cracks on the side façade and upper support of the bridge.

Fig. 10. Cracks in the bridge's side support and center column were automatically detected.

Researchers are developing new architectures and algorithms to improve the accuracy and efficiency of crack detection.

Insight Detector provides information on detected cracks' size, depth, and location. However, it should be noted that the mathematical Model of the Insight Detector tools has some limitations. The quality of the Model can affect the accuracy of crack detection. Cracks may be detected incorrectly if the Model contains noise or other errors. Also, the characteristics of cracks, including their size, depth, and shape, can affect the accuracy of crack detection. Small cracks or cracks with complex shapes may be detected incorrectly. Finally, environmental conditions can affect the accuracy of crack detection. For example, shadows or reflections may incorrectly identify cracks.

Furthermore, inaccuracies and uncertainties may arise from pre-trained models. Using advanced deep learning models and eliminating erroneous data identified as cracks through personal intervention or automatic elimination can lead to more accurate results. The aim is to improve the current approach for rapidly detecting damage. This may require thoroughly examining damage characteristics, including determining crack depths. Research is currently being conducted to enhance the efficacy of the current methodology for expeditiously assessing the extent of damage. Following the completion of a rapid assessment using this approach, a more comprehensive examination of damage characteristics, such as the assessment of the size of cracks, may be necessary.

The DADT model combines the 3D model obtained with the detected cracks. The objective of the DADT output is to integrate the geometric data obtained from the 3D model with the damage that has been defined and measured. The method is capable of detecting fractures in 3D images independently. Based on the stable characteristics of the image in Bentley's Context Capture collection, which was used to train this work, this method is currently regarded as the gold standard for crack analysis. Various machine learning and deep learning techniques were employed to identify different types of cracks on the surface of a textured 3D model.

4.3. Accuracy analysis of 3D model and detected bridge cracks

Accuracy analysis was performed to determine the compatibility of the 3D Model and point cloud data with the reference data. Accuracy analysis is the final step to measure the accuracy and reliability of the study. A coordinate comparison was made for the accuracy analysis by taking the same points from the reference coordinate with 14 ChP from the 3D Model and point cloud data. Total-station was accepted as reference data for accuracy analysis. Eq. (4) was used for accuracy analysis. As a result of the comparison of the coordinate data taken from the reference data and the 3D data, the square mean errors of the X, Y, and Z coordinates $RMSE_{x,y,z\ (cm)} = 0.331,\ 0.274,\ 1.866$ are given in Table 3.

Following the geometric accuracy analysis of the 3D Model, a second

Table 3
Accuracy evaluation of 3D model data for the reference data.

No	Vx	Vy	Vz
1	−0.155	0.397	1.913
2	0.426	−0.308	−0.097
3	−0.649	0.279	1.823
4	0.015	0.024	−1.454
5	0.035	0.010	1.124
6	−0.417	0.255	1.389
7	0.500	−0.208	−0.540
8	0.331	0.286	0.923
9	0.172	0.350	0.227
10	0.419	0.351	−1.255
11	0.213	0.112	4.085
12	0.125	0.028	−1.588
13	0.319	−0.334	2.715
14	−0.026	0.400	2.668
$RMSE_{x,y,z}$	0.331	0.274	1.866

*$V_{x,\ y,\ z}$ and $RMSE_{x,\ y,\ z}$ values are in cm.

analysis was conducted to assess the reliability of the cracks identified through automatic detection on the surface. Manual measurements from the surface were compared with the lengths of vector data obtained from automatic detection. An expert manually performed the reference data collection for the cracks on the bridge using measurement tools. The points the expert operator could not reach were analyzed through images. Following a visual inspection of the field, 38 cracks were identified. Of these, 20 were measured by the operator in the field, while the remaining 18 points were measured on the 3D Model. The length of the 20 cracks measured in the field was also measured using the 3D Model, and the analysis was performed by calculating the difference between them. To assess the accuracy of the data, Eq. (4) was employed, resulting in the calculation of an RMSE value (Table 4).

The comparison between the manual measurements and the automatic detection from the 3D model yielded an RMSE value of 0.391 cm, indicating high accuracy in crack detection. Moreover, our automated detection system identified all the cracks detected by the field practitioner, along with additional minor cracks that were not noticed during the manual inspection. This demonstrates the effectiveness of the proposed methodology in detecting cracks, including those that may be overlooked during conventional inspections. The accuracy of the crack detection method is further evidenced by the minimal discrepancies between the lengths of cracks measured manually and those detected

Table 4
Accuracy analysis of cracks detected from the 3D Model by photogrammetry for the bridge.

Crack No	Traditional measurement (cm)	Automatic detection (cm)	$\lvert D_i \rvert$(cm)	$RMSE_D$
1	8.48	7.37	−1.10	0.391
2	12.36	11.97	−0.39	
3	6.59	7.77	1.18	
4	10.56	8.84	−1.71	
5	48.12	47.32	−0.80	
6	24.58	23.67	−0.91	
7	14.85	15.99	1.14	
8	15.69	16.84	1.15	
9	13.21	11.38	−1.83	
10	4.87	6.37	1.50	
11	15.37	16.45	1.08	
12	27.84	26.86	−0.98	
13	7.60	9.58	1.98	
14	4.85	7.30	2.45	
15	4.88	6.76	1.88	
16	16.23	15.32	−0.91	
17	32.85	33.00	0.15	
18	24.78	24.94	0.16	
19	12.84	11.59	−1.25	
20	88.47	88.59	0.12	

automatically, confirming the robustness of the proposed system in practical applications.

The second stage of the accuracy analysis of the cracks entailed a visual inspection, during which almost all cracks were successfully identified. However, some cracks in areas where the shadow fell were not recognized. The test run results confirm that all components of this technique function efficiently. The methodology achieves satisfactory accuracy; a visual inspection reveals that most cracks are recognized. However, the accuracy of the results may be compromised if the user has more advanced models. This is especially true given that the training libraries for crack segmentation methods are tailored to each field of study. The efficacy of the process is contingent upon the quality of the image data. The impact of factors such as image size, resolution, blur, and distortion must be considered. However, this is beyond the scope of this research. The accuracy of the findings from this research is contingent upon the effectiveness of the SfM and deep learning algorithms utilized in the segmentation methods. The efficacy of this study's deep learning outcomes is significantly contingent upon the quality and quantity of data and annotations utilized in training the models.

Several environmental factors influenced the accuracy of crack detection using UAV photogrammetry and DADT model visualization. The presence of shadows, particularly those cast at different times of the day, significantly impacted the clarity of the captured images, which led to potential inaccuracies in detecting cracks. For example, shadows can obscure fine details, impeding algorithms' ability to segment cracks accurately. This effect was particularly evident in structures with complex geometries, where shadowing was more prevalent. Furthermore, the material properties of the structures, such as reflectivity, also affected the accuracy of the detection process. The presence of reflective surfaces resulted in glare within the images, reducing the contrast required for accurate crack detection.

Furthermore, seasonal alterations and fluctuations in daylight conditions exerted an additional influence on the outcomes. Images captured under varying lighting conditions, such as during dawn or dusk, exhibited reduced detection accuracy due to the diminished light intensity and increased shadows. Although the study did not quantify the impact of these factors, it is estimated that the accuracy of crack detection could vary by approximately 10–15 % depending on the time of day and the presence of shadows. Furthermore, the structure's material properties may also influence the accuracy of the results, particularly in cases where the structure in question exhibits high reflectivity. Notwithstanding the proposed methodology's efficacy, the previously mentioned environmental factors impose constraints. The variability in lighting and material properties necessitates meticulous planning of image capture and may require post-processing adjustments to ensure consistent accuracy. It would be beneficial for future work to focus on the development of adaptive algorithms that can compensate for these environmental variances, thereby improving the robustness of crack detection in diverse conditions.

The accuracy of crack detection in the proposed methodology is significantly influenced by surface roughness. During the analysis, it was observed that areas with higher surface roughness, such as those with uneven concrete textures or significant wear, presented challenges in accurately detecting and delineating cracks. Irregular surface features often create shadows and reflections in the captured images, which could be mistaken for cracks or obscure actual cracks, leading to potential false positives or missed detections. The sections where crack detection was most challenging included areas exhibiting high wear and tear, where the surface had undergone significant erosion, and regions displaying heavy staining or discoloration. In these regions, the distinction between cracks and surface features was less clear, necessitating more sophisticated analysis and, in some cases, manual verification to ensure accuracy. Notwithstanding these challenges, the proposed method demonstrated efficacy in most cases. However, it is crucial to acknowledge that extreme surface roughness represents a significant limitation and may necessitate further refinement in future iterations of the methodology.

4.4. Structural inspection with DADT model in VR platform

The creation of 3D models obtained by photogrammetry and their subsequent transfer to VR platforms is an increasingly popular topic within the field of DT. The 3D Model obtained by photogrammetry represents a digital copy of the real-world object. This is the first and most crucial stage of the DT concept. As previously stated, creating an accurate model of an object in a digital environment and the subsequent maintenance of this Model to ensure its currency and sustainability are costly and time-consuming processes. Consequently, photogrammetric models offer a significant advantage in terms of time and cost when creating DTs. In this study, a DT was obtained by creating a DADT model by combining the 3D Model produced in this study and the detected cracks. Although these models represent an alternative to on-site inspection, VR platforms are the most up-to-date means of delivering them to other experts.

Consequently, presenting models created with VR can be a complete alternative to on-site inspections. VR platforms permit users to enrich the real world with digital content through a device (usually a pair of glasses) they view [80]. The 3D Model obtained by photogrammetry can be integrated into VR platforms. This integration is usually realized using a specific platform's software development tools and APIs. The transfer of the Model and DT to this platform enables users to interact with the real world. This type of technology has many potential applications [81,82]. For instance, it can be employed in education, virtual tourism, product promotion, industrial design, engineering analysis, and numerous other domains. The technology can be used to add information on real-world objects or to examine digital objects interactively [83]. Consequently, transferring DTs of 3D models obtained by photogrammetry to virtual reality platforms has significant potential for entertainment and business applications. This technology allows users to have new experiences by digitally enriching the physical world.

There are several considerations when integrating 3D models and DTs created by photogrammetry into VR platforms. Firstly, 3D models can often be large and complex, necessitating optimization for practical use on VR platforms. Reducing model size is essential for fast loading and viewing on multiple devices. VR platforms generally support specific 3D model formats. Consequently, it may be necessary to convert the 3D models obtained from photogrammetry into appropriate formats. For example, standard 3D file formats such as OBJ, FBX, STL, or USDZ are commonly used [84]. Since DTs created by photogrammetry can be integrated into real-world objects or scenes with VR content, it allows users to see 3D models or information superimposed on real-world objects while viewing them through their browser, which can be the basis for DT. Therefore, the data added to the Model is essential. VR platforms use specialized algorithms and technologies to accurately position and track users' devices in the real world. This ensures that the DT obtained by photogrammetry is accurately positioned in the real world. The resulting model is also essential in representing the real world.

Numerous popular platforms for storing, viewing, and sharing 3D models and DTs produced by photogrammetry with WEB-based VR are important for WEB-based VR projects. Popular platforms used for this purpose are Sketchfab, Unity3D, Unreal Engine, Google Poly, Mozilla Hubs, and Amazon Sumerian (Mouzakis et al. 2021). These platforms have advantages and disadvantages. These platforms provide straightforward access to 3D content and enable users to view it through their browsers. This facilitates the sharing of content with a broad audience, and they often offer user-friendly interfaces, making the process of uploading, viewing, and sharing content simple. Many platforms are compatible with standard VR devices. This enables users to access 3D content and VR experiences across different devices. Platforms allow users to share their content easily. It is possible to share content via social media, websites, or email [85].

In addition to these and similar advantages, the platforms' most significant disadvantages are the uploaded models' capacities and the lack of structural inspection tools. Therefore, as the study aims to transfer the produced DADT model to experts with VR platforms and perform structural inspections, a VR platform that allows structural inspection was used instead of a WEB-based VR (Fig. 11). Stratbox VR tool [86], a new platform, was used for these purposes. The VR platform employed in this study, Stratbox VR, was selected as a readily available solution that offers sophisticated capabilities for processing extensive photogrammetric models and enabling remote collaboration between experts. The Stratbox VR platform was selected based on its capacity to open complex 3D models [86], a crucial requirement for comprehensive structural investigations.

In contrast to other web-based VR platforms, Stratbox VR facilitates detailed DADT integration, thereby enabling precise measurements and real-time analyses within a virtual environment. This tool offers a seamless extension of capabilities to standalone computers and metadata databases, providing users with versatile options for comprehensive data exploration. When the virtual reality headset is worn, teams of experts can meet remotely in the virtual world and perform analyses from 3D models. This enables remote collaboration to become more effective. The most important feature of the tool is the ability to open complex and large data-storing photogrammetric models on the platform. It was, therefore, selected as a VR platform for the study. Stratbox VR is a robust platform for the development of VR applications and the integration of 3D models into the virtual reality environment in technical fields such as structural engineering [86]. The platform facilitates the high-resolution visualization of 3D models within a virtual environment, thereby enabling users to engage in interactive experiences within that environment. The construction of a VR module with Stratbox VR is comprised of several key stages. The initial step involves importing the 3D models into the platform in either OBJ or FBX format. Subsequently, operations such as object manipulation, measurement, and analysis are conducted on these models within a virtual reality environment. The Stratbox VR platform offers multi-user support, thereby facilitating collaboration between users situated in disparate locations within the same virtual environment [86]. One of the most significant advantages of this platform is its capacity to process large data sets with optimal performance, ensuring a seamless VR experience. Stratbox VR also facilitates real-time collaboration, enabling project teams to simultaneously examine and work on the same model. The VR module developed with Stratbox VR in this study exemplifies the potential of virtual reality in structural investigations. The module allows for comprehensive examination and analysis of structural models remotely and with the involvement of multiple users [86].

Figs. 12 and 13 illustrate the measurements taken on the VR platform and the 3D Model. Upon examination of Fig. 12, the crack length, as measured on the 3D Model at 20.045 cm, was recorded as 20 cm on the VR platform. The discrepancy between the two measurements is minimal. When Fig. 13 is examined, the measurement on the Model, which was 75.46 cm, was 75.4 cm on the VR platform. The differences between both measurements are minimal, and these results demonstrate that the VR tool can be employed in the structural inspection phase.

Although our team did not develop Stratbox VR, it was selected with great care based on its superior performance in managing the complex data requirements of structural health monitoring. The platform's distinctive capacity to facilitate collaborative, remote inspections and its robust management of voluminous data sets render it an optimal selection for this study. The measurements from the virtual reality platform demonstrated high accuracy with minimal discrepancies compared to the original three-dimensional model, further substantiating its efficacy for structural inspection.

4.5. User experience and feedback

To evaluate the VR platform's usability and effectiveness for bridge inspection, five civil engineering experts were asked to assess the system

Fig. 11. Showing the bridge's DADT model and its representation on a virtual reality platform for analysis purposes.

based on five key criteria. Each expert interacted with the VR-based DADT model, and their experiences were evaluated based on the following criteria: ease of use, visual clarity, measurement accuracy, accuracy of representation, and overall satisfaction. The evaluations are given in Table 5.

Upon analysis of Table 5 regarding ease of use, experts found the VR interface intuitive, user-friendly, and straightforward to navigate, noting a minimal learning curve. The experts assigned an average score of 8.6/10 to the VR interface, indicating high satisfaction. Regarding visual clarity, the VR system was commended for its high-resolution visualization of 3D models, which facilitates effective cracks and structural details inspection. The average score for this aspect was 9/10, reflecting the high-resolution visualizations that allow for clear inspection of other structural details. Regarding measurement accuracy, the experts rated the VR system 8.6 out of 10. This is because the measurements taken in the virtual reality environment were found to be in close alignment with those obtained through traditional methods, with only minor discrepancies noted. In terms of accuracy of representation, the system was rated an average score of 8.8/10 by experts for accurately reflecting real-world measurements, with only minor discrepancies observed. The experts were satisfied that the VR model accurately represented the physical structure, exhibiting only minimal inconsistencies. The overall satisfaction score was 8.8/10, indicating that the experts expressed high satisfaction with the system. The experts appreciated the high level of detail with which remote inspections could be conducted.

The experts provided predominantly favorable feedback, underscoring the potential of the VR platform to optimize the structured inspection process. The experts commended the capacity to interact with 3D models within a virtual setting, which they regarded as a notable advancement over conventional techniques. Furthermore, it was observed that the VR environment allows for more precise, time-efficient, and engaging inspections than traditional methods. The experts proposed minor enhancements, including adding more customizable features to the VR interface, to improve the platform further. The evaluation concluded that the integration of VR into structured inspection is not only feasible but also highly effective. Furthermore, the VR platform is a valuable tool for structured health monitoring and offers a viable alternative to on-site inspections. The feedback and scores indicate that the VR platform enhances inspection, increasing accuracy, efficiency, and user engagement.

5. Conclusion

This study aims to improve the inspection of buildings, which is laborious, subjective, costly, and difficult to document. The proposed methodology paves the way for a more objective and efficient assessment of structures. The methodology involves processing many images through SfM-based photogrammetry to generate a simplified polygonal surface model. While the process can be advanced with SfM without the necessity of pre-calibration, there may be instances where pre-calibration is required in specific areas. Accordingly, it is essential to gather data that is tailored to the specific study area in question. Subsequently, the identified cracks are automatically detected by the deep learning model, which is integrated with the methodologies to produce a DADT. In contrast to existing methods that rely on DT modeling of structures for structural health monitoring, the proposed technique reduces the need for user intervention.

Furthermore, it generates a short model suitable for rapid assessments and storage, providing significant advantages in cost, speed, accuracy, and applicability in structural inspections. Moreover, integrating information derived from image data is possible, and the

Fig. 12. Measurement on the VR platform (top) and 3D Model (bottom) with the DADT model of the bridge.

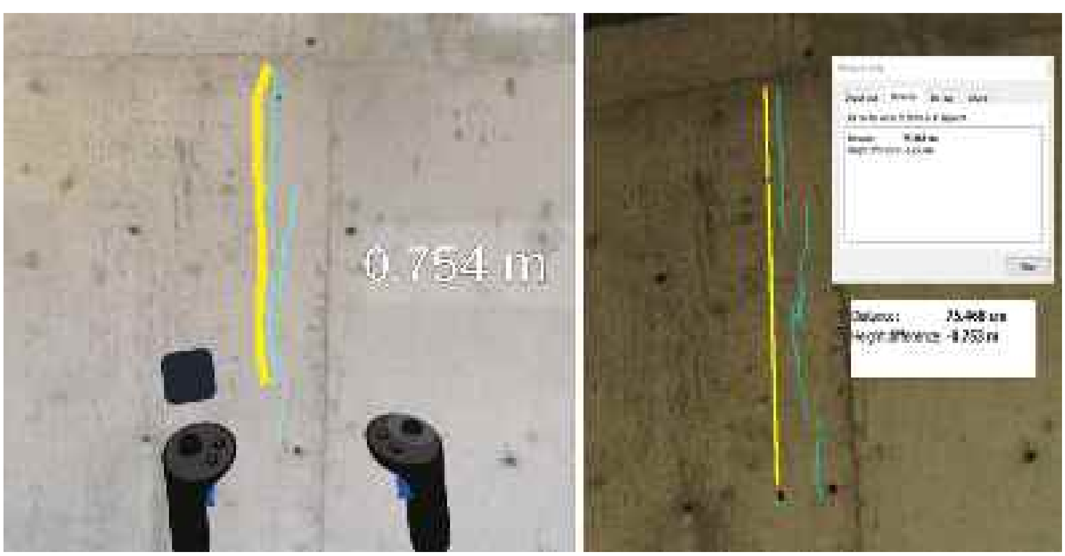

Fig. 13. Measurement on the VR platform (left) and 3D Model (right) with the DADT model of the bridge.

approach can be applied to various assets. To be more precise, this method allows for updating the model rather than initiating a new process from the outset. Furthermore, incorporating new data allows continuous integration of the existing DADT model. This approach enables adapting existing data and new information to the DADT model. The approach's effectiveness is contingent upon the quality of the image data. It is essential to consider the influence of different factors, such as image size, resolution, blur, and noise. Textures with low roughness or insufficient redundancy in the images are more likely to fail.

Additionally, environmental conditions, such as various shadows and different types of structures, harm the effectiveness of this method. Furthermore, it is essential to acknowledge that various factors, including time, period, season, daylight conditions, and building materials, may influence the method's accuracy. These conditions may result in inaccuracies and uncertain crack segmentation.

The findings and results of this study demonstrate the effectiveness of the method. This technique allows for the scanning, detecting, and retrieving information about small objects of interest, including

Table 5
The experts evaluated the VR-based DADT model according to five key criteria.

Experts No	Ease of Use	Visual Clarity	Measurement Accuracy	Accuracy of Representation	Overall Satisfaction
1	9	8	8	9	9
2	8	10	9	9	9
3	8	9	9	8	8
4	9	9	8	9	9
5	9	9	9	9	9
average	8.6	9	8.6	8.8	8.8

distortions such as deflections and cracks in reinforced structures. As an illustration, Table 4, which presents the results of the metric analysis, demonstrates that even cracks measuring less than five centimeters are identified with high sensitivity. In general, it is observed that the proposed method achieves outstanding success in terms of quality in 3D model generation. Moreover, this achievement has significantly improved the accuracy of crack detection in an automated manner through machine learning and deep learning techniques. It is crucial to highlight that the training model utilized should align with the experimental data, with clearly delineated subjective evaluations.

Consequently, this approach can expedite low-cost inspections, obviating the necessity for on-site inspections for damage detection. This study posits that the most significant advantage of this framework is its capacity to facilitate real-time use and accelerate the inspection process through the integration of virtual reality (VR) applications. The potential for expanding the reach of these results to a broader user base has become more feasible with the advent of contemporary internet technology. This study aims to demonstrate that it is possible to achieve a realistic experience by visualizing the obtained models with VR and that structural inspections can be performed quickly and effectively. It is shown how this can contribute to the current applications of engineering studies in building management by developing a functional design integrating DADT and VR.

Consequently, a comprehensive and accurate representation of the natural world is contingent upon an accurate and expedient data collection process and its portrayal within the DT concept. In developing a DT, photogrammetry methodologies are the most effective means of capturing the full spectrum of the Model. The DT, which emerges through the meaningful interpretation of the obtained data, plays a pivotal role in the analysis and representation by transferring it to the user through visualization tools such as VR. After the study, the structural 3D models were inspected and analyzed, transferred with VR visualization tools, and presented to different users. The findings will contribute to developing the optimal representation scenarios in future DT studies and the inspection and analysis of 3D models through integration with VR. Although not examined within the scope of this study, the experiences of experts in performing crack analyses and user feedback through virtual reality platforms can provide pioneering information for other studies. Considering the equipment, software, and expertise required to apply this method is essential. In addition, future studies should investigate the user-friendliness of these platforms, the difficulties encountered in practice, and potential improvements. Finally, although the proposed methods seem favorable for structured inspections, it is essential to consider the potential privacy and security issues associated with using DT and virtual reality platforms. It is paramount to subject the guidelines on data protection and privacy standards during the use of these technologies to rigorous scrutiny.

CRediT authorship contribution statement

Abdurahman Yasin Yiğit: Writing – original draft, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Murat Uysal:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Project administration, Methodology, Investigation.

Author Contribution

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Abdurahman Yasin Yiğit and Murat Uysal. The first draft of the manuscript was written by Abdurahman Yasin Yiğit, and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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.

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Data availability

Data will be made available on request.

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