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The future of conservation: Citizen Science models for the Photomonitoring of cultural heritage

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ABSTRACT: This study investigates the effectiveness of photomonitoring as a remote sensing technique for cultural heritage conservation, focusing on the Aurelian Walls (Rome) and the Church of Santa Apollonia (Ferrara), Italy. Using mobile devices such as smartphones and tablets, structural changes—including brick detachment and vegetation growth—were detected through Structural Similarity Index (SSI) mapping. The results highlight both the advantages and limitations of mobile-based monitoring, emphasizing its flexibility and rapid deployment. Key challenges include variations in pixel size and lighting conditions, which influence data consistency. Despite these limitations, the study supports the potential of citizen science integration to enhance spatial and temporal data collection. By leveraging crowdsourced imagery, monitoring efforts can become more comprehensive and cost-effective. The findings align with broader citizen science initiatives, demonstrating how non-invasive, mobile-based techniques can contribute to sustainable heritage preservation. Future research should focus on optimizing data acquisition and processing methodologies to improve the robustness of this approach.

KEY WORDS: Photomonitoring, Structural Similarity Index, Cultural Heritage Monitoring, Mobile Sensing, Citizen Science, Remote Sensing, Image-Based Analysis

1 INTRODUCTION

The preservation of cultural heritage is a crucial endeavor, safeguarding the tangible expressions of human history and identity. The monitoring of immovable cultural assets—including monuments, archaeological sites, and historic buildings—is essential to ensure their longevity and structural integrity. While traditional monitoring methods have long been utilized in heritage conservation, recent advancements in image analysis techniques, coupled with the growing role of citizen science, have significantly enhanced these practices. Cultural heritage sites face numerous threats, including environmental factors such as weathering, pollution, and natural disasters, as well as human-induced damages such as vandalism and urban expansion. Regular monitoring is essential for detecting early signs of deterioration, enabling timely interventions to prevent further damage and preserve the historical value of these sites. Additionally, continuous assessment supports informed decision-making regarding conservation strategies and resource allocation.

Historically, cultural heritage monitoring has relied on several established techniques. Visual inspections remain a fundamental approach, with conservators and archaeologists conducting systematic assessments to identify surface anomalies, structural cracks, or material degradation. However, this method is inherently subjective and may fail to capture subtle changes over time. Standard photography has been widely used to document sites, facilitating comparative analysis, yet it is often insufficient for detecting underlying structural issues or material compositions. Furthermore, environmental monitoring devices such as dataloggers provide valuable data on temperature, humidity, and vibrations affecting cultural assets. While effective, these sensors often require intrusive installation, which may pose risks to fragile structures.

In recent decades, the integration of advanced image analysis techniques has revolutionized cultural heritage monitoring, offering precise and non-invasive methods for assessing and preserving historical sites. The fusion of image analysis with geomatics and remote sensing technologies has significantly expanded heritage monitoring capabilities. The use of satellite imagery, such as data from Sentinel-2, allows for large-scale monitoring of archaeological sites, providing critical insights into environmental impacts and structural changes over time [1]. The incorporation of artificial intelligence (AI), particularly deep learning algorithms, has enhanced damage assessment accuracy in cultural heritage conservation. Automated detection and classification of deterioration patterns improve the efficiency of preservation efforts [2].

Moreover, linking hyperspectral imaging with other non-destructive analytical methods has further advanced research potential in this field. The integration of hyperspectral imaging with tensor-based learning models has improved the automated inspection of cultural monuments, allowing for detailed material characterization and defect classification, enhancing

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the accuracy of preservation strategies [3]. The application of unsupervised clustering techniques to hyperspectral images has been explored for monitoring cultural heritage degradation, enabling the detection of decomposition and corrosion levels, providing valuable data for conservation efforts [4]. Deep learning methods, such as autoencoders and Generative Adversarial Networks (GANs), have been successfully employed for anomaly detection on ancient stone stele surfaces [5], while convolutional neural networks (CNNs) have been utilized to identify structural damage in heritage buildings [6]. By processing high-resolution images, these AI-driven techniques facilitate the timely detection of defects, supporting proactive conservation efforts.

These image-based techniques offer several advantages over traditional methods: they are non-invasive, minimize direct interaction with artifacts, and generate high-resolution data that can be quantitatively analyzed. Furthermore, their digital nature allows for the creation of permanent records that can be revisited for future studies or restoration initiatives.

In 2022, the Italian Ministry of Culture and the CERI Research Center at the University of Rome Sapienza entered into a collaboration agreement to develop new guidelines for the monitoring of deformations that affect cultural heritage sites. Within this framework, our research group is testing various innovative, non-invasive monitoring techniques, from the landscape scale down to individual cultural heritage buildings. Photomonitoring has emerged as a cost-effective, precise, and rapid alternative to traditional analytical methods [7; 8]. By leveraging low-cost tools such as smartphones and entry-level cameras, photomonitoring enables accurate multitemporal analysis to detect vegetation growth, mortar detachment, and structural deterioration. Based on Digital Image Processing principles, this approach extracts both qualitative and quantitative insights into structural changes by analyzing and comparing images of the same area taken at different time intervals [9;10]. This paper explores the potential of photomonitoring through case studies, including the Aurelian Walls in Rome and S. Apollonia Church in Ferrara. The results demonstrate its effectiveness in providing detailed insights into structural changes, offering a sustainable solution for heritage management.

Having established the reliability of photomonitoring, the next objective is to involve communities in data collection through mobile and web applications. Initiatives such as IntelligEarth exemplify the intersection of technology and citizen science. This startup aims to revolutionize heritage monitoring by integrating crowdsourcing systems and citizen participation, enabling real-time reporting and analysis of environmental risks to cultural sites.

Citizen science—the active involvement of non-professional researchers in scientific initiatives—has become an invaluable component of cultural heritage monitoring and conservation. Integrating citizen science not only complements traditional monitoring efforts but also democratizes the preservation process, fostering a sense of collective responsibility. Equipped with smartphones and digital cameras, individuals can capture and upload images of heritage sites, contributing to large-scale monitoring databases. This approach significantly expands the spatial and temporal scope of data collection beyond what professional teams alone can achieve. Furthermore, engaging the public in heritage monitoring raises awareness about cultural preservation. Educational programs and workshops can empower communities to take an active role in conservation efforts.

Recent case studies highlight the effectiveness of citizen participation in heritage monitoring. The Tirtha project, launched in 2023, exemplifies the integration of technology and public engagement in cultural heritage preservation. This web platform enables crowdsourcing of heritage site images to generate detailed 3D models using advanced photogrammetry techniques. Contributors submit photographs that are processed to create accurate three-dimensional representations of cultural landmarks [11]. Monitoring and documenting remote heritage sites pose significant challenges for large heritage organizations. By encouraging tourists and local residents to share images captured during their visits, organizations can collect valuable data to assess the condition of sites, especially those that are unstaffed or in remote locations. This approach proved particularly valuable during the COVID-19 pandemic, ensuring continued monitoring despite travel restrictions [12].

The role of citizen science in cultural heritage conservation extends beyond data collection, fostering increased public awareness and community engagement. A compelling example of this dynamic is presented in the study of Kumar [13], which analyzed the response to the 1966 Florence flood and demonstrated how crowdsourcing efforts—long before the internet era—enabled effective heritage recovery through monetary donations, volunteer labor, and material support. The study further identified key motivational factors for public participation in such initiatives, including direct calls to action, media influence, and personal connections to affected cultural assets. These findings suggest that properly structured citizen science initiatives have the potential to mobilize extensive public participation in cultural heritage conservation, even in the aftermath of disasters.

The monitoring of immovable cultural heritage is a complex yet evolving field that has been greatly enhanced by technological advancements. While traditional methods have provided the foundation for conservation practices, the integration of sophisticated image analysis techniques has significantly improved the precision and efficiency of monitoring efforts. Simultaneously, the rise of citizen science has introduced a collaborative dimension, enriching data collection and fostering public involvement. Together, these advancements contribute to more effective and inclusive strategies for preserving the invaluable cultural legacies of humanity.

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2 MATERIALS AND METHODS

2.1 Instrumentation and Source Data

In the frame of this work, the acquisitions have been performed with two different sensors, one for each site. In both cases, it has been chosen a multi-temporal approach to monitor the evolution of the phenomenon over time, providing a more comprehensive and accurate perspective.

The first dataset of images was taken using a Tablet Samsung Galaxy Tab S7+, whose features are shown in Table 1.

Table 1 - Samsung Galaxy Tab S7+ characteristics

Sensor	13 MP
Sensor size	1/3.4"
Focal length	3 mm

To acquire the second dataset, a Smartphone Samsung Galaxy A54 was used, whose characteristics are shown in Table 2.

Table 2 - Samsung Galaxy A54 characteristics

Sensor	12 MP
Sensor size	1/1.56"
Focal length	6 mm

As for the acquisitions, the images taken with the tablet were captured manually, while a tripod was used for those acquired with the smartphone. In order to keep the same position and the same camera orientation between one acquisition and another, it has been used the software of feature tracking CARE, that allows to obtain the same exact position of the previous acquisition. This is essential to ensure the best performance during the analysis, giving a more accurate result in the co-registration process.

Data collection lasted for more than a year. The tablet dataset has been collected in two phases, the first one from November to December 2022; the second one from December 2023 to November 2024. The smartphone dataset has been acquired over a period of one year, from February 2024.

Table 3 - Images characteristics

Subject	Date	Dimensions	Distance	Pixel Size
K11-K12 section	27-12-2022/19-01-2024	6.27 MB – 5.84 MB	30 m	19,3 mm
K12-K13 section	19-01-2024/19-09-2024	6.67 MB – 6.19 MB	32 m	20,6 mm
Sant' Apollonia Church	13-06-2024/26-09-2024	9.56 MB – 8.39 MB	6 m	2,67 mm

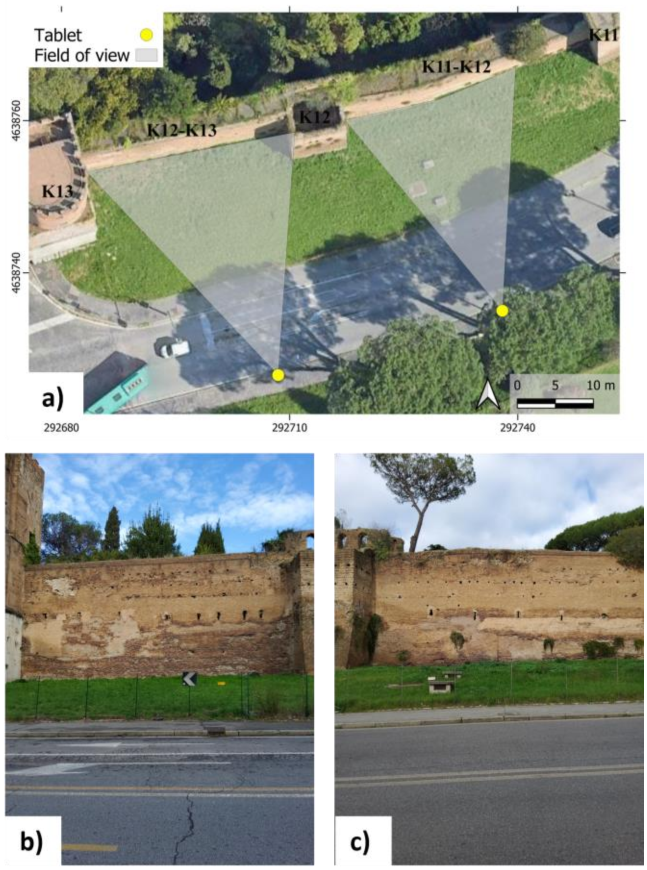

Fig. 1 Map showing the Aurelian Wall cases of study and the positions of acquisition (a). Frame of the K12-K13 section (b). Frame of the K11-K12 section (c).

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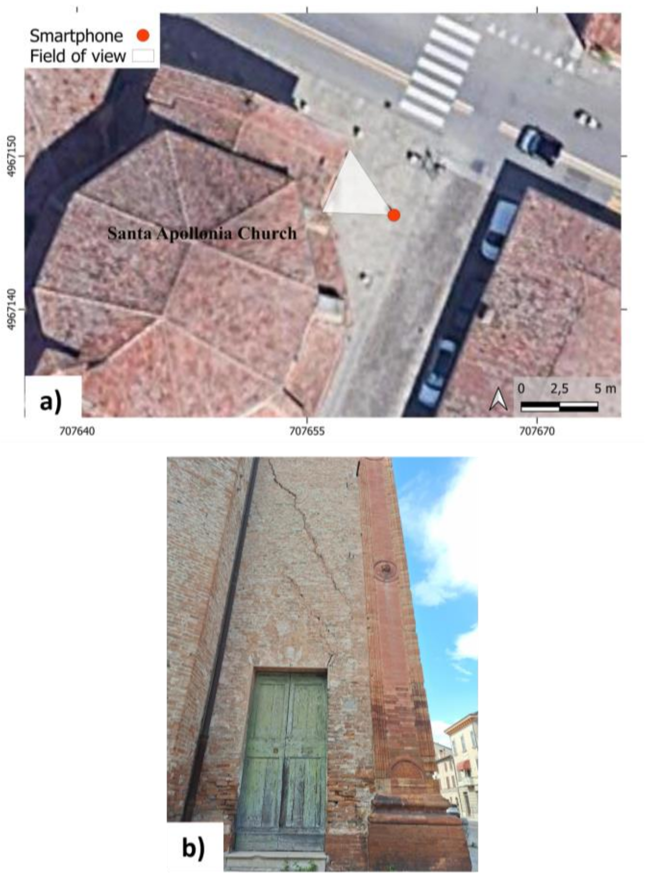

Fig. 2 Map showing Santa Apollonia Church case of study and the positions of acquisition (a). Frame of acquisition (b).

2.2 *Methodology*

The data acquired for this study were processed using Change Detection (CD) algorithms. Change Detection is a Digital Image Processing (DIP) technique that allows to identify variations between images acquired at different time intervals by comparing a reference image (master) with one or more successive images (slave) [14]. Digital images, represented as numerical matrices, enable the identification of features such as points, lines, patterns, color, brightness, and contrast. The comparison of these features between temporally successive images allows for the precise detection of changes within the area of interest [9]. Several Change Detection methods have been developed to date. Pixel-based approaches directly compare intensity values between successive images. Statistical approaches, such as the Mean Squared Error (MSE) and the Peak Signal-to-Noise Ratio (PSNR), quantify variations based on error metrics [14, 15]. Perceptual-based methods, such as the Structural Similarity Index (SSIM), analyze changes while accounting for human visual perception [16]. The accuracy of Change Detection, regardless of the method adopted, depends on the quality of the acquired images and the ability to distinguish actual structural modifications from variations induced by atmospheric conditions or illumination differences. Additionally, the presence of distinctive patterns or appropriate speckle models in the scene is also essential to ensure robust identification of corresponding features in successive images. Therefore, accurate image co-registration is essential to guarantee proper spatial alignment between consecutive datasets, minimizing geometric distortions that could compromise the analysis [16]. The CD approach implemented within the software utilizes the Structural Similarity Index (SSIM) method [16; 17]. SSIM is an algorithm developed to quantify image similarity by analyzing three fundamental components: luminance, contrast, and structure [17]. Compared to conventional metrics such as MSE and PSNR, SSIM is based on a perceptual model, offering a more accurate assessment of visually perceptible modifications [16]. This method has demonstrated considerable potential for detecting changes due to its robustness and accuracy [18].

The SSIM index is defined by the following equation (Eq. 1):

$$SSIM(x,y) = [l(x,y)]^{\alpha} \times [c(x,y)]^{\beta} \times [s(x,y)]^{\gamma} \quad (1)$$

where l(x,y) represents luminance, which evaluates the difference in brightness between the two images, c(x,y) expresses contrast, which differentiates the intensity range between the brightest and darkest regions of the images, and **s**(x,y) represents structure, which compares the local luminance pattern between two images to assess similarity and dissimilarity. The exponents α, β and γ are positive constants that govern the weight of each component in the final computation. The algorithm is applied to local windows within the images and returns a value ranging from 0 to 1, where **0** indicates a complete change and **1** indicates an area where no changes have been detected. Intermediate values suggest partial variations, indicating potential structural modifications or illumination changes. The Change Detection analysis in the IRIS software begins with the selection and uploading of the master and slave images, followed by an additional image co-registration phase to achieve perfect dataset alignment [7]. The next step involves selecting the Window Size (WS) parameter. This parameter is crucial as the software employs a sliding window approach, computing the SSIM index on patches defined by the Window Size (WS) and assigning the calculated SSIM value to the central pixel of each patch.

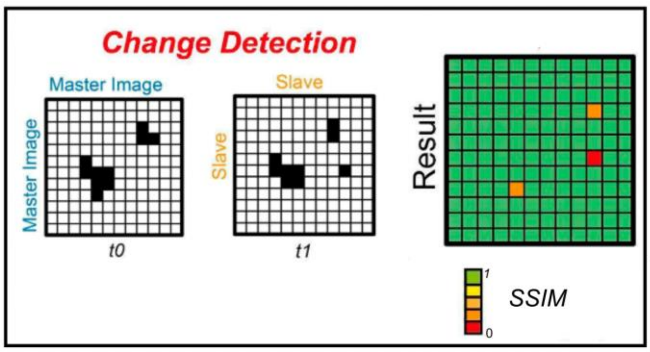

Fig. 3: Conceptual scheme illustrating the process of change detection (CD) analysis. Two images are compared to identify changes that occurred during the time interval t0–t1

Once the desired Window Size is selected, the next step involves assigning the weight of the individual contributions in the SSIM computation. This step is critical for ensuring the

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correct execution of Change Detection. The software allows for adjustment of the α, β and γ exponents, exponentially increasing the analysis sensitivity based on specific cases. Operating at a local scale, the software iteratively evaluates image similarity within small pixel subsets defined by the WS, enabling the automatic detection of change regions.

The choice of the Window Size (WS) is fundamentally informed by the expected scale of detectable changes within the monitored structures. A properly defined WS allows the analyst to selectively filter out minor disturbances or non-structural changes that are not relevant to the analysis objectives. This tuning capability is particularly useful when addressing noise induced by lighting variations or acquisition-related inconsistencies, such as slight displacements, shadows, or differences in ambient conditions.

To further refine the detection process, the software supports semi-automatic calibration of the exponential weighting factors α, β, and γ within the SSIM algorithm. These parameters respectively control the contribution of luminance, contrast, and structural components, and their adjustment is essential for minimizing false positives caused by non-structural changes (e.g., shadow displacement or illumination shifts). By modulating these parameters in accordance with the selected WS, it is possible to enhance the robustness of the analysis, isolating meaningful structural variations while attenuating the influence of irrelevant fluctuations. This methodological flexibility is key to adapting photomonitoring workflows to diverse environmental and acquisition conditions.

The result of this analysis is a raster map that visualizes SSIM values for each individual pixel through a color gradient. Green indicates an SSIM value of 1, implying no change, while blue represents an SSIM value of 0, indicating a complete change.

3 CASE STUDY

One of the selected case studies is the Aurelian Walls in Rome, a monumental archaeological structure that once served as the primary defensive boundary of the city and now forms a significant part of Rome's UNESCO World Heritage designation. As the largest surviving monument in the city, the walls hold immense historical and architectural value. However, they are increasingly threatened by invasive vegetation, including species such as *Hedera helix* L., *Ficus carica* L., and *Capparis orientalis* Veill. (*Capparis spinosa* L.), with *Ailanthus altissima* emerging as the most invasive and difficult species to control [19, 20, 21, 22].

Geologically, the Aurelian Walls are located in an area characterized by Quaternary volcanic formations and Holocene alluvial deposits from the Tiber River. Constructed under Emperor Aurelian between 270 and 275 AD, with subsequent completion under Emperor Probus, the walls originally extended approximately 19 km, though only 12.5 km remain today due to partial demolitions. Structurally, they consist of a combination of tuff and brick masonry, with an inner core composed of loosely bonded tuff blocks. Over the centuries, conflicts and environmental factors have contributed to their deterioration, prompting numerous restoration interventions. Notably, during the 16th century, Pope Pius IV commissioned extensive reinforcements to enhance their stability [23, 24]. More recently, the Capitoline Superintendence has undertaken conservation projects aimed at safeguarding the remaining sections and preventing structural collapses.

The second case study focuses on the Church of Santa Apollonia in Ferrara, a city recognized as a UNESCO World Heritage Site since 1995. Originally built in the 15th century, the church underwent significant reconstruction in 1612, transforming into an oratory with an expanded classical octagonal layout. Further modifications were made in 1662, including the incorporation of the portal from the Church of the Holy Spirit (*Chiesa dello Spirito Santo*), which had been demolished in 1839. The church remained closed since 1975 and was later deconsecrated. Over time, it has fallen into severe neglect and structural decay. Santa Apollonia has since been placed under state management as part of a broader restoration and redevelopment initiative aimed at repurposing its interiors into an exhibition space for the nearby National Archaeological Museum of Ferrara. The building, like many others in the region, is constructed on permeable fluvial sand deposits, which have contributed to significant water infiltration and accelerated degradation. Located north of the so-called Isola di Sant'Antonio, the structure exhibits pronounced signs of moisture-induced deterioration, with severe cracking observed along the left lateral wall, highlighting the urgent need for intervention.

4 RESULTS

Over a time span of more than a year, numerous changes have been identified in the two datasets. The changes observed during this period affect the vertical external curtain of the Aurelian Walls and the wall facing of Santa Apollonia church and consist mainly in detachments of bricks or mortar and vegetation growth. The product of the analysis is shown as a Structural Similarity Index Map where the changes are differentiated on the SSI values. Areas where no changes are present are highlighted in green, while changes are highlighted in red/purple, depending on their magnitude.

4.1 Aurelian Walls

<u>K11-K12 section</u>: The map in Fig. 4 c) shows some brick detachment on the external curtain. These bricks have a low similarity index value and are highlighted in red. Although the primary objective of the analysis was to detect structural changes, in this specific case the SSIM mapping also revealed variations associated with the growth of invasive vegetation (see upper-left portion of the image). These changes, while not structural in nature, contribute to the overall degradation of the wall surface and are thus relevant for conservation monitoring.

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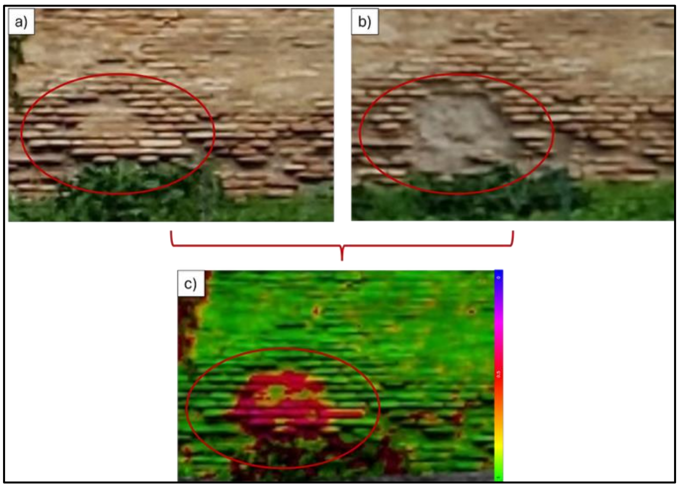

Fig. 4 - Detail of the Change Detection Map showing the bricks detachment from the K11-K12 section.

K12-K13 section: The map in Fig. 5 c) shows the vegetation growth. The areas of growth can be seen in red due to their low similarity index value.

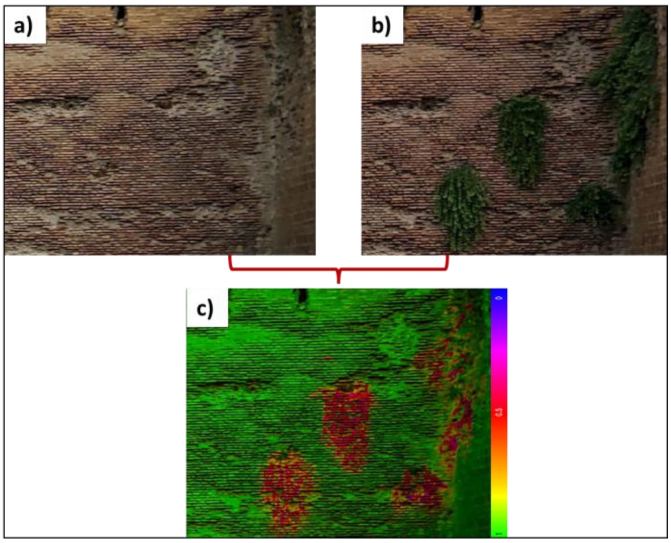

Fig. 5 - Detail of the Change Detection Map showing vegetation growth from the K12-K13 section.

4.2 *Sant'Apollonia Church*

Sant'Apollonia Church: The map in Fig. 6 c) shows a brick detachment in conjunction with the pre-existing crack.

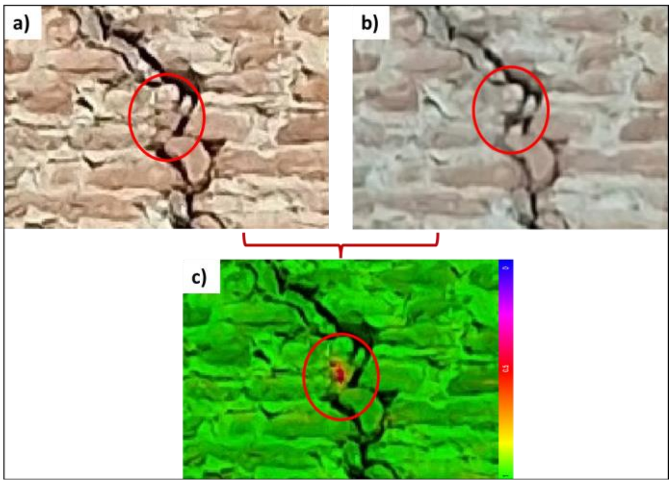

Fig. 6 - Detail of the Change Detection Map showing the brick detachment from the facing wall of Santa Apollonia Church.

Sant'Apollonia Church: In the Change Detection map in Fig. 7 c) it is shown, in purple, a mortar detachment connected to a pre-existing crack.

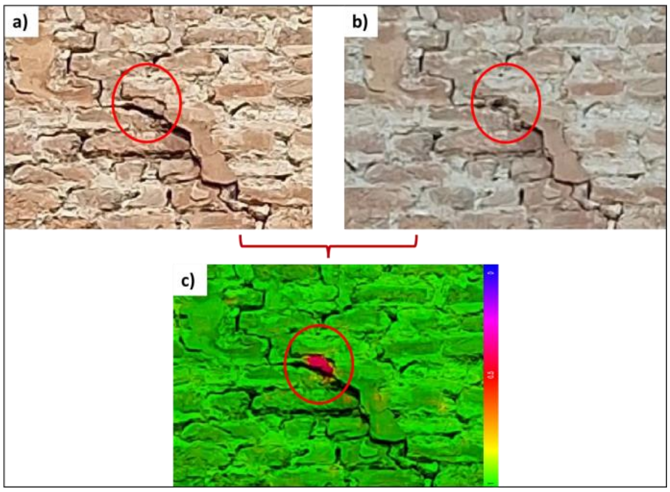

Fig. 7 - Detail of the Change Detection Map showing mortar detachment from the facing wall of Santa Apollonia Church.

5 DISCUSSIONS

The results of this study highlight both the effectiveness and the limitations of using mobile devices, such as smartphones and tablets, for environmental and cultural heritage monitoring. A key logistical advantage observed during field activities was the increased speed of repositioning and orienting the sensor when used manually compared to tripod-mounted systems. In this context, the tablet proved more efficient than the tripod-mounted smartphone, allowing for immediate sensor realignment and reducing the time required for data acquisition. This aspect is particularly relevant in scenarios where monitoring must be performed rapidly or in spatially constrained environments, confirming previous findings on the advantages of mobile device-based monitoring methodologies [12].

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The type of changes detected by the two sensors was comparable, suggesting that smartphone and tablet cameras can provide similar results in image-based monitoring. However, a critical aspect to consider is pixel size, which depends not only on the intrinsic characteristics of the sensor but also on the distance from the observed object. In field conditions, this distance is often dictated by logistical constraints rather than experimental design, making it a variable that is not always controllable. Since pixel size directly affects the level of detail in image analysis, these factors must be carefully considered when designing a monitoring approach based on mobile sensors. Previous studies on cultural heritage monitoring through crowdsourcing emphasize the importance of such considerations, particularly when comparing images acquired with different devices under varying shooting conditions [13, 25].

Another critical factor influencing data quality was the variability in lighting conditions. Sudden changes in natural light posed challenges for image acquisition, affecting both processing and interpretation of results. This issue is well-documented in the literature, particularly regarding the impact of brightness variations on image-based analyses [25]. In some cases, excessive differences in lighting conditions between successive images introduced artifacts or inconsistencies in the final data, highlighting the need for adaptive calibration techniques or post-processing corrections to minimize these effects.

To address these lighting-related challenges, during this study we experimented with the adjustment of the α, β, and γ exponential parameters in the SSIM computation. Fine-tuning these parameters proved effective in minimizing the influence of illumination variation between successive image acquisitions. By reducing the contribution of luminance and contrast inconsistencies, the analysis becomes more sensitive to actual structural changes rather than to superficial alterations induced by light fluctuations. As a result, this approach enhances the robustness of the change detection process by suppressing noise and emphasizing the “true” changes that are structurally relevant to the monitored object.

An alternative but more computationally intensive strategy could involve the use of a redundant analytical framework, leveraging a broader image database for each observation. This would allow for comparative filtering and normalization across multiple acquisitions, thereby reducing the risk of localized errors introduced by individual source images. While this method could significantly improve result stability, it requires higher processing power and longer computation times, which may limit its applicability in real-time or field-based contexts.

Additionally, adjusting the Window Size (WS) also contributed to filtering the results based on the expected scale of the changes of interest. Smaller WS values allowed for detection of fine-grained alterations, while larger WSs enabled the system to disregard minor fluctuations and focus on broader structural modifications. This flexibility supports the customization of the methodology to different conservation goals, depending on whether fine detail or macroscopic patterns are prioritized. Moreover, the application of photomonitoring for field-based heritage monitoring must also consider several site-specific environmental factors that may compromise the accuracy and interpretability of the results. As discussed in [26], there are a number of additional techniques and methodological improvements that can be adopted to enhance the overall accuracy, precision, and sensitivity of the analysis. However, the effective implementation of these advanced strategies requires careful calibration and expert knowledge, underscoring the importance of involving trained professionals in the design and interpretation of photomonitoring protocols.

Future studies should explore solutions such as High Dynamic Range (HDR) imaging or automated color correction algorithms to mitigate the impact of uncontrollable lighting variations and improve the robustness of mobile-based monitoring techniques. Alternatively, integrating the workflow presented in this study with Citizen Science approaches would enable the collection of large datasets with high temporal resolution, allowing for the calibration of AI models and mitigating the issue of varying lighting conditions and/or shadows.

Despite these challenges, the results demonstrate that effective monitoring can be achieved without the installation of fixed cameras or permanent sensors, relying solely on mobile devices. This outcome is particularly significant in the context of non-invasive cultural heritage monitoring, where minimizing physical interference is often a priority. Similar conclusions have been reached in Citizen Science studies, which emphasize how mobile technology can be leveraged for large-scale data collection while maintaining high methodological rigor [27, 28]. The ability to conduct fully contactless monitoring without requiring pre-installed instrumentation broadens the applicability of these methodologies, particularly in remote or sensitive sites where conventional instrument installation is impractical.

Overall, these findings support the potential of mobile device-based monitoring approaches as viable alternatives to traditional fixed-sensor systems, offering a flexible and scalable solution for environmental and cultural heritage analysis. However, further refinement of data processing techniques is needed to account for environmental variability and ensure consistency across different devices and observational conditions.

6 CONCLUSIONS

The primary objective of this study was to assess photomonitoring as a remote sensing technique for the monitoring and preservation of cultural heritage. The results demonstrate that photomonitoring represents an effective and non-invasive approach to detecting structural variations, such as mortar detachment in the masonry of the Aurelian Walls and the Church of Santa Apollonia in Ferrara. The use of widely accessible devices, including smartphones, tablets, and entry-level cameras, makes this methodology not only cost-effective but also adaptable to the specific requirements of different monitored sites.

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The potential integration of citizen science into this framework presents a promising opportunity for expanding spatial and temporal data collection. Volunteers, acting as "sensor-visitors," could contribute images and observations that complement the work of professional conservation teams. This collaborative approach has the potential to enhance data coverage, bridging the gaps between scheduled professional surveys and ensuring more continuous monitoring of degradation dynamics. As noted by Bonney et al. [27], citizen science has been successfully implemented across various scientific fields, significantly improving data collection and public engagement. The economic implications of photomonitoring are particularly relevant, considering the extraordinary volume of images generated daily. It is estimated that in 2023, approximately 4.7 billion photographs were taken per day, predominantly using smartphones (93%), resulting in an annual total of approximately 1.8 trillion images. This statistic highlights an immense, yet largely untapped, visual resource that could be harnessed for cultural heritage monitoring. Through crowdsourcing and advanced data analysis, the simple act of taking a photograph can be transformed into a valuable tool for conservation. This approach not only reduces costs but also increases the frequency and geographical coverage of observations. As the quality of images and computational capabilities continue to improve, the integration of citizen-generated data into heritage conservation strategies could evolve into a sustainable and scalable solution [12].

The findings of this study align with a broader context of citizen science initiatives, which have demonstrated dual benefits: enhancing scientific productivity and democratizing research. Unlike basic crowdsourcing, citizen science projects are designed to achieve specific scientific objectives, involving non-expert volunteers in both data collection and analysis [26]. Contributions from participants are not limited to quantitative data but often include qualitative observations, reports of unauthorized interventions, and even personal narratives related to historic sites. As highlighted in studies such as that of Constantinidis [28], these elements provide valuable contextual information that can influence both short-term conservation decisions and long-term management strategies.

Looking ahead, the integration of photomonitoring with structured citizen science programs could be further explored through collaborations with other institutions (i.e. Superintendences for Cultural Heritage), and local governments. A promising development in this direction is the potential use of civil service programs for structured photomonitoring campaigns. By engaging volunteers through civil service initiatives, it would be possible to create systematic and large-scale monitoring efforts that ensure sustained data collection and improved methodological rigor. This approach could also provide training opportunities, fostering a new generation of conservation advocates equipped with digital skills relevant to heritage preservation.

As imaging technologies and computational capabilities continue to advance, the integration of citizen-generated data into professional conservation strategies could evolve into a sustainable and idely adopted practice. Future research should focus on refining methodologies to optimize data acquisition and processing while exploring policy frameworks that support the ethical and effective implementation of citizen science in heritage conservation. By embracing photomonitoring as a collaborative tool, the preservation of cultural heritage can be made more accessible, inclusive, and resilient to emerging threats.

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