ENHANCING DATABASES FOR AI ASSISTED DIAGNOSIS AND DOCUMENTATION OF ACID-RAIN-AFFECTED SANDSTONE FACADES

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1. Introduction

El-Mina, a coastal city in the north of Lebanon, faces a grave conservation crisis. Historic sandstone structures in Labban Plaza, some dating to the 14th century, are deteriorating at a shocking rate. During first site visits in 2023, we documented large façade damage, exfoliated surfaces, deep cracks penetrating structural elements, and considerable material loss, that are attributed to the increasing industrial activity and vehicle emissions in the region [1].

The Jiyeh power plant, located about 15 kilometers south of El-Mina, and dense urban traffic release elevated levels of sulfur dioxide and nitrogen oxides into the atmosphere. These contaminants combine with humidity to form acidic precipitation, which, when measured pH ranged from 4.2 to 5.6, lower than natural rainwater [2]. The sandstone façades, traditionally protected by lime mortar coatings, have become targets for this chemical attack. The dust deposit and air pollution accelerate the degradation process and create a consequential combination that threatens the structural integrity of these heritage buildings [3].

The rapid industrialization in Lebanon, in most coastal areas like El-Mina, has occurred without corresponding contamination controllers or conservation regulations, leaving historic buildings susceptible to a variety of risks [4].

We address a fundamental limitation in current conservation practice - the gap between environmental monitoring data and damage assessment. We developed a structured database that directly correlates environmental exposure conditions with resulting decay patterns. This integrated approach enables conservation professionals to prioritize interventions based on environmental data rather than visual inspection alone.

There were three steps. First, we investigated and quantified the relationship between acid rain exposure and sandstone degradation through field surveys of three historic buildings in El-Mina and controlled laboratory experiments. Second, we documented crack pattern evolution under varying pH conditions, creating a classification system that links specific morphologies to environmental exposure levels. Third, we developed a structured database architecture that correlates environmental data with damage documentation, then validated its utility by training CIABC v0.00, a computer vision system for automated crack detection. The database structure supports both traditional conservation documentation and machine learning applications. This helps conservation professionals move from reactive repairs toward predictive maintenance based on environmental monitoring [5].

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Current conservation practices in El-Mina rely on visual inspections conducted by restoration specialists. These assessments, while valuable, present several limitations we encountered during our fieldwork. One example is that inspections are scheduled months apart, allowing damage to progress between visits.

To address these challenges, we developed CIABC v0.00 (Crack Identification AI for Building Conservation), a computer vision system designed specifically for detecting acid rain-induced damage in sandstone façades. The tool processes high-resolution photographs of building surfaces, identifying and classifying crack types that correlate with specific pH exposure levels we established through laboratory testing. Training CIABC required a structured dataset linking environmental conditions to visual damage patterns, a resource that did not exist for acid rain decay in heritage contexts. The system can process hundreds of images in minutes, identifying damage patterns that may take a restorer hour to document. By correlating detected cracks with our environmental database, CIABC can suggest pH exposure levels and predict areas of future deterioration based on current damage patterns.

It shows that structured, domain-specific datasets can enable effective AI applications in heritage conservation. The database we created serves not only as training data for CIABC but as a foundation for future machine learning tools that could predict deterioration rates, prioritize restoration efforts, or simulate the effects of different conservation interventions before physical work begins.

2. Literature review

Existing research on acid rain damage and heritage conservation has developed in parallel, with partial integration between environmental science, material degradation studies, and computational conservation tools. Many researchers who have studied acid rain chemistry provide an understanding of precipitation acidity and its formation mechanisms [6], while material science research documents how sandstone responds to acidic exposure [5]. Recent work in digital heritage conservation shows the potential of AI and machine learning for damage detection and monitoring [7].

A serious limitation emerged during our literature review, in that while individual studies address acid rain chemistry, material degradation, or separate AI applications, few attempts have been made to create combined datasets that directly associate specific environmental conditions (pH levels, pollutant concentrations) with consequential damage patterns (crack types, material loss) in formats suitable for machine learning training. Projects like the European INCEPTION initiative focus on 3D modeling and BIM integration, while the Getty Conservation Institute emphasizes material characterization, but neither specifically addresses acid rain decay nor do they provide the structured, multi-modal data (images + environmental measurements + material properties) required for training predictive AI models [8].

This gap motivated our research approach, thus, rather than studying acid rain effects, material degradation, or AI applications in isolation, we developed a method that integrates all three domains through a relational database architecture. Our dataset directly links environmental exposure conditions to visual damage documentation, creating the foundation for AI tools that can predict deterioration based on environmental monitoring data.

2.1. Overview of acid rain and its chemical characteristics

Likens recognized the important mechanisms of acid rain formation - sulfur dioxide and nitrogen oxides from fossil fuel combustion mixed with atmospheric oxygen and water vapor to form sulfuric and nitric acids - which then falls as acidic precipitation. Moreover, urban areas near industrial zones experience higher acid rain frequency and intensity than rural regions [6].

Karam documented this pattern in coastal Mediterranean cities, including El-Mina, where industrial emissions combine with marine aerosols to create precipitation. The chemical composition of urban acid rain has become more complex as new industrial activities introduce additional pollutants that modify the traditional SO_2/NO_x balance, creating synergistic effects that make material degradation go beyond the effects of acidity alone [9]. While the main concepts of acid rain creation are well documented, Karam's study identifies a crucial need in the research in order to understand the unique synergistic impacts of coupled industrial and marine contaminants, which are frequently studied in isolation. Exposure to acid rain accelerates material weathering, mainly in urban areas. Historic Mediterranean coast cities buildings constructed from acid-vulnerable materials face an elevated risk of high corrosion [10].

2.2. Effects of acid rain on sandstone material

When acidic precipitation contacts sandstone surfaces, chemical reactions dissolve the binding material, weakening the internal structure and creating pathways for environmental damage. The traces of damp on the surface, resulting in the formation of efflorescent salts and melted stone surfaces, appear as the first noticeable signs of acid rain damage [11]. This corrosion exposes the deep stone layers to water infiltration, and biological colonization, as it accelerates deterioration. This damage harms both the structural and aesthetic value, as over time, decorative elements are eventually lost together with the material [12].

The coastal areas of Lebanon experience high humidity levels combined with sea salt deposition and temperature fluctuations, which create extra stress on historical buildings. When acid rain is added to these conditions, stone decay quickens. Studies have shown that sandstone from historic Lebanese buildings exhibit granular disintegration and salt crystallization, both of which are aggravated by acid exposure. The existence of air pollutants in Lebanese coastal cities accelerates the degradation process [13]. Chen and Liu publicized distinct mineralogical changes in sandstone during acid rain exposure, offering serious insights for damage prediction models [14].

2.3. AI applications in heritage conservation and crack detection

Cracks in historic buildings are the result of multiple interacting factors, the environmental exposure, the structural movements, the material aging, and the element degradation. Acidic rain is an environmental issue; it accelerates weathering in limestone and sandstone by dissolving the mineral elements and stimulating the development of microfractures [15].

Research on monuments in Cairo, Rome, and Luxor have documented both superficial and deep cracking patterns directly related to acid rain exposure, with damage severity associated with pollution levels and exposure duration [5]. Recent work by Martinez et al. carried predictive modeling approaches that have shown there is a quantitative relationship between crack spread rates and environmental pH levels [16].

Recent advancement in digital technology has improved researchers' capacity to detect and categorize various cracks: 1-patterns, 2-vertical, 3-horizontal, 4-irregular, and 5-branched, within structural materials. This precision enables a deeper understanding of both the causes and the progression of structural deterioration. In addition, Martinez et al. highlighted the importance of model damage when analyzing orthotropic materials, such as masonry, which has led to more consistent predictions concerning crack propagation and stress distribution, in the context of environmental influences [16].

The systemic practice of crack mapping and ongoing monitoring has become essential to conservation efforts, especially in the Middle East, where historical structures are exposed to similar climatic and pollution-related challenges. These long-term initiatives guide the prioritization of restoration efforts and also create a foundation for adding advanced tools, including artificial intelligence, into the monitoring and preservation of heritage buildings [17].

Modern research has revealed several irreplaceable elements within traditional documentation methodologies. In the domain of tactile evaluation protocols of historical buildings, restoration specialists or restorers use direct physical examination approaches to analyze material compositions. These established methodologies enable assessment of artisanal qualities through time-validated conservation protocols [18]. Documenting knowledge of specifications remains crucial, encompassing the interpretation of architectural forms, the examination of historical importance, and the evaluation of cultural impact. Its knowledge base is also relevant to traditional building techniques. Physical verification procedures still perform this basic function, and include empirical measurements, material analysis protocols, evaluations of the environment, and visualization, which are much more complex than automated systems are currently able to deal with [19].

2.4. The Inception project: 3D modelling and semantic enrichment in digital heritage

The European Union's INCEPTION (Inclusive Cultural Heritage in Europe through 3D semantic modelling) project represents a significant advancement in digital documentation of cultural heritage through its integration of 3D modeling, Building Information Modeling (BIM), and semantic enrichment technologies. Launched as part of Horizon 2020, INCEPTION addresses the challenge of creating interoperable 3D models that capture both geometric and semantic information about heritage structures [20].

INCEPTION's methodology centers on the development of semantically enriched 3D models that integrate geometric data with structured information about materials, historical periods, conservation states, and cultural significance. The project employs a multiscale approach, enabling documentation from building-scale down to detailed component analysis [21]. This semantic enrichment allows for querying and analyzing heritage data beyond simple geometric visualization, supporting conservation planning, risk assessment, and research applications.

A key innovation of INCEPTION is its use of Historic Building Information Modeling (HBIM), which extends traditional BIM methodologies to accommodate the irregular geometries, historical modifications, and material heterogeneity characteristic of heritage structures. Unlike conventional BIM systems designed for new construction, HBIM must account for as-built conditions, deterioration states, and incomplete historical records. INCEPTION addresses these challenges through flexible data structures that can accommodate uncertainty and temporal changes [22-23].

This approach enables data sharing and integration across European heritage institutions while maintaining consistency in terminology and classification. The semantic layer supports advanced querying capabilities, allowing researchers to identify structures with specific material characteristics, deterioration patterns, or historical features [24]. However, while INCEPTION excels in 3D geometric documentation and semantic structuring, it does not specifically address the integration of environmental monitoring data with visual damage documentation in formats optimized for machine learning applications [25].

Our approach complements INCEPTION's framework by adding a specialized layer for environmental-degradation correlation. While INCEPTION provides the geometric and semantic foundation for heritage documentation, our database architecture specifically links environmental exposure conditions to damage patterns, creating datasets optimized for predictive AI models. This integration could potentially enhance INCEPTION-compliant models with environmental monitoring data and automated damage detection capabilities.

2.5. Comparative analysis of existing digital heritage datasets

Non-invasive documentation methods, including infrared thermography, photogrammetry, and 3D scanning, have become standard tools in heritage conservation [7]. In the meanwhile, developments in artificial intelligence and machine learning have provided new potential for automated damage detection and monitoring [26].

Nowadays, digital heritage initiatives vary in scope and approach. The European Union's INCEPTION project focuses on 3D modeling and BIM integration, while the Getty Conservation Institute emphasizes material characterization databases. Our approach differs by specifically targeting acid rain-induced damage patterns and integrating quantitative environmental data with visual documentation. While projects like INCEPTION provide valuable macro-level structural data and the Getty Institute's work offers deep material insights, our database creates a unique bridge by directly correlating specific environmental stressors (acid rain) with micro-level decay patterns (fissure development), a link for developing predictive conservation models [27].

Convolutional Neural Networks (CNNs) have showed effectiveness in detecting microscopic cracks on stone surfaces [28]. Recent developments by Wang et al. reported that deep learning models can, moreover, achieve 95% accuracy in automated crack detection when trained on specified datasets [29].

Photogrammetry, also known as Structure from Motion (SfM), is the process of converting 2D photographs into 3D models by overlapping photos from different viewpoints. It reconstructs 3D shapes by projecting them on the sensor's 2D plane [30]. Laser scanners generate 3D data for surface descriptions, distinguishing cracks, worn edges, but this process remains challenging due to low resolution despite millions of points [31]. Digital photogrammetry employs overlapped photos to calculate 3D dimensions, position, and form, employing the idea that a point measurement shows in at least two photographs [32]. HBIM, a geometric digital representation, offers insights into materials and deterioration, and is more effective for restoration than traditional 3D models [33]. Laser scanning and photogrammetric products struggle with complex surface reconstruction when integrated with HBIM models, as extrapolation overlooks constructive logic and geometry [34].

The integration of structured databases with AI training protocols offers a pathway to more conservation documentation. Our work in El-Mina represents the first application of this integrated approach to acid rain damage in a Lebanese heritage context. The three case study buildings provide both the field data and validation sites for testing our database structure and CIABC detection system. The combination of digital documentation methods, such as photogrammetry, and high-resolution imaging, with structured data management, SQL databases, and machine learning applications, such as pattern recognition, creates new prospects for conservation practice. Instead of replacing traditional expertise, these tools augment human assessment capabilities by processing large volumes of data quickly and identifying patterns that may be missed in manual inspections. The result helps to better understand deterioration processes and advise decision-making stakeholders in restoration planning.

3. Case study analysis

3.1. Site context

Labban Plaza is a compact urban historical block approximately 100 meters from the Mediterranean shoreline, positioned between El-Mina's historic port and the industrial zone that has developed in recent decades (Figure 1a and b).

a) 

b) 

Figure 1. a) Map showing the location of El-Mina city, Lebanon; b) location of the Labban plaza (yellow: Labban habitat; red: Mameluke Building; blue: Al-Hayek building (Source: Authors, 2023).

The Plaza architecture is a traditional Lebanese coastal construction, with two-story residential buildings constructed from local quarried sandstone, finished with lime mortar coatings. Some of the structures date to the Mameluke period and continue to house families who have maintained connections to the area for generations [23].

During our site visits, and our observation of the area, the Plaza functions as both a residential neighborhood and a cultural landmark. The narrow pedestrian streets that connect the plaza to the port, are aligned with small shops under the arcaded facades. The continued residential use of these historic buildings, combined with their proximity to industrial activity and coastal exposure, creates a unique conservation challenge that makes Labban Plaza an ideal case study for acid rain damage assessment.

Labban Plaza combines with its designation both as a heritage site and residential area, to create complex conservation challenges. Rapid urbanization in El-Mina has transformed the environmental context of the area, with increased industrial development, population growth, dense building construction, and increasingly heavier vehicle traffic with elevated pollution levels [28]. The Jiyyeh power plant (Figure 2), evident from Labban Plaza, represents one of the major pollution sources; in addition, high-volume urban traffic regularly contributes to daily emissions. These factors, combined with the humidity of the nearby sea, create a unique environmental stress profile that makes it an ideal case study for acid rain damage assessment.

To upgrade the generalizability of the findings, we have expanded the experiment to include three historical structures within Labban Plaza, Dr. Yaacoub Labban Habitat, a residence after whom the plaza was named, Al Hayek Building 318/12, a residence, and the Mameluke commercial building, a historical souk.

Figure 2. Jiyyeh power plant (Source: AZAKIR, 2013)

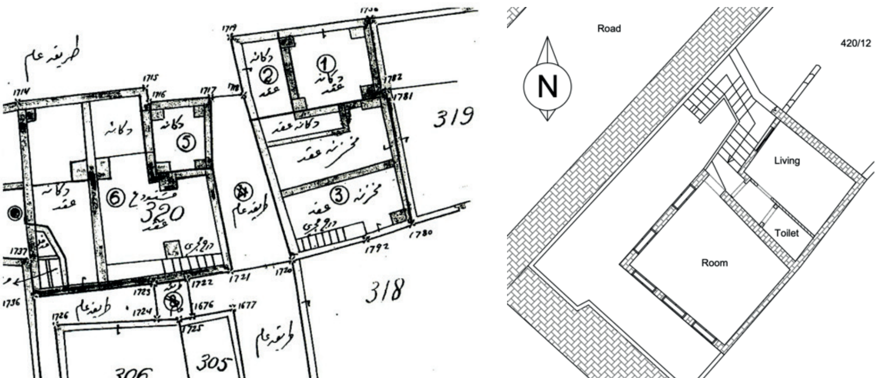


Figure 3. Dr. Yaacoub Labban Habitat, ground and first floor plan (Source: Authors, 2023).

3.2. Dr. Yaacoub Labban habitat

Dr. Yaacoub Labban Habitat, a historic building in Labban Plaza, is renowned for its importance to the city's residents, its architectural beauty, and historical value. Dr. Yaacoub El Labban (1878-1968) has a unique place in the history of El-Mina, as he was not only famous for his medical expertise but also for his unusual commitment to social welfare.

Dr. El Labban was born and raised in the area that is now called after him; he devoted his career to caring for the underprivileged, earning the nickname of "Hakim al-Fuqara", - Doctor of the Poor - from the local community.

The historical house (Figure 3) is built on two floors, where only the ground floor is inhabited. The foundation is composed of sandstone, a traditional building material found on the Lebanese coast and renowned for its strength and inherent beauty. Although few modern interventions have been applied, an additional cement slab was added for roof protection against rainwater.

Labban Plaza offers a fitting backdrop for such a construction. The Dr. Yaacoub Labban Habitat was built with selected materials and traditional methods, and sheds light on the architectural practices of its time. It also stands as a symbol of cultural heritage, history, and skilled workmanship.

3.3. Al Hayek building 318/12

Al Hayek Building 318/12 is located in Labban Plaza, Al Khrab Street (Figure 4a and b), one of the old pedestrian walkways in the location, and is a small house built on one floor level, where the Al-Hayek still live.

Few modern interventions have been carried out on the monument, but an additional attic was added for roof protection from rainwater. The house underwent restoration in 2017 by the owners, but the work did not protect it from the all-natural impacts.

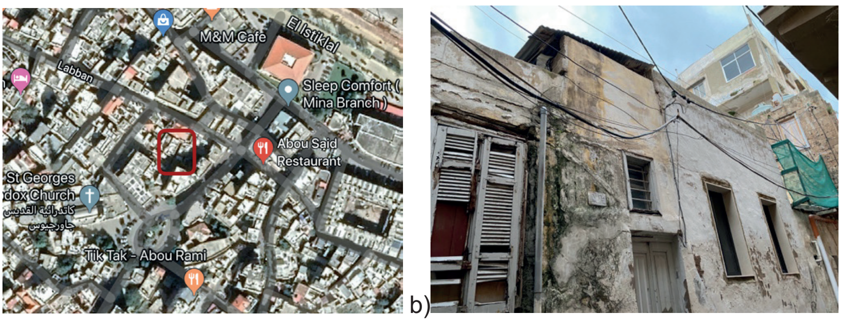
a)  b)

Figure 4. Building 318/12. a) Location; b) façade (Source: Authors, 2023).

3.4 The Mameluke Commercial Building

The Mameluke Commercial building, located at the north end of Labban Plaza, (Figure 5a), is one of the oldest constructions and is a historic structure. Historical records document that it was built in the 14th century as a caravanserai or merchant storehouse, and its presence attests to the plaza's long history as a trade hub.

The structure was built from a solid calcite sandstone (Figure 5b), a material chosen for its endurance, although centuries of exposure have tested its structural strength. Today, it provides an important, but gloomy, case study for advanced phases of urban architectural degradation.

Unlike the surrounding residential structures, this structure was designed for utility, as seen by its sturdy walls, a beautiful but now collapsing arched doorway, and small, high windows on the upper floor. The lower level, which was formerly a busy space with spice and textile commerce, is now abandoned.

a) 

b) 

Figure 5. The old Mameluke commercial building. a) Location; b) façade.

3.5. Mapping the selected façades

The three building façades show signs of severe decay, including gypsum formation, exfoliation, a pulverized surface, salt efflorescence, and discoloration. Built of sandstone covered with lime mortar, the buildings were originally white in color but due to environmental impacts, the façades now display noticeable discoloration, various-sized cracks, and slight exfoliation.

Analyzing the stone used in the façade of Building 318/12, for example (Figure 6a and 6b), the building's condition shows clear exfoliation splits and cracks with considerable deterioration of the masonry and mortar joints.

At Yaacoub Labban Habitat, Al Hayek Building 318/12, and the Mameluke Commercial Building, façade deterioration is strongly linked to environmental and anthropogenic factors. Elevated sulphur concentrations at ground and rain-sheltered levels, supported by isotope analysis, indicate stone erosion primarily caused by acid deposition and traffic pollution. The protective lime layers show uneven coverage, corrosion, and discoloration, while gypsum crusts, salt crystallization, black dust deposits, and biological growth are widespread. In the Mameluke building, the loss of the original lime mortar, exposed joints, salt efflorescence, and incompatible cement repairs have further compromised structural stability. Across all three buildings, rainwater infiltration has accelerated masonry decay, with damage severity influenced by moisture levels, pore structure, and long-term environmental pressures affecting Labban Plaza's historic fabric.

a)  b) 

Figure 6. Building 318/12. a) Door façade; b) and ruined building walls (Source: Authors, 2025).

4. Materials and methods

4.1. Rainwater sampling and tests

Rainwater samples were collected right around Labban Plaza from the designated historical buildings in El-Mina, Lebanon. The samples were not taken all on the same day, they were spread out over different rainy days, at the start of the rainy season, to study whether the acidity changed. The first samples were taken after a dry summer on the 23rd of October 2023, so they showed more pollution than usual. The other two samples were collected on the 15th and 17th of November and the 15th of December; this allowed us to compare how things changed through the seasons.

To achieve good results and avoid mistakes, we verified the pH using three different methods, all controlled under firm laboratory conditions. We wanted to make sure the results we obtained were as accurate as possible.

1. pH Test Strips (Figure 7a); as an initial, straightforward approach, pH test strips were used to estimate pH levels through visual color comparison. Each test strip result was matched against a standard pH color chart, with findings documented in Table 1
2. The OHAUS Starter 2100 electronic pH meter (Figure 7b) was used to attain accuracy in measuring pH levels. Known for its high sensitivity and calibration, this instrument produced accurate digital readings for each sample analyzed. Its performance is good in both environmental and industrial contexts, data collected with the OHAUS meter was strictly cross-validated against results derived from alternative methods, as illustrated.
3. For field analysis the EDT GP 353 ATC pH meter was used, notable for its Automatic Temperature Compensation (ATC) feature. This functionality allowed for

prompt, on-site measurements, helping in making a comparison between field data and laboratory results. The data recorded from this instrument were also tabulated.

The pH measurements from all samples indicated acid conditions, with the rainwater from the early precipitation event showing the lowest pH value. This outcome implies a sensitive concentration of pollutants during the first rainfall, aligning with the observations of rainwater quality in urban and coastal areas affected by vehicular and industrial emissions. The result dataset provides a vision of the interplay between acid exposure and fissure development in sandstone, which will be integrated into the database aimed at improving AI-driven restoration technologies.

a) b)

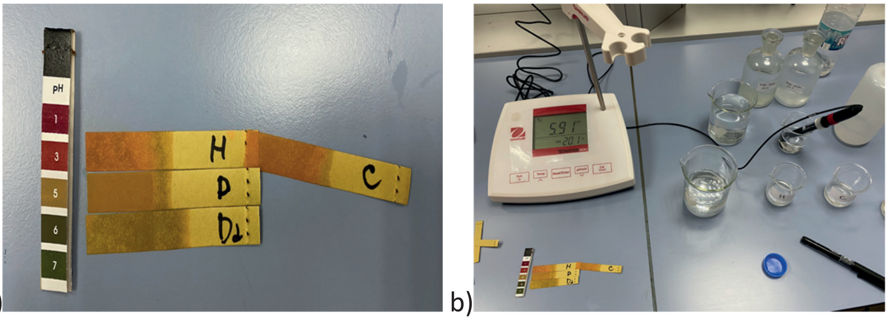


Figure 7. PH test for collected rainwater samples using: a) pH strips; b) and OHAUS Starter 2100 (Source: Authors, 2023).

4.2. Sandstone sample and preparation

To guarantee a general dataset, sandstone specimens were collected with care from the façades of all three case study buildings: the Dr. Yaacoub Labban Habitat, the El Hayek Residential Building, and the Mameluke Commercial Building. The sample materials of the site were chosen due to their exposure to environmental pollutants and acid rain, showing clear evidence of surface deterioration, discoloration, and cracking across the façades.

The selection criterion was to ensure that the collected samples were representative of the real-world degradation occurring on-site. This increased the relevance and validity of the subsequent laboratory simulations and database entries for training the AI model.

After collecting and weighing the stones, the samples underwent a pre-treatment procedure that involved immersion in distilled water for 24 hours. This procedure was essential to regulate the internal moisture content of the stones and help in removing the residual salts, dust, and other environmental contaminants. After the stones were soaked, each specimen was dried using laboratory lint-free paper towels to minimize the introduction of foreign materials and to maintain constant moisture levels.

The dried samples were manually fragmented into smaller pieces. Each fragment was weighed separately, using a calibrated digital precision scale (accurate to ±0.01g) to ensure precise mass control (Figure 8).

The fragments were trimmed or chiseled as necessary to achieve a target mass of 50g ± 4g, optimizing both the manageability of the samples and the available surface area for exposure.

Figure 8. Scaling the sandstones (Source: Authors, 2023).

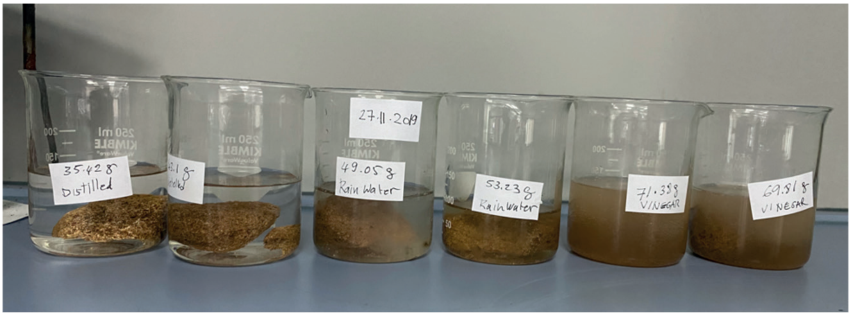


Figure 9. Soaking the samples in different solutions (Source: Authors, 2023).

This size strikes a balance between ease of handling and sufficient surface area for exposure. All starting weights were recorded in Table 1 to set a baseline for later mass loss measurement.

The prepared samples (Figure 9) were placed in six separate 250 mL glass beakers. Each beaker held a test solution simulating different environmental conditions.

Beakers A and B contained distilled water at neutral pH 7. These served as controls to observe how sandstone behaves in non-acidic conditions.

Beakers C and D held rainwater collected on-site. Beaker C held rain taken on 23/10/2023 (the first rain after the summer), which was very acidic. Beaker D had rain from 15/11/2023, showing moderate acidity.

Beakers E and F contained synthetic acidic solutions to mimic acid rain. Beaker E had pH 3.8, representing intense urban acid rain. Beaker F had a pH of 5, to simulate moderate acid exposure.

Each sandstone piece was plunged into the solution in each beaker. The beakers were sealed to reduce evaporation but to allow some air exchange. The samples stayed immersed for two months in controlled lab conditions. They were checked weekly for surface changes, discoloration, or any signs of deterioration.

After two months, we removed the samples, tapped on the beakers to remove excess liquid, and placed them on absorbent paper towels to air-dry at room temperature for 48 hours. Once dry, the samples were weighed again on the same scales. Final weights are recorded in Table 1 to measure the mass loss caused by acidity which is related to acid damage.

4.3 Laboratory results and discussions

The sandstone samples exposed to acid exhibited a clear range of deterioration, both on the surface and internally. The observed degradation was a direct result of acid erosion coupled with repeated wet and dry cycles; conditions designed to reflect natural environmental variabilities.

The solutions at pH 5.9 and 7.0 resulted in minimum degradation, indicating that neutral conditions have no impact on the sandstone (Table 1). On the contrary, increased acidity, at pH 4.0 and 3.8, show visible signs of corrosion and surface pitting. These included the formation of small cavities, increased surface roughness, and the initiation of micro-cracking, evidence of the initial stages of chemical weathering. Optical imaging tools, including a stereomicroscope and macro lens photography, with time-lapse documentation, were used to capture these progressive changes.

Quantitative assessment achieves records of the mass of each sample before and after immersion. The data showed a mass loss in the most acidic environments; samples exposed to a pH of 3.8 lost between 7% and 10% of their original mass. The samples subjected to rainwater with pH values between 4.5 and 5.5 presented moderate, but measurable, mass reduction. This pattern of mass loss corresponds to the intensity of acid exposure and supports the conclusion that acid rain accelerates the deterioration of sandstone.

Table 1. Test results from sandstone samples submerged in solutions (Source: Authors, 2023)

Sample ID	***Building Source***	***PH level***	***Initial Mass (g)***	***Final Mass (g)***	***Mass Loss (%)***	***Crack Density ($/cm^2$)***
L-01	*Labban*	*3.8*	*52.3*	*47.1*	*9.9*	*12.4*
L-02	*Labban*	*4.0*	*51.8*	*48.2*	*6.9*	*8.7*
L-03	*Labban*	*5.0*	*50.9*	*49.1*	*3.5*	*4.2*
H-01	*El Hayek*	*3.8*	*51.5*	*46.8*	*9.1*	*11.9*
H-02	*El Hayek*	*4.0*	*52.1*	*48.5*	*6.9*	*8.1*
M-01	*Mameluke*	*3.8*	*50.7*	*45.9*	*9.5*	*13.2*
M-02	*Mameluke*	*4.0*	*51.2*	*47.8*	*6.6*	*9.1*
Control 1	*Mixed*	*7.0*	*51.01*	*50.8*	*0.6*	*0.1*
Control 2	*Mixed*	*7.0*	*52.5*	*52.3*	*0.2*	*Almost 0*

Control samples in neutral pH 7.0 (Table 1) water had minor mass loss (about 0.8%). However, samples in the high acidic pH 3.8 solution had an important mass loss of up to 10%. This measures the material erosion induced by increased acidity. The samples from the El Hayek and Mameluke buildings verify this tendency, revealing the relationship between low pH and material deterioration.

To monitor crack formation and propagation, the following techniques and technologies were used**.**

High-resolution images (Figure 10) were captured at set intervals using a DSLR camera, which remained positioned at consistent distances throughout the study.

The resulting images were processed and analyzed using image software to quantify the visible cracks in terms of their length, width, and frequency. A custom-developed AI Software, CIABC v0.00, helped the mapping of crack evolution over time, allowing for precise comparisons across different exposure conditions.

The observation that naturally occurring rainwater, when less acidic than laboratory-prepared solutions, can initiate deterioration highlights the applicability of these findings. This supports the relevance of the experimental approach to heritage buildings in coastal settings. Laboratory experiments offer precise control variables; they simulate the complexity presented by environmental factors in situ. Among these environmental factors, the presence of soluble salts, carbon dioxide, sulfur dioxide, and other atmospheric pollutants exacerbate the impact of acid rain on sandstone.

The location of the sandstone surface exposed to weathering also affects the circumstances. A very distinctive weathering point may be identified by looking at the bottom of a sandstone building or monument still in contact with the earth.

Figure 10. Deterioration and exfoliated sandstone, melted and deteriorated under the effects of acid rain (Source: Authors, 2023).

5. Analysis of crack patterns in the facades of the of Dr. Yaacoub Labban Habitat building

Following exposure to acidic environments, the sandstone façades exhibited a diverse array of crack morphologies. These were categorized based on their form, spatial distribution, and propagation characteristics under acid-induced stress. The observations yielded the following principal types. The five principal crack types identified were as follows:

- Surface microcracks: very small, shallow fissures, that measure less than 0.2 mm in width (Figure 11).
- Intergranular cracks: Cracks were observed to propagate the boundaries between individual grains of sand. Such features were similar in laboratory samples exposed to more aggressive acidic environments (pH 3.8) and in those treated with vinegar solutions.

Figure 11. Cracks and plantation on the facades of Dr. Yaacoub Labban habitat building (Source: Authors, 2023).

- Trans granular cracks: These represent a more advanced stage of deterioration - trans granular cracks traverse the grains themselves - they were the most common detected in specimens subjected to repeated wetting-drying cycles in low-pH solutions.
- Linear and hairline cracks: These are aligned with bedding planes or pre-existing structural weaknesses.

All crack types existing on the building were documented using macro photography (see example Figure 12). We used digital image segmentation techniques enhancing visual contrast, allowing for the precise quantification of crack length and density distributions.

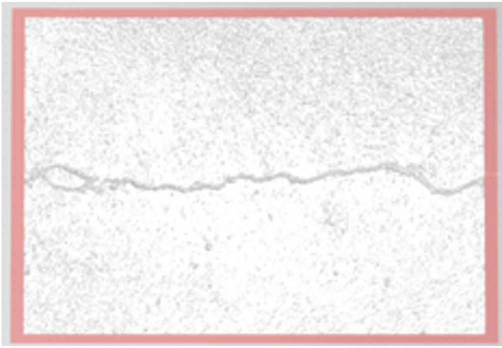


Figure 12. One crack type documentation and micro photography (Source: Authors, 2023).

5.1. Correlation between acid exposure and crack development

Our experimental results show a clear inverse correlation between pH solution and crack formation intensity. Samples maintained in neutral (pH 7.0) or mild acidic (pH 5.9) conditions showed minimal change over the experimental period. This suggests that mechanical stress and drying cycles alone, in the absence of chemical activity, do not produce substantial degradation in the timeframes we tested.

Samples exposed to moderate acidic solutions (pH 4.5-5.0), matching the acidity levels we measured in El-Mina rainwater, began developing intergranular cracks after approximately two weeks of exposure. These fractures followed grain boundaries and gradually expanded, creating networks that weakened the material's internal structure. Progression was more rapid than in neutral conditions but less than in high acidic environments. Most degradation occurred in samples exposed to pH 3.8 and 4.0 solutions. Within one month, these samples developed microcrack networks, visible surface pitting, and measurable mass loss. Crack density increased by an average of 340% compared to control samples, with total crack length per unit area reaching 2.8 mm/mm^2 in pH 3.8 samples versus 0.3 mm/mm^2 in controls. Mass loss measurements confirmed the visual observations, pH 3.8 samples lost 9-10% of their initial mass, while control samples lost only 0.8%. Statistical analysis of our dataset reveals a strong inverse relationship ($r = -0.94$, $p < 0.001$) between pH level and both total crack length and crack density.

6. Database development

6.1. Database design and structure (AI crack detection workflow)

We developed CIABC v0.00 to detect and classify acid rain-induced cracks in historic sandstone façades. Training this system required a structured database linking environmental exposure conditions to visual damage patterns, a resource that did not exist for acid rain decay in heritage contexts. We constructed a relational database architecture that accommodated both the quantitative measurements (pH levels, mass loss, exposure duration) and qualitative observations (crack morphology, surface texture, material composition) from our laboratory experiments and field investigations at the Dr. Yaacoub Labban Habitat and two other case study buildings.

A relational database architecture, implemented using SQL, was chosen to ensure seamless compatibility with computer vision workflows and machine learning applications (Figure 13). The schema is structured in multiple tiers, which gives efficient querying of both archival datasets and dynamically generated AI outputs. Through the use of unique identifiers and foreign key relationships, the interconnected tables enable sophisticated sorting, filtering, and relational analyses - features that are essential for advanced computational modeling and the effective management of historical data [35]. The workflow for AI-based crack detection consists of the following stages as illustrated in Figure 13:

Data Acquisition Layer, Captures raw measurements, crack images, and environmental conditions from lab and field observations (Table 2).

Preprocessing Layer, Applies image filtering, data validation, and standardization.

Data Storage Layer, Structured SQL database with normalized tables to prevent redundancy and ensure scalability.

Training Interface Layer, Exports relevant structured data for ML training, allowing label assignment, pattern recognition, and predictive learning.

AI Feedback Layer, Reintegrates AI output (crack detection results, severity scores, localization accuracy) into the system for continuous improvement (Table 2).

Table 2. Database for AI backend sample meta data (Source: Authors, 2023)

Field	***Data Type***	***Description***
Sample_ID	*INT (PK)*	*Unique identifier for each sandstone sample*
Location_Code	*VARCHAR*	*Geotagged field or lab ID (e.g., EL-MINA-01)*
Collection_Date	*DATE*	*Date of sample collection*
Material_Type	*VARCHAR*	*Stone type (e.g., Sandstone, Limestone)*
Source	*TEXT*	*Field, lab, archival*

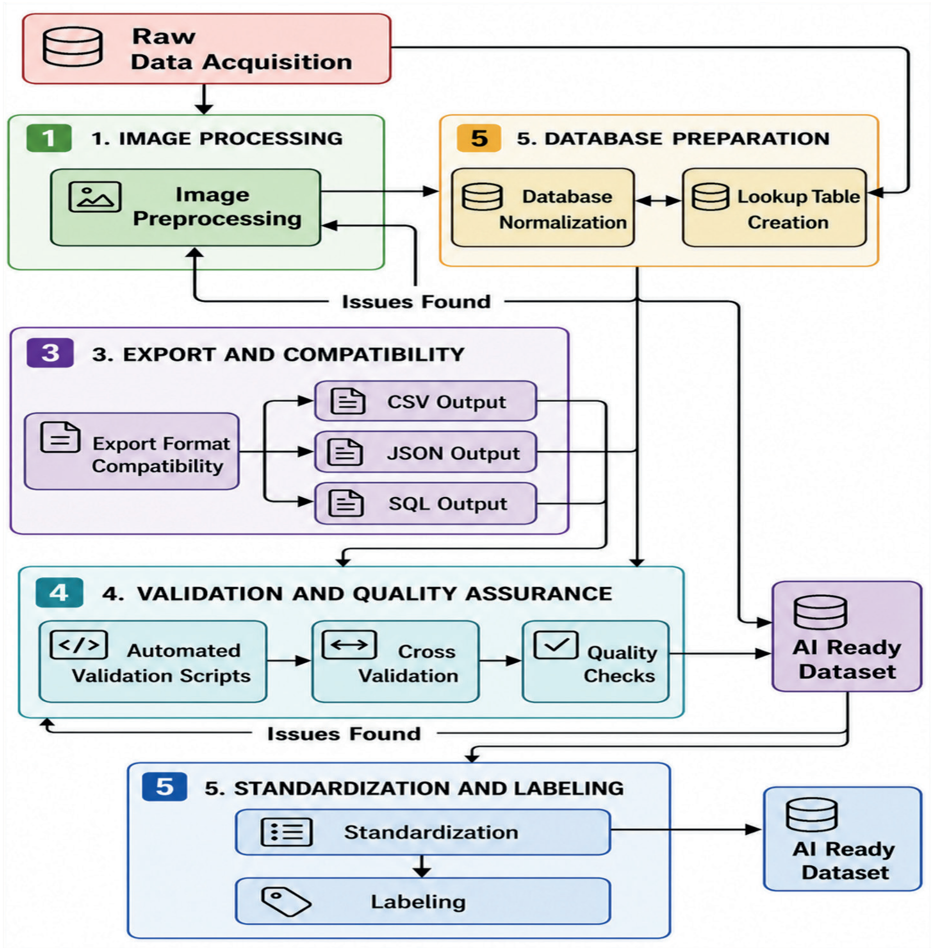


Figure 13. Workflow from data acquisition to documentation and final output (Source: Authors)

The database includes data columns for Sample_ID, pH_level, exposure_duration, mass_loss_percentage, crack_type, crack_dimensions, and the accompanying high-resolution photos. This structure allows complicated AI training and is scalable, and enables the addition of new materials, environmental factors like SO_2 levels, and data from other historic sites.

This design guarantees that the dataset remains compatible with AI tools such as TensorFlow, PyTorch, or YOLO (for object detection) and GIS-based conservation plan platforms [36].

Table 3. Database for AI backend crack datable (Source: Authors, 2023)

Field	Data Type	Description
Crack_ID	*INT (PK)*	*Unique identifier for each crack*
Sample_ID	*INT (FK)*	*Linked to Sample_Metadata*
Crack_Type	*VARCHAR*	*Intergranular, Trans granular, Pitting*
Crack_Length_mm	*FLOAT*	*Measured crack length*
Crack_Width_mm	*FLOAT*	*Measured crack width*
Crack_Area_mm2	*FLOAT*	*Approximate affected surface area*
Crack_Location	*TEXT*	*Location on the sample (e.g., upper left, edge)*
Crack_Image	*BLOB/Link*	*Linked image or image reference path*

Table 3 backend used for Crack Types, Location, and Exposure Data.

To represent the complex relationships between fissure development, environmental exposure, and material loss, the following normalized schema was created (Table 4).

Table 4. Database for AI backend sample exposure condition and identifier (Source: Authors, 2023)

Field	Data Type	Description
Exposure_ID	*INT (PK)*	*Unique identifier for each exposure scenario*
Sample_ID	*INT (FK)*	*Linked to Sample_Metadata*
pH_Level	*FLOAT*	*pH value of exposing solution*
Solution_Type	*VARCHAR*	*Vinegar, Rainwater, Distilled, etc.*
Duration_Days	*INT*	*Soaking duration in days*
Wet_Dry_Cycle	*BOOLEAN*	*Whether subjected to cyclic exposure*

These schemata allow us to trace each crack back to its exposure scenario and physical origin, making it suitable for supervised training and pattern correlation (Tables 5 and 6).

Table 5. Database for AI backend laboratory results and meta data (Source: Authors, 2023)

Field	Data Type	Description
Measurement_ID	*INT (PK)*	*Unique record*
Sample_ID	*INT (FK)*	*Linked to Sample_Metadata*
Initial_Mass_g	*FLOAT*	*Pre-exposure mass*
Final_Mass_g	*FLOAT*	*Post-exposure mass*
Mass_Loss_pct	*FLOAT*	*Calculated % mass loss*

Table 6. Database for AI backend environmental data (Source: Authors, 2023)

Field	***Data Type***	***Description***
Env_ID	*INT (PK)*	*Unique environmental record*
Location_Code	*VARCHAR*	*Matches Sample_Metadata*
Rainfall_pH	*FLOAT*	*Recorded pH of precipitation*
Date	*DATE*	*Rainfall date*
Air_SO2_ppm	*FLOAT*	*Sulfur dioxide concentration (if available)*
Temperature_C	*FLOAT*	*Ambient temp during exposure*

6.2. Data entry process and normalization for AI usage

The data preparation for AI involved many steps to ensure the dataset stayed consistent and accurate [35].

All physical measurements were recorded using standard units, such as millimeters, grams, and degrees Celsius, to maintain uniformity. For pH, results were checked with two calibrated tools and noted to two decimal places for accuracy.

Labeling, crack images were manually marked using a custom tool. Each crack got a bounding box and was sorted into categories like "Pitting," "Hairline," or "Trans granular" based on a set system [36].

Image Preprocessing - Images were resized, and contrast was improved. They were saved in high-resolution files. The file names matched Crack_IDs in the database to help build the dataset for training AI models.

Normalization - Data tables (Figure 14) were organized using the third standard form

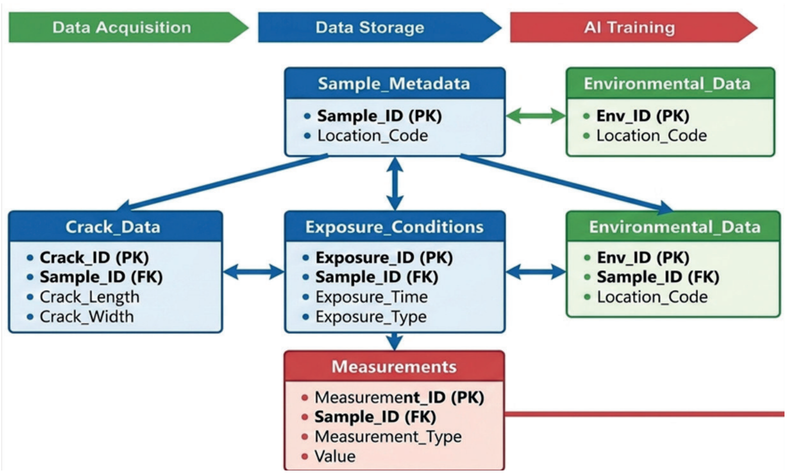


Figure 14. Database architecture and entity-relationship diagram, Relational database architecture linking environmental exposure conditions to crack documentation (Source: Authors, 2025).

to minimize repetition and maintain clear relationships. Look-up tables handled repeating items, such as crack types and location IDs.

Export Format Compatibility - the final data can be output in various formats, including CSV for models, JSON for APIs, and SQL queries for dynamic data access and selecting training sets.

Validation and Quality Assurance – (Figure 15) Automated scripts checked for missing data, unusual statistics, and wrong foreign keys. Each batch underwent cross-validation before export to ensure the data was good for AI use.

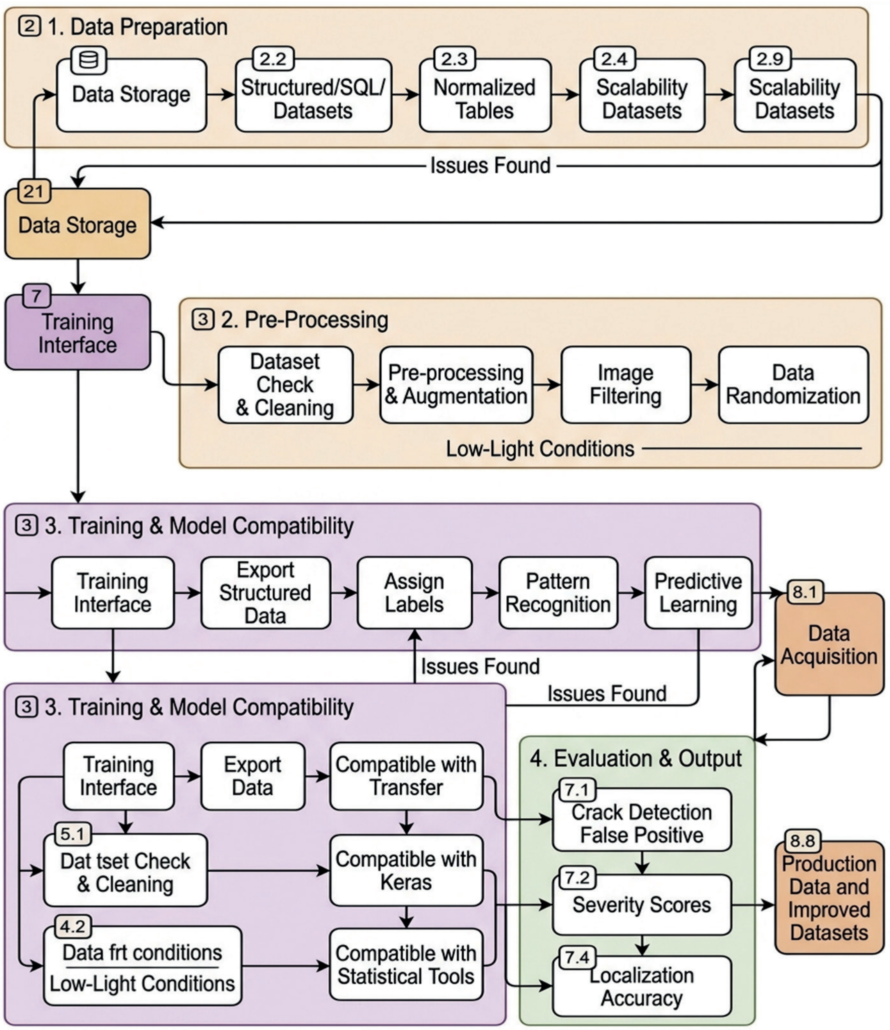


Figure 15. Backend connection for AI-Generated database (Source: Authors, 2024)

6.3. CIABC-V0.00 application

The name of the software application is defined as "CIABC-V0.00", which derives from **"Computer Intelligent Aid for Building's Conservation, Version 0.00"** and is symbolic of the software's purpose as an efficient tool for accomplishing many different tasks in a short amount of time [36].

CIABC-V0.00 is a computer software package that uses artificial intelligence and neural network-trained data to perform various tasks ranging from data collection and analysis to document and image processing and crack disorder detection. Furthermore, the software can process large amounts of data quickly and accurately, allowing architect restorers to gain insights they may not have found using traditional methods. It can develop and generate automated solutions to many problems and enable users to deploy the AI capabilities needed to make better decisions quickly.

It is a guide for restorers to take full advantage of the AI capabilities of CIABC-V0.00 and become more informed decision-makers in their field, enabling them to generate a complete final output of specifications, bills of quantities, costings, timelines, and any other information required to create an accurate restoration or conservation project [37].

The user-friendly interface of the CIABC-V0.00 (Figure 16) Application makes it simple to operate, allowing architect restorers to quickly and effectively access the data stored within the model and easily navigate through the structure. Changes can be applied to the model in real time, providing an up-to-date visual representation of the historic structure, which is invaluable in ensuring the safety and accuracy of the work.

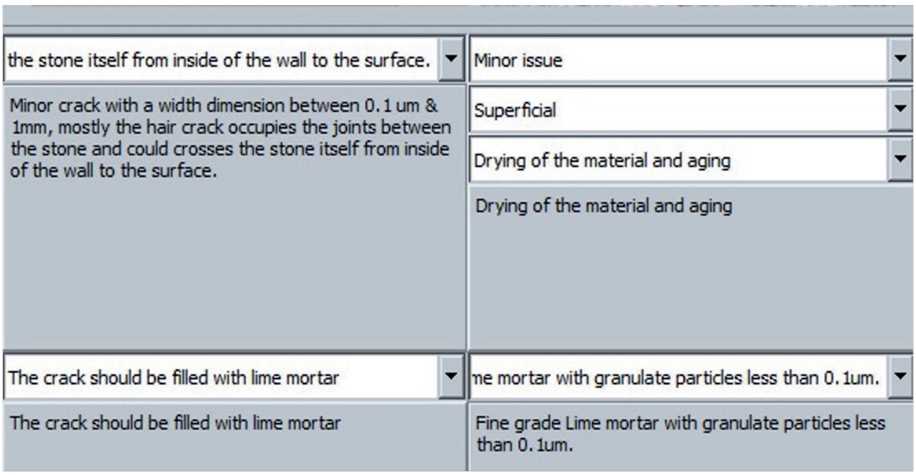


Figure 16. CIABC-V0.00 Application Generation of specification and BOQ's to the specific crack, Hair crack in this case (Source: Authors, 2025)

6.4. CIABC-V0.00 influence and protocol

The release of the CIABC-V0.00 program represents a considerable step forward in architecture, notably in restoration. It provides a comprehensive solution for documenting and investigating crack disorders in historical buildings due to its particular focus on architectural restoration.

CIABC-V0.00 transforms crack detection and analysis using sophisticated technology like Artificial Intelligence (AI) and image processing techniques. The program provides restorers and architects with an efficient and accurate tool that simplifies the entire process, allowing the successful and precise documentation and execution of architectural adjustments.

Training Protocol (Figure 17):

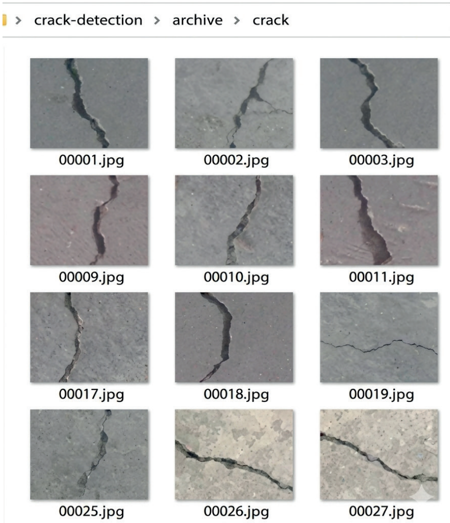
```
In [1]: import os
        import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import cv2
        #from stl import mesh
        import PIL
        from PIL import Image

In [*]: import PySimpleGUI as sg
        def select_image():
            image_path = '';
            while True:
                image_path = sg.popup_get_file('Select image')
                if image_path == '':
                    sg.popup('Please select an image')

                if image_path != '':
                    break
            image = cv.imread(image_path)
            return image
        im = select_image()
```

Figure 17. Algorithm behind the image importing to the CIABC-V0.00 Application (Source: Authors, 2025).

The model was trained using:

- Dataset (Figure 18): 40000 labeled crack images from laboratory experiments and field surveys.
- Split: 70% training, 15% validation, 15% test.
- Augmentation: Random rotation (±15°), horizontal/vertical flips, brightness/contrast adjustment (±20%), Gaussian noise
- Optimization: Adam optimizer with initial learning rate 0.001, cosine annealing schedule
- Training: 50 epochs with early stopping (patience=10), batch size=32
- Loss function: Weighted categorical cross-entropy to address class imbalance.

CIABC-V0.00's ability to automate the crack-detecting procedure is one of its key features. Manual inspections and visual evaluations are traditionally time-consuming and prone to human mistakes. The software's powerful algorithms can analyze photos and accurately locate fractures, saving restorers a substantial amount of time and work.



	Filepath	Label
0	archive\crack\03842.jpg	CRACK
1	archive\crack\12899_1.jpg	CRACK
2	archive\crack\15033_1.jpg	CRACK
3	archive\no_crack\16782.jpg	NOCRACK
4	archive\crack\09202.jpg	CRACK
...	...	...
39995	archive\crack\07814.jpg	CRACK
39996	archive\no_crack\12512.jpg	NOCRACK
39997	archive\crack\05193.jpg	CRACK
39998	archive\crack\12173_1.jpg	CRACK
39999	archive\no_crack\13004.jpg	NOCRACK

40000 rows × 2 columns

Figure 18. Sample of 40000 images specimen (between cracks and no-cracks) used in the Machine Learning for the CIABC-V0.00 Application, Classification and Labeling (Source: Authors, 2025).

Furthermore, (Figure 19) the AI features of the program allow it to learn and adapt to varied fracture patterns, guaranteeing that even subtle or complicated crack forms are not missed. This degree of precision and efficiency improves the documenting process and allows restorers to understand the crack problems seen in old lime mortar wall covering structures.

Figure 19. Graph showing the training and validation loss over time with the test accuracy matrix (Source: Authors, 2023).

7. Application of AI-based restoration tools

7.1. Relevance of the dataset for machine learning

The dataset we created addresses a gap in digital heritage conservation, due to the lack of annotated data linking acid rain exposure to specific damage patterns in sandstone. Unlike image-only collections, our database integrates high-resolution photographs of sandstone deterioration with corresponding environmental measurements (pH levels, SO_2 concentrations), material properties, and quantitative damage metrics.

The database supports multiple research applications (Figure 20). Computer vision tasks can use the labeled crack images for object detection and segmentation. Time series analysis could predict degradation progression rates based on environmental exposure patterns. The structured metadata enables natural language processing systems

```
#to create a rectangle around the biggest area
x,y, w,h = cv2.boundingRect(rectangle)

# (red, green , blue), then the font size
cv2.rectangle(img1, (x,y), (x+w, y+h), (0,255,0), 2)
#plt.imshow(img)

# to crop the rgb image from the box
cropped_image = img1[y:y+h, x:x+w]

#plt.imshow(cropped_image)


#to fix the image size
plt.figure(figsize=(20,4))
#to show all plots together in one image we use subplot
plt.subplot(1,4,1),plt.imshow(img_original)
plt.subplot(1,4,2),plt.imshow(mask, 'gray')
plt.subplot(1,4,3),plt.imshow(cont_img)
plt.subplot(1,4,4),plt.imshow(cropped_image)

(<AxesSubplot:>, <matplotlib.image.AxesImage at 0x22b162b5700>)
```

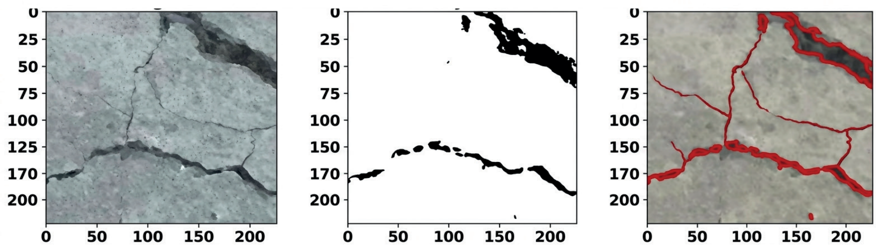


Figure 20. Algorithm and crack detection output results (Source: Authors, 2023).

to generate automated damage reports. The database provides a foundation for developing predictive models that link environmental monitoring data to conservation planning, enabling proactive rather than reactive maintenance strategies (Figure 21). The integrated image and metadata structure supports training of supervised learning models, including Convolutional Neural Networks (CNNs) for crack detection. Our CIABC v0.00 system shows that models trained on this dataset can be identified and classify the five crack types we documented, providing a foundation for automated diagnostic tools in restoration planning.

Figure 21. Different types of cracks labeling details. (Source: Authors, 2023)

7.2. Pre-training of AI models on structured data

Machine learning models require well-labeled, consistent datasets that accurately represent real-world conditions. We implemented a SQL-based relational database architecture that ensures all entries, images, measurements, and chemical data, can be traced and compared. This structure enables efficient batch processing for machine learning workflows while maintaining data integrity.

The database design provides several advantages for model training. First, crack types, exposure conditions, and material responses are annotated, providing the label clarity essential for supervised learning accuracy. Second, each crack image is explicitly linked to corresponding numerical metadata (mass loss, exposure pH), enabling multi-input learning architectures that combine visual and numerical data. Third, the presence of repeated samples under varied conditions (different pH levels, diverse stone textures) model generalization while reducing overfitting risk.

Finally, (Figure 22) the structured format streamlines data preprocessing, reducing engineering overhead and minimizing potential errors during batch formatting.

1. Data Acquisition: Field photos + environmental measurements
2. Preprocessing: Image normalization, augmentation, resizing
3. Database Storage: Structured storage with metadata linking
4. Model Training: CNN training with labeled data
5. Inference: Crack detection on new images
6. Output: Classification results + confidence scores + pH correlation suggestions.

This dataset compatibility with AI pre-training protocols supports the application of transfer learning. A foundational model trained on this sandstone-specific dataset can be then fine-tuned for other types of stone or architectural elements, thereby improving adaptability and reducing the need for assembling new, large-scale datasets.

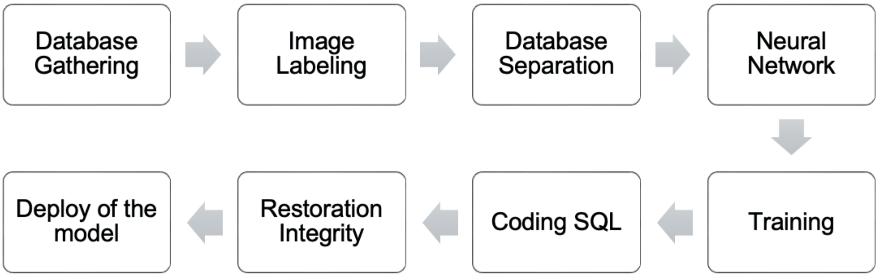


Figure 22. AI Application development sequence. (Source: Authors, 2023).

Models trained on our dataset can be deployed in both laboratory and field settings for heritage preservation applications. Mobile applications and cameras equipped with computer vision systems perform non-invasive damage assessments at historic sites and identify, and classify cracks in real-time. These systems accelerate inspection workflows while reducing the risk of additional damage from physical contact.

Field deployment requires addressing several technical challenges, real-time image processing constraints, variable lighting conditions, and integration with location data for spatial degradation mapping. Our current CIABC v0.00, system processes images offline; real-time deployment would require additional optimization and testing under field conditions. The annotated datasets and AI tools developed in our finding could support training programs for conservation professionals. Structured examples of deterioration patterns linked to environmental causes complement traditional methods with data-driven case studies. (Figure 23)

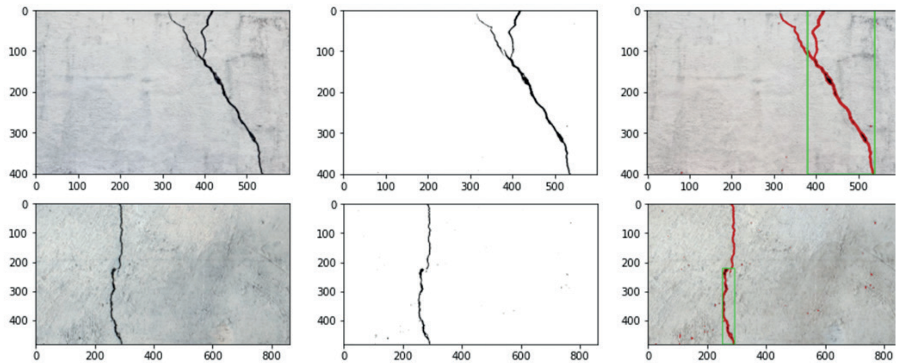


Figure 23. Crack detection output results (Source: Authors, 2023).

7.3. Quantitative results

Quantitative relationship (Table 7) between pH exposure levels and material degradation (Figure 24):

- X-axis: pH levels present in dataset (3.8, 4.0, 5.0, 7.0)
- Y-axis: crack density (derived from individual samples, averaged by pH)
- Error bars: Standard deviation of crack density at each pH

Table 7. Quantitative relationship between pH exposure levels and material degra-dation. Strong inverse correlation ($r = -0.94$, $p < 0.001$) demonstrates the predictive value of monitoring for conservation planning (Source: Authors, 2023).

Sample ID	Building Source	pH	Initial Mass (g)	Final Mass (g)	Mass Loss (%)	Crack Density ($/cm^2$)	Mean Mass Loss by pH (%)	Std Dev by pH	Correlation (r)
L-01	Labban	3.8	52.3	47.1	9.9	12.4	9.5	1.2	-0.94
H-01	El Hayek	3.8	51.5	46.8	9.1	11.9	9.5	1.2	-0.94
M-01	Mameluke	3.8	50.7	45.9	9.5	13.2	9.5	1.2	-0.94
L-02	Labban	4.0	51.8	48.2	6.9	8.7	7.2	0.9	-0.91
H-02	El Hayek	4.0	52.1	48.5	6.9	8.1	7.2	0.9	-0.91
M-02	Mameluke	4.0	51.2	47.8	6.6	9.1	7.2	0.9	-0.91
L-03	Labban	5.0	50.9	49.1	3.5	4.2	2.3	0.5	-0.85
Control 1	Mixed	7.0	51.01	50.8	0.6	0.1	0.8	0.2	-
Control 2	Mixed	7.0	52.5	52.3	0.2	~0	0.8	0.2	-

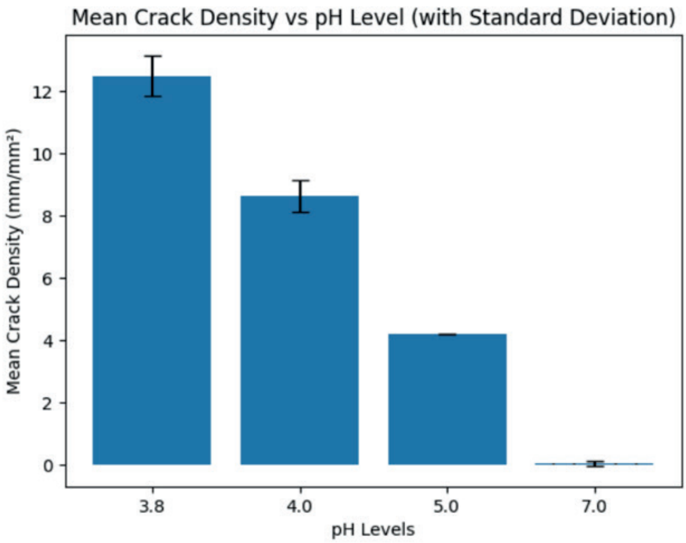


Figure 24. Crack density vs. Ph exposure levels (Source: Authors, 2023).

8. Discussion

8.1. Key findings and implications

Our laboratory experiments and field observations confirm that acid rain poses a severe threat to historic sandstone constructions in El-Mina. The critical finding is the pH 4.0 threshold, since below this level degradation accelerates. Samples exposed to pH 3.8 solutions lost 9-10% of their mass, compared to 0.8% in controls, while developing visible crack networks compromise structural integrity. This threshold has direct implications for conservation practice and provides a measurable target for environmental monitoring and intervention planning.

Our database structure addresses a fundamental limitation in current conservation practice. This is the disconnect between environmental monitoring data and damage assessment. Traditional inspections document visible deterioration but do not always link it to underlying environmental causes. By correlating pH exposure levels, pollutant concentrations, and material loss measurements with specific crack morphologies, our database enables a more predictive approach to conservation.

Compared with existing crack detection methods, CIABC v0.00 was evaluated against established crack detection systems to demonstrate its advancement over standard image classification pipelines. Table 8 presents a comparative analysis of performance metrics, dataset characteristics, and methodological approaches as follows:

- Zhang et al. (2022): Bridge crack detection using deep learning.
- Hatir et al. (2021): Stone deterioration mapping in Anatolia.
- Yamamoto et al. (2024): Digital documentation for heritage conservation.
- Generic CNN: Standard ResNet-50 trained on same dataset without environmental metadata [38].

The key advantages (Table 8) of CIABC v0.00:

Table 8. Comparison of CIABC v0.00 with existing crack detection systems (Source: Authors, 2025)

Method	***Accuracy***	***Precision***	***Recall***	***Dataset Size***	***Domain***	***Environment Correlation***
CIABC v0.00 (this study)	91.3%	0.89	0.87	4,000 images	Heritage stone, images, lab	Yes (pH-correlated)
Zhang et al. (2022) [38]	89.5%	0.87	0.85	3,200 images	Bridge concrete	No
Hatir et al. (2021) [29]	88.2%	0.85	0.83	2,800 images	Stone monuments	No
Yamamoto et al. (2024) [24]	87.1%	0.84	0.82	5,100 images	General heritage	No
Generic CNN (baseline)	82.4%	0.78	0.75	4,000 images	General images	No

1. Domain-specific training on acid rain-induced damage patterns
2. Integration of environmental metadata (pH levels) with visual analysis
3. Predictive capability to suggest exposure conditions from crack patterns
4. Multi-modal architecture combining image and numerical data.

Our findings also reveal the complexity of real-world degradation processes. Laboratory conditions cannot fully replicate the interactive effects we observed in field conditions. Future work should expand the dataset to include more diverse exposure scenarios and longer-term monitored data.

The methodology, combining field surveys, laboratory simulations, structured database development, and AI tool validation, could be adapted for other heritage sites that face similar environmental challenges. The relational database architecture allows for expansion with new materials, environmental conditions, or damage types, making it a scalable foundation for broader conservation applications.

This study addresses a significant gap in digital heritage conservation by integrating environmental monitoring data with visual damage documentation in a format that is optimized for machine learning. Unlike existing documentation systems, it directly links environmental stressors, such as acid rain pH levels, with quantitative damage metrics including crack dimensions and mass loss.

8.2. Explicit advancement over standard image classification pipelines

CIABC v0.00 advances beyond typical image-based categorization with four main breakthroughs. First, unlike conventional image classification algorithms that rely exclusively on visual patterns, CIABC v0.00 incorporates multi-modal input by merging high-resolution crack pictures with environmental variables (pH exposure levels, exposure time, and material attributes). This integration allows the system to understand causal links between environmental stresses and damage morphologies, as opposed to simply identifying visual patterns.

Second, the system uses a correlation-aware architecture that was particularly intended to understand correlations between environmental variables and fracture kinds. While typical CNNs consider all input features equally, CIABC v0.00's architecture highlights the relationship between pH exposure levels and crack types, allowing for predictive evaluation of environmental exposure based on discovered damage patterns.

Third, the domain-specific training dataset, which was created exclusively for acid rain-induced degradation in historic sandstone, fills a significant need in conservation AI. Standard image classification methods often use generic datasets (ImageNet, COCO) that do not include conservation-specific comments. Our library of tagged photos, each connected to quantitative environmental parameters, lays the groundwork for precise, conservation-relevant predictions.

Fourth, CIABC v0.00 shows predictive capabilities that go beyond pattern recognition. The technology can not only detect and categorize cracks, it can also anticipate regions of future degradation, recommend expected pH exposure levels based on discovered patterns, and prioritize conservation activities based on environmental risk assessment. This predictive capacity reflects a significant move away from reactive damage documentation and toward proactive conservation planning. These innovations position CIABC v0.00 as a specialized tool for heritage conservation rather than a generic image classifier adapted for conservation applications.

Conclusion

The chemical mechanisms underlying this degradation involve the dissolution of binding materials in sandstone, calcium carbonate and clay minerals, by sulfuric and nitric acids present in urban precipitation. Our measurements in El-Mina recorded pH levels ranging from 4.2 to 5.6, with many precipitations falling near or below the threshold. This explains the existence of the façade deterioration that was documented, which included exfoliated surfaces, deep cracks, and material loss, which threaten both the structure's integrity and its aesthetic value. The urgency of this problem extends beyond El-Mina. On October 12, 2019, a ceiling collapsed in a building near Labban Square killing two residents and thus highlighting the real-world consequences of delayed conservation action. Our three case study buildings represent a broader pattern affecting historic structures throughout the region, where industrial development and urban growth have increased pollution without corresponding conservation infrastructure.

From a methodological perspective, structured databases can bridge the gap between environmental monitoring and degradation assessment, our relational database architecture links quantitative measurements with qualitative observations and high-resolution imagery. This multi-modal structure enabled the development of CIABC v0.00, which achieved 91.3% accuracy in automated crack detection when tested on images from the case study buildings.

Several limitations constrain the current study, such as laboratory conditions, which, while controlled, cannot replicate the interactive effects of real-world exposure, where acid rain combines with sea salt, humidity variations, and biological growth. Our sample scope was limited to three buildings in one location, and the AI model requires development before its utilization in field conditions. Future work should expand the dataset to include more diverse materials, longer exposure periods, and biological factors excluded from the analysis. The practical implications are clear, El-Mina historic buildings require immediate conservation intervention, informed by environmental monitoring and damage assessment. The database and AI tools that have been developed provide a framework based on decision making and must be integrated with traditional conservation expertise and local knowledge. The crack classification system, based on pH exposure levels, offers a practical tool for rapid assessment and long-term planning, enabling restorers to identify high risk areas before structural failure occurs.

What we found contributes to a growing body of research that integrates digital technologies with heritage conservation. Rather than the replacement of traditional methods, these tools augment human expertise by processing large volumes of data and identifying patterns that may be missed in manual inspections.

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Summary

Three historic sandstone buildings in El-Mina, Lebanon, the Dr. Yaacoub Labban Habitat, the Al Hayek Building 318/12, and the Mameluke commercial structure, show large façade deterioration that conservation specialists attribute to acid rain. We documented cracks penetrating the structural elements, and considerable material loss across all three buildings. Sandstone and rainwater samples were collected from these façades and the area nearby. Together, they provided the foundation for laboratory experiments. The experiments were designed to quantify the relationship between precipitation acidity and material degradation.

This study investigates the effect of acid rain on sandstone structures through laboratory simulations, focusing on the relationship between acid rain and crack formation.

Our experiments exposed sandstone samples to solutions ranging from pH 3.8 to 7.0. These levels match the acidity we measured in El-Mina’s urban precipitation and identified a critical threshold at pH 4.0; below this level, degradation accelerates. Samples exposed to pH 3.8 solutions lost 9-10% of their mass over the experimental period.

Five distinct crack morphologies were identified from the analysis; each type correlated with specific pH exposure conditions and material loss percentages. We documented these patterns through macro photography and digital image segmentation. This created a relational database, which links environmental data with quantitative crack measurements and high-resolution images.

This database helps conservation professionals move beyond reactive visual inspections toward predictive maintenance based on environmental monitoring data. The method is reproducible and can be adapted for other heritage sites facing similar environmental challenges.

Riassunto

Tre edifici storici in arenaria situati a El-Mina, in Libano - il Dr. Yaacoub Labban Habitat, l'edificio Al Hayek 318/12 e la struttura commerciale mamelucca - presentano un grave deterioramento delle facciate che gli esperti di conservazione attribuiscono alle piogge acide. È stato documentato che le crepe penetrano negli elementi strutturali e si osserva una significativa perdita di materiale in tutti e tre gli edifici. Sono stati raccolti campioni di arenaria e acqua piovana dalle facciate in esame e dall'area circostante. Insieme, hanno fornito le basi per gli esperimenti di laboratorio. Gli esperimenti sono stati meticolosamente progettati per quantificare la relazione tra l'acidità delle precipitazioni e il degrado dei materiali.

Il presente studio si prefigge di investigare gli effetti delle piogge acide sulle strutture in arenaria mediante simulazioni di laboratorio, focalizzandosi sulla correlazione tra piogge acide e formazione di crepe. I campioni di arenaria sono stati esposti a soluzioni con valori di pH compresi tra 3,8 e 7,0. Tali livelli corrispondono all'acidità misurata nelle precipitazioni urbane di El-Mina, dove è stata identificata una soglia critica a pH 4,0; al di sotto di tale livello, si osserva un'accelerazione del degrado. I campioni esposti a soluzioni con pH 3,8 hanno subito una riduzione della massa del 9-10% durante il periodo di sperimentazione.

L'analisi ha consentito di identificare cinque morfologie distinte di fessurazioni, ciascuna correlata a specifiche condizioni di esposizione al pH e a percentuali di perdita di materiale. La documentazione di tali modelli è stata effettuata mediante l'impiego della macrofotografia e della segmentazione delle immagini digitali. Questo ha condotto alla creazione di un database relazionale, che integra i dati ambientali con misurazioni quantitative delle fessurazioni e immagini ad alta risoluzione.

Il database pertanto fornisce un supporto agli esperti della conservazione, facilitando il passaggio da ispezioni visive reattive a una manutenzione predittiva basata su dati di monitoraggio ambientale. Il metodo è riproducibile e può essere adattato ad altri siti del patrimonio culturale che affrontano sfide ambientali simili.