Smart environmental monitoring of aerobiological and microclimatic threats for preventive and planned conservation in museums and archives: the CRISALIDE platform

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Abstract

Museums and archives, housing valuable tangible heritage, face diverse threats to preservation. Even in controlled environments, the slow impact of various factors poses risks. Micro-organisms' primary sources of contamination are transported on human beings or airborne through doors and windows. Under favourable microclimatic and nutritional conditions, influenced by temperature, relative humidity, and poor ventilation, deposited biological particulate matter can develop and grow, triggering its biodeteriogenic action. Exhibits, often organic, are vulnerable to cellulolytic and lipolytic actions of bacteria like Streptomyces, fungi including Aspergillus and Penicillium, and others. Because effective mitigation hinges on timely, well-targeted responses by conservation staff, the *Crisalide research project* was framed not as a single tool but as an IoT-oriented monitoring ecosystem: environmental parameters are captured by a lattice of wireless sensing nodes, then federated, normalised, and interrogated through a platform designed for near-real-time situational awareness and standards-compliant interoperability. This approach offers valuable technological integration for monitoring built cultural heritage and what it holds inside.
The paper sets out the aims of a monitoring architecture designed to acquire heterogeneous measurement streams from a distributed array of sensors installed on artefacts and within their enclosures, then convert those observations, through structured processing and inference, into decision-ready knowledge about the evolving condition of materials and systems. The early identification of emerging damage is emphasised to ensure that the timing and proportionality of any response align with the principle of minimum intervention, prioritising swift, low-impact measures over disruptive remediation. At the methodological core is a prognostic framework that models how damage from biological contamination worsens over time. It does this by combining continuous bioaerosol monitoring with multivariate environmental analytics to find early signs of biohazard states before they become apparent. This creates a strong evidence base for preventive conservation, enabling timely, proportionate interventions that follow minimal-impact principles.

1. Introduction

Microclimatic governance in spaces dedicated to the display and safeguarding of artworks is here conceived as the coordinated regulation of temperature, relative humidity, illuminance and radiant exposure, and indoor air quality across both macro-environments (galleries, storage rooms, transit areas) and micro-environments (display cases, storage crates, transport enclosures). This rule is crucial to preventive conservation and goes well beyond a mere technical method; it protects the cultural value of collections without compromising their material integrity. In terms of science, it helps manage kinetics and dose, limit cumulative light exposure, control the rates at which temperature and relative humidity fluctuate, which induce hygro-mechanical stress, and lower pollutant and particulate loads that speed up chemical and biological reactions. Changing these variables reduces the likelihood of threshold occurrences, such as spore germination or faster acid hydrolysis. This lowers both material and immaterial dangers in a measurable way. Curators have long recognised that departures from suitable microclimatic conditions, whether sustained biases in the average values or abrupt temporal gradients, can initiate or amplify deterioration through chemical instability, physical stress–relaxation and fatigue, or the stimulation of biological activity.
Since the cumulative hazard to sensitive substrates is determined by both absolute levels and fluctuation kinetics, this concept extends the scope of environmental control beyond simply choosing set points to include regulating variability and the pace of change. The expected service life of a heritage object is, in practical terms, contingent upon these regimes: carefully tuned conditions slow the accrual of damage, whereas poorly controlled or poorly buffered environments accelerate it. Even in institutions that maintain nominally "controlled" climates, subtle interactions among visitor loads, ventilation behaviour, pollutant ingress, case buffering capacity, and housekeeping practices can exert slow yet consequential effects on collections. Since different materials and assemblies are susceptible to different types of microclimate, it is necessary to consider the whole microclimatic profile (means, variance, and transients) at scales ranging from the room to the case, and to tailor mitigation measures accordingly. According to BS EN 16893:2018, the main ways microbes spread in collecting environments are through particles shed by people (such as lost skin cells) and through aerosols from outside sources that enter through openings like windows and doors. When biological particles are deposited on substrates that are likely to be affected, they can change from passive residues to active biodeteriogenic agents. This happens when the right microclimates are present, which are usually characterised by poor ventilation, high relative humidity, and temperatures favourable for microbial metabolism, as well as nutrient films available. In these circumstances, well-documented taxa, such as Streptomyces (bacteria) and Aspergillus and Penicillium (filamentous fungi), exhibit cellulolytic and lipolytic activities that can degrade organic components of collections (e.g., cellulose- and protein-based materials), thus hastening material fatigue and fidelity loss at both microscopic and macroscopic levels. (Abe and Murata, 2014). The basic architecture of the *Crisalide research project*, which was designed to implement a

Figure 1. Reggio Emilia, Italy. The pilot site of the Planisphere Room at the Panizzi Library.

Figure 2. Bologna, Italy. The pilot site of the Rare Manuscripts Room at the Archiginnasio Library.

platform for the collection and management of environmental parameters using a distributed wireless sensing infrastructure integrated into an Internet-of-Things (IoT) framework, is described in this paper. Rather than a single tool, the platform is articulated as an interoperable ecosystem in which sensing nodes continuously stream measurements that are normalised, time-synchronised, and analysed to support anticipatory conservation practice. In this perspective, museum and library professionals are expected to act rapidly and proactively, aligning operational responses with early indications of risk to minimise intrusive interventions.

Within the proposed architecture, the IoT layer provides the connective tissue for the system: it enables machine-to-machine communication among instruments, fixtures, and embedded devices; orchestrates edge acquisition and secure transport of telemetry; and exposes standard interfaces for data exchange and remote interrogation. It also enforces time-synchronised sampling and semantic metadata, supports fault-tolerant buffering during network outages, and scales from case-level sensors to building-wide deployments, ensuring traceable, high-integrity data streams for analytics and decision support. The technology turns ordinary monitoring into decision-ready intelligence for preventive conservation by turning different observations into a coherent, queryable flow (Malagnino et al., 2021). Harnessed in this manner, digital infrastructure offers a more incisive pathway for monitoring the built heritage and the collections it shelters. Effective conservation requires a thorough, multisource evidence base that triangulates environmental, microbiological, and imaging data to support timely, proportionate decisions. When implemented, this involves outfitting the artefact and its immediate environment with complementary sensors to interpret measurements of the current condition of constituent materials, quickly spot damage patterns, and guide change activities based on the principle of minimal involvement. The raw telemetry then requires structured processing and inference, from cleaning and temporal alignment to feature extraction and probabilistic modelling, so that signals are translated into actionable knowledge that can guide timely, proportionate preventive measures.

1.1 Preventive conservation in the context of library standards and the *Crisalide research project* methodology

Archival and bibliographic materials, especially parchment, are naturally fragile. The materials and methodologies employed in production impose limitations on their long-term durability. As these supports get older, they go through a typical but uneven process of deterioration due to chemo-physical drift, which affects their surface and mechanical behaviour over time (e.g., plasticisation, embrittlement, hydrolysis, oxidative cross-linking). Poor management can accelerate the trajectory further. For instance, improper handling and housing, microclimates that are not set up well, and insufficient ventilation or buffering can make chemical, physical, and biological harm worse and can cause irreversible loss. In this context, anticipatory conservation is not just a good idea; it is also a basic rule for taking care of collections. It depends on constantly putting in place technological protections and behavioural rules for environmental protection, pollution control, housekeeping, handling standards, and risk-informed storage. The components framework collaborates to prevent the onset of an issue, mitigate its advancement, and diminish its severity. The goal is twofold: either practical or moral, stabilise fragile assets by planned, ongoing actions that minimise disruption and maximise long-term viability.

Preventive conservation is best understood as an organised set of steps to minimise the likelihood and potential effects of adverse events when an item interacts with its surroundings. The method is based on risk management and focuses on maintaining stable conditions, limiting exposure to known deterioration agents, and changing daily habits so that vulnerabilities are not worsened or triggered. In this regard, preventive care is both theoretically and operationally different from restoration, which is a way to treat someone. It deals with harm that has already happened and tries to fix, stop, or make up for it in the object's structure.

A program based on preventive conservation aims to delay the need for restoration work or, at the very least, make it less

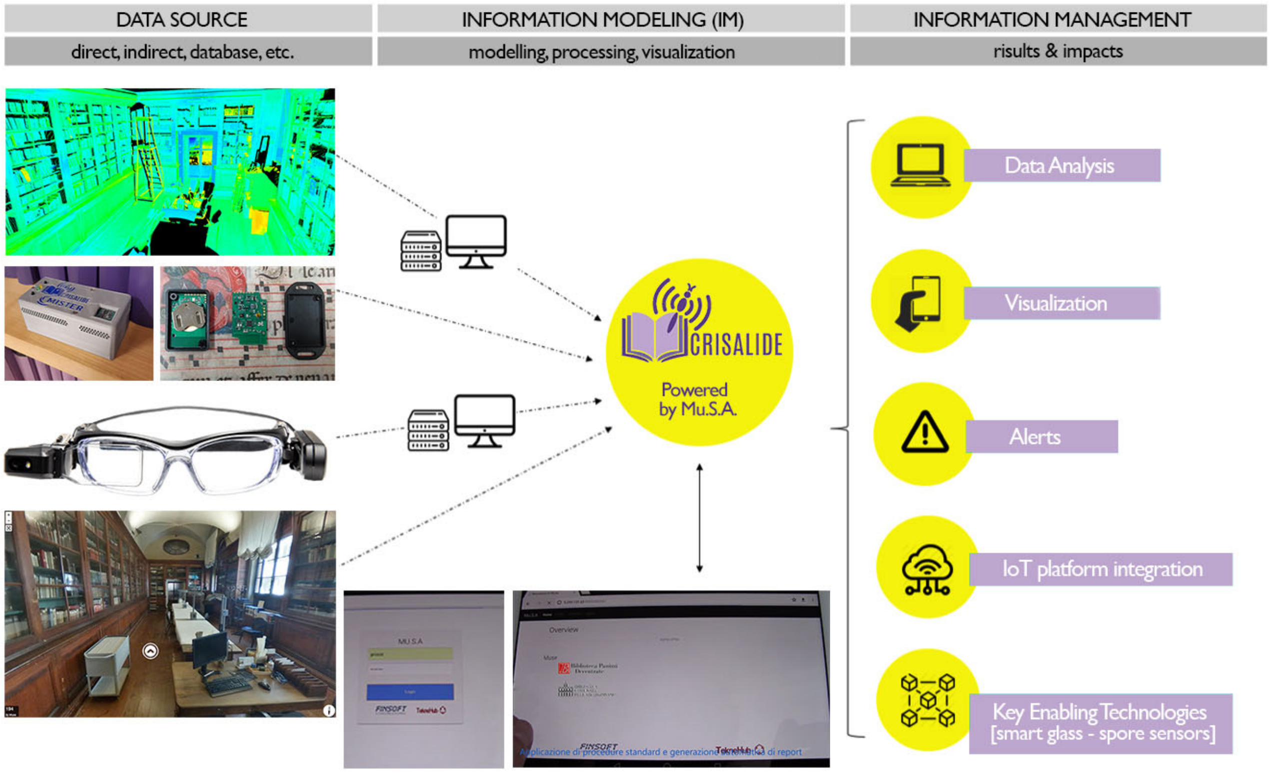

Figure 3. *Crisalide research project* logical framework.

necessary and less severe when it does occur. This is not just a matter of money, even though restoration procedures are usually expensive, time-consuming, and disruptive. It is also a matter of ethics and care with materials, since invasive procedures carry risks and may, despite best practices, make the object's future stability less sure. Preventive techniques, on the other hand, favour activities that are small, reversible, and constantly maintained that stabilise circumstances, extend service life, and keep both substance and meaning with as little interference as feasible. The collection of sampled data subsequently necessitates an advanced platform that, beyond conventional data management and processing systems, can aggregate the extensive data generated by the sensor nodes of the monitoring system, ensuring remote accessibility, queryability, and interoperability among concurrent users (Montuori, 2024). To test the proposed approach's functionality, replicability, and transferability, field trials were conducted under standard operating conditions in two pilot settings: the Planisphere Room of the *Panizzi Library* in Reggio Emilia and the Manuscripts and Rare Books Room of the *Archiginnasio Library* in Bologna. In these settings, a demonstrator prototype was deployed to continuously monitor aerobiological particulate alongside thermo-hygrometric regimes, yielding the *in situ* evidence required to evaluate performance in real use (Montuori, 2025). The collaborative effort with the library institutions' administrative management enhanced the system's applicability and reliability in addressing biodeteriogenic risks in the most critical environments, where particularly fragile artefacts, especially parchments, are kept, and where anthropic impact on biodeteriogenic risk is potentially higher. Aerobiological sampling was performed using sensors designed explicitly by the project collaboration to collect fungal spores in the atmosphere via suction of predetermined, continuous air volumes, employing the volumetric approach. Monitoring of interior environments was conducted at both pilot locations, and the outdoor air in the surrounding areas was also evaluated for comparative analysis, as a substantial proportion of biological contaminants originates from the exterior environment. (Libert et al., 2019). Aerobiological analysis assesses the amount of airborne spores, which is important for determining the likelihood that living organisms will damage conserved heritage. To learn more about how fungi spread and how they affect parchment materials, Aspergillus and Penicillium spores produced on sheep parchment were investigated at the TekneHub laboratories of the Technopole of Ferrara at both pilot sites. The monitoring tool detected and followed the spread of fungal contamination using a machine learning algorithm. For biological sampling, two wireless digital thermohygrometers were used to record temperatures and relative humidity inside and outside. These were made specifically for the project partnership so that the platform could directly interrogate them. These gadgets, which came in many sizes, including one the size of a credit card, were placed near manuscripts and provided important information. Docked in an integrated scheme that couples biological sampling, environmental monitoring, and controlled data accessibility, the system strengthens conservation practice in settings that house fragile holdings (e.g., manuscripts and parchments) by consolidating evidence and speeding informed action. Operationally, the platform then serves as a role-aware dashboard, granting users with differentiated authorisation remote, real-time access to measurements and analytics, together with in-platform processing tools that turn heterogeneous inputs into decision-ready information. The creation of an immersive graphical interface that works best in a virtual world that can be accessed on mobile devices. A three-dimensional database was initially captured using a terrestrial laser scanner to develop a digital twin within a BIM environment. (Chiabrando, Lo Turco and Rinaudo, 2017). Driven by the need for a representation that mirrored the pilot settings more faithfully, a shift away from a conventional 3D model was undertaken in favour of an immersive environment assembled from spherical-image datasets. Enabled by recent advances in image processing and the growing computational headroom of commodity hardware, the digital twin realised through spherical-image compositing proved the most effective route to combine the required sense of presence with lean file footprints, thereby remaining compatible with a networked application designed to organise, query, and provide controlled access to the captured information. (Nagy and Ashraf, 2021). Designed to simulate natural viewpoints, the digital replica offers uninterrupted, smoothly transitioning perspectives that improve spatial navigation, full 360° coverage on the horizontal plane with approximately 180° in the vertical, a result made possible by a photospheric dataset that captures the observable environment from multiple vantage points (Evangelou, Gkeli, and Potsiou, 2022). Interactivity is backed by in-scene identifiers anchored to sensor locations, enabling on-demand, real-time retrieval of the associated measurements and metadata directly within the immersive view. Collectively, the approach to interface development provides a highly effective decision-support framework. Coupling transparent access to underlying datasets through immediate, embodied engagement with place, the interface meets and arguably helps to set current benchmarks for accessibility and user interaction in heritage informatics (Martinelli et al., 2023).

2. Parchment sampling for biological decay classification

A range of complementary detection and identification methods, from culture-based and microscopic examinations to molecular and sequencing-driven assays, enable the catalogue and spatial mapping of the microbial diversity colonising historic parchment. This represents a crucial stage towards the implementation of effective preservation methods. (Shu and Huang, 2022). This strategy averts permanent damage over time, allowing the public to access these documents without substantial losses. However, the selectivity of the media, temperature, and duration can pose difficulties for cultivating bacterial and fungal structures using standard in vitro methods. (Rakotonirainy, Heude, and Lavédrine, 2007; Nautiyal and Dion, 2008). Using molecular approaches makes species-level attribution more reliable, which gets around the problems that come with only using culture or morphology-based identification (Michaelsen, Piñar, and Pinzari, 2010). At the same time, omics frameworks, which are increasingly commonly used in studies of cultural heritage, give us the depth we need to measure biodeterioration and figure out how microbial communities break down materials (Marvasi et al., 2019; Beata, 2020). In particular, proteomics can analyse residual trace proteomes identified on parchment pages, thereby offering a valuable perspective on the health conditions of the

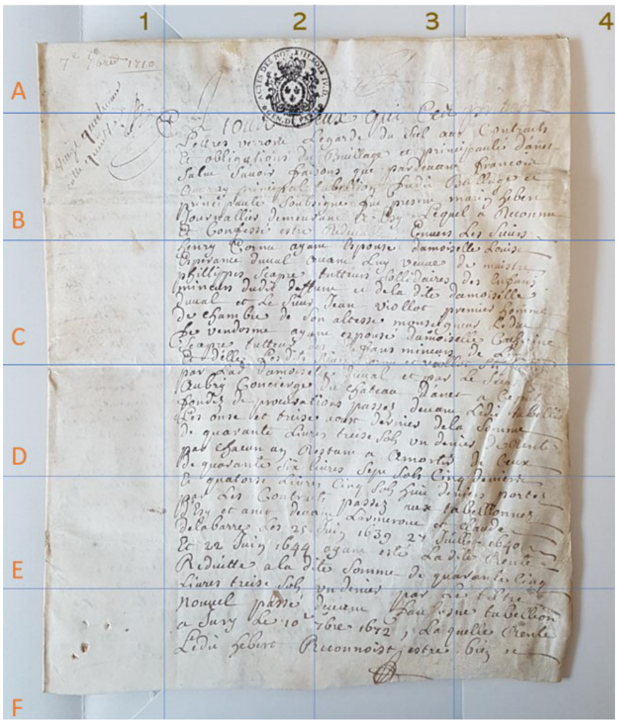

Figure 4. Handwritten sheep parchment document (393×594 mm) selected for analysis, stored in a repository with controlled HVAC conditions. The parchment displays characteristic fungal stains, later investigated through stereoscopic and scanning electron microscopy to assess colonization patterns and select sampling points.

Figure 5. Composite image sequence progressively zooming into the parchment sampling area: from the calligraphic trace to the microscopic identification of the parchment substrate (optical magnification 5:1). Images were acquired by the author at Labo.R.A. – Laboratory of Architectural Restoration, Department of Architecture, University of Ferrara, using an optical bench with a Canon R5 mirrorless camera equipped with a Canon MP-E 65mm f/2.8 macro lens.

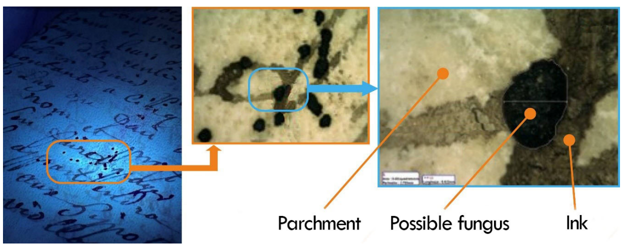

Figure 6. Composite image sequence obtained under fluorescent light, showing the progressive magnification at 5:1 used to identify the parchment areas selected for sampling. The sequence highlights contaminated zones affected by fungal colonization, guiding the choice of sampling points for further analysis.

subject investigated (D'Amato, 2017). This is why the approach focused on the microbial threats to a handwritten document from the eighteenth century that lacks historical or cultural significance. A thorough research and evaluation of microbial presence and diversity were performed together on the sheep parchment to create a dataset for machine learning training (Florian and Manning, 2000; Pinheiro et al., 2019; Pyzik et al., 2021). Various visualisation methods, including stereoscopic, optical, fluorescence, and scanning electron microscopy, were utilised to reveal and assess specific features and patterns. Conventional culture methods were employed to isolate the pertinent microbial contaminants. The phenotypic procedures were executed to aid in partial identification, and comparisons were made with illustrated references of established species.

The document under examination (Figure 4) is a handwritten sheep parchment manuscript (393×594mm), preserved within a document repository located in a facility equipped with its own heating, ventilation, and air conditioning system. Consequently, the document has been properly stored to ensure its preservation. This parchment was selected because of the characteristic fungal stains commonly observed on its surface (Figure 5-6). A stereoscopic microscope was utilised for visual screening to assess twenty-four sampling locations (A-F/1-4). A scanning electron microscope was utilised to examine the fungal mycelia and reproductive structures at elevated magnification levels. The ink pigment constituents, chiefly ferric pyrogallate, influence fungal colonisation; nonetheless, the sampling locations were chosen based on the presence of stains and fungal structures, such as spores or mycelia. Sample rows B, D, E, and F showed single or multiple stained particles. In contrast to the relatively scarce fungal structures shown in A and C, rows B, D, E, and F had a lot of stained particles. B3, D2–D3, and E3–E4, for example, contained many spores and mycelial fragments. Owing to the markedly greater fungal burden relative to the other sampled locations, E3 was consequently designated as the high-stain reference point for subsequent analyses.

The decision was made to proceed non-invasively under the most adverse conditions, where invasive sampling for document examination is prohibited, such as for valuable documents. As a result, a different non-invasive sampling approach was developed to detect possible fungi on the parchment surface. The sampling process was conducted with the highest level of accuracy in the TekneHub facilities, and all staff members had the necessary tools to prevent cross-contamination. Two copies were made at each step, and each was placed in a sterilised container and sent to the lab separately to ensure there was enough material for molecular analysis later.

All apparatus components were previously sterilised using UV light and stored in secure, sterilised containers until use. Biological material was visually examined on each filter tip to assess the effectiveness of the non-invasive methodology. Pattern classification and biological identification entail mathematical and statistical modelling to analyse diverse attributes or structures. Image matching techniques and the creation of colour levels or pattern analysis underpin these simulations. (Yu et al., 2022; Shi et al., 2022). The major purpose was to achieve data levels that exhibit a strong connection, generally within a specific range. The spatial representation of data levels facilitates the formation of patterns by employing data regions inside each specific location. For example, many recognition tasks employ different methods to extract features; yet, these models do not possess the inherent capability to generate unique characteristics for particular locations. On the other hand, convolutional neural networks (i.e., CNNs) are very good at getting spatial information and interactions between layers from images. This helps to explain the unique properties of the topic in the image (Tasci, Uluturk, and Ugur, 2021; Alireza, Ahmad, and Swamy, 2023). Image classification and recognition in deep learning is the use of an artificial neural network that delivers pertinent image data (Wang, Ran, and Fang, 2023). Deep learning methodologies, including forward and backward propagation methods for error assessment, are utilised to improve the loss function. The process entails the iterative refinement of the network's weights to enhance the accuracy of the recognition model. Subsequently, this paradigm facilitates the recognition of new images. To avoid redundant learning, CNNs have been extensively developed and effectively applied in numerous pattern analysis systems to establish a link between neural networks and representation (Yamaç et al., 2021).

This is especially beneficial in overcoming the challenge posed by limited-size datasets. Defining a three-channel input layer for red-green-blue images and adjusting various elements of the neural network's architecture and parameters, the *Crisalide research project* approach employs a customised CNN methodology. (Roy etal., 2023). The architecture was retuned along several axes to improve the network's ability to find and track contamination on insulator surfaces. For example, kernel footprints were resized, the depth of the convolutional stack was changed, non-linearities were rethought in type and placement, receptive-field and filter-bank dimensions were recalibrated, batch-normalisation layers were added and re-parameterised, and the terminal classifier was reformulated with a softmax head. At the centre of the contribution lies a methodology that couples feature selection with convolutional neural classifiers for pattern discrimination. Eschewing a single-backbone design, the architecture is expanded by concatenative growth, in which supplementary convolutional and kernel layers are interleaved with drop-block regularisation stages and residual blocks; this layered integration deepens the feature hierarchy, enhances representational richness, and, in turn, improves classification performance.

This approach leads to an advanced machine learning architecture that operates within the *Crisalide* framework to select the best features during training, ensuring the best possible performance. The sampling procedure used data from two pathogenic fungal species that affect parchment: *Penicillium* and *Aspergillus*. Using a spatial transformer network, the fungal samples underwent a pattern transformation, enabling more detailed analysis of changes in fungal characteristics.

3. Predictive models for airborne particles risk assessment in archives and museum collections

The safeguarding of archival and museum collections, particularly those comprising biologically sensitive materials such as parchment, represents one of the most critical challenges in the field of preventive conservation. Rather than being passive substrates, parchments act as highly complex micro-ecosystems (Cappitelli et al., 2010), with organic composition, leftover nutrients, and ambient conditions providing a rich foundation for microbial colonisation. The simultaneous presence of various fungal species, such as *Aspergillus* and *Penicillium* (Grabek-Lejko et al., 2017), results in dynamic interactions that are challenging to record using traditional monitoring methods. Traditional methodologies, including static sampling (Kraková et al., 2017) and culture-dependent procedures, have been beneficial in exposing the microbial richness that lives on parchment surfaces. However, such technologies only provide a fragmented view of ongoing biological processes and cannot forecast the evolution of microbial risks over time, providing a limited picture of a continually changing biological system.

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This methodological limitation underscores the potential of artificial intelligence to transform conservation strategies (Zhang et al., 2021). Specifically, a Large Language Model-based approach enables the detection of correlations between contamination and microclimatic conditions that remain invisible to conventional techniques, offering not only more accurate diagnostic capabilities but also valuable predictive insights. These insights support not only the preservation of objects but also the optimisation of conservation environments. In this way, artificial intelligence fosters the implementation of planned conservation strategies, facilitating timely and well-targeted interventions that enhance the long-term sustainability of cultural heritage management. Specifically, biodiversity data acquired from microbiological characterisation can be converted into biological features useful for training prediction algorithms. Machine learning models can detect latent patterns and predict when biodeteriogenic organisms may flourish by linking microbial presence with environmental parameters such as temperature, humidity (Frankel et al., 2012), and airborne particulate matter (Cristina et al., 2012). The shift from observational studies to predictive analytics is a critical step towards the establishment of adaptive surveillance strategies for heritage protection. Within this paradigm, the *Crisalide research project* employs machine learning to discover dynamic patterns in bioaerosol presence, allowing museums and archives to transition from episodic monitoring to continuous and adaptive environmental surveillance laying the groundwork for a new approach in archival and museum conservation.

3.1 Machine learning approach for adaptive environmental surveillance

The adoption of CNNs has already demonstrated its effectiveness in the classification of microscopic images of fungi (Zhang et al., 2017), offering high accuracy in distinguishing morphologically similar species. CNNs can function as a diagnostic layer within a broader decision-support infrastructure by transferring these approaches to aerobiological datasets collected in heritage environments, thereby providing automated recognition of airborne contaminants (Tahir et al., 2018). One of the most pressing challenges in this field lies in the scarcity of annotated datasets specific to cultural heritage. To overcome this limitation, the technique of data augmentation becomes essential (Liu et al., 2020). This strategy, which artificially expands the dataset through rotations, transformations, and contrast adjustments of microscopic and aerobiological images, is crucial in enhancing the robustness of predictive models. These strategies strengthen the reliability of automated recognition systems, ensuring that even limited training data from heritage collections can be effectively leveraged for practical applications.

These systems' predictive dimension spans many scales, from the storage location (i.e., the historic building itself) to its content (i.e., museum and archival treasures).

Analogies with biotechnological research provide a valuable framework for conceptualising this process: just as predictive models are used to predict fungal growth dynamics in bioreactors by integrating data on temperature, nutrient availability, and pH, similar algorithms can be applied to cultural heritage, where temperature, relative humidity, and airborne particulate concentrations predict biodeterioration (Narayanan et al., 2020). The concentration of biodeteriogenic agents in the air is not a constant metric; it varies in response to changes in environmental conditions. Temperature influences both the metabolic rate of microbes and the volatility of airborne particles, resulting in seasonal and diurnal fluctuations in spore loads. Relative humidity has a significant impact on spore viability, germination capacity, and the persistence of fungal propagules in suspension, frequently converting microclimatic changes into abrupt alterations in the level of biological risk. However, it's the airborne particulate matter that serves as both a carrier and a nutritional source, exacerbating these dynamics. Its role in accelerating the transit and deposition of spores onto vulnerable surfaces such as parchment, paper, and textile fibres underscores the need for preventive measures. The interaction of these variables produces highly non-linear patterns of contamination that are virtually undetected using typical observational approaches. Therefore, the inclusion of temperature, humidity, and particle data into machine learning models not only enables the identification of previously unknown relationships and the prediction of airborne contamination peaks but also has significant practical implications. This predictive ability facilitates the design of adaptive monitoring systems that can provide early warnings, thereby reducing the temporal gap between the emergence of critical conditions and the implementation of preventive conservation measures. The practical implications of this predictive insight are far-reaching, offering a valuable foundation for reducing exposure to environmental risks through the timely scheduling of planned conservation interventions, ensuring that preventive measures are strategically programmed rather than merely reactive, in accordance with changing microclimatic conditions.

Hence, these analogies prove the viability of applying predictive control to highly varied and vulnerable contexts like archives and museums. Furthermore, the use of adaptive learning methods ensures that prediction models are constantly updated with new real-time data obtained by automated sensing. This adaptability, a key feature of the system, improves the system's responsiveness, allowing conservation measures to evolve with environmental changes and microbial dynamics, thereby reassuring about the system's robustness.

3.2 From sampling to CNN-based classification

The methodological framework adopted in this stage of the research was designed to integrate traditional microbiological protocols with advanced computational modelling. The process began with the acquisition of samples from parchment artefacts and continued through their laboratory cultivation, morphological and molecular characterisation, and finally the development of CNNs for automated recognition. Each phase of this workflow was conceived to generate high-quality, structured datasets capable of sustaining predictive models for the surveillance of microbial contamination in cultural heritage environments.

The acquisition of samples was carried out under strictly controlled conditions in order to minimise the risk of additional contamination and to preserve the integrity of the artefacts. Sterile cotton swabs were gently applied to both the surface and the microfissures of parchment fragments previously selected for their representativeness of typical conservation problems. In some instances, parchment specimens were deliberately inoculated with reference strains of Aspergillus and Penicillium, two genera frequently associated with biodeterioration processes in archives, libraries, and museums. This procedure, widely documented in conservation microbiology, ensured the availability of experimental controls and positive references for subsequent analyses. All swabs were immediately transferred into sterile tubes containing saline solution with 0.05% Tween-80, a medium chosen to maximise spore recovery and homogenisation prior to plating.

Cultivation of the microbial load followed standardised mycological procedures of the Microbiology and Pathology Laboratories of the University of Ferrara. Aliquots of the suspension obtained from each swab were streaked on different agar media, including malt extract agar and potato dextrose agar, which provide optimal conditions for fungal growth. Plates were incubated at 25 °C and 30 °C under controlled humidity, allowing both mesophilic and xerophilic taxa to develop. The incubation period extended over seven to ten days, with daily inspection under stereomicroscopy to monitor colony morphology, pigmentation, and sporulation. Representative colonies were sub-cultured onto fresh plates in order to establish pure isolates, subsequently identified using both macro- and micro-morphological criteria. This stage generated a baseline catalogue of the biodiversity colonising parchment specimens, essential for building the biological ground truth against which computational models could be trained (Figure 7).

In parallel, microscopic preparations were obtained from pure colonies by mounting spores and hyphal fragments in lactophenol cotton blue solution and imaging them under high-resolution optical microscopy. Each image was digitised at 40 and 100x magnification, building a dataset of visual features characterising the morphotypes of interest. To ensure reproducibility, multiple images were acquired for each isolate, capturing variations in orientation, lighting, and focus. These microscopic datasets were complemented by molecular analyses, specifically ITS-rDNA sequencing, which provided taxonomic validation of morphologically identified isolates. The combination of culture-based, morphological, and molecular datasets allowed the construction of a reliable and multidimensional reference for subsequent machine learning applications.

The development of convolutional neural networks relied upon these curated image datasets. Pre-processing was applied to standardise image dimensions, eliminate background noise, and normalise pixel intensity distributions. Data augmentation techniques, including rotations, flips, zooms, and brightness variations, were implemented to expand the training dataset artificially, addressing the inherent limitation of small sample sizes typical for this specific application in cultural heritage preservation. This approach increased the diversity of training examples while preserving the biological relevance of the morphological features (Figure 8).

Backed by the software development team inside the *Crisalide research project* consortium, the implementation followed a reproducible, open-source toolchain widely adopted in computational bioimage analysis. Data curation and preprocessing pipeline were developed in Python v.3.10, using NumPy v.1.21.1 and Pandas v.2.3.1 for input-output and metadata handling, scikit-image – Skimage v.0.25.2 and OpenCV for denoising, normalization, and background correction, and PyimageJ library for microscope-native operations such as bit-depth harmonization and tile export; inputs were resized to 224×224 pixel, maintaining aspect ratio with letterboxing when necessary. Network training was performed in TensorFlow/Keras v.2.15 and, in confirmatory runs, results were cross-checked on PyTorch v.2.4.1, to ensure reproducibility with alternative training stacks, as widely established in previous studies on fungal detection and medical image classification. Transfer learning was implemented via model zoos (i.e., TensorFlow and PyTorch), providing ImageNet-pretrained VGG16 model (Simonyan and Zisserman, 2014) and ResNet backbones (He et al., 2015). To address limited training data typical of cultural-heritage imagery assessment, literature-consistent data augmentation via Albumentations v.1.4 3 libraries (for random rotations and reflections, mild elastic/affine transforms, brightness and

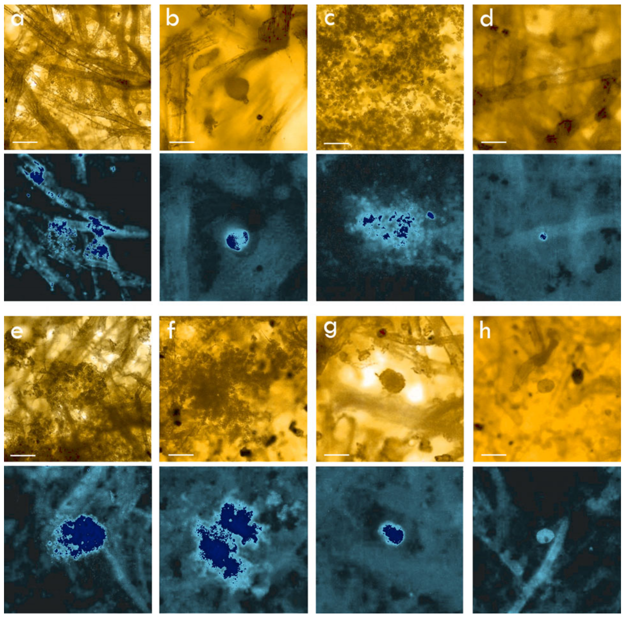

Figure 7. Optical microscopy images acquired in brightfield (top) and fluorescence (bottom), forming a dataset of visual features representative of the target morphotypes. Scale bar = 40 µm. Multiple frames were collected for each isolate to capture variations in orientation, illumination, and focal depth. Images were standardised to 224×224 pixels with aspect ratio preserved through letterboxing, ensuring consistent inputs for network training.

contrast jitter, Gaussian noise/blur) was adopted, with parameter ranges constrained to preserve diagnostically relevant morphologies. Class imbalance was mitigated through weighted cross-entropy and on-the-fly class-balanced sampling; hyperparameters were selected via stratified 5-fold cross-validation with a specimen-level split to prevent leakage.

The stochastic gradient optimisation employed the Adaptive Moment Estimation algorithm (i.e., Adam) with cosine learning-rate annealing and the EarlyStopping technique on validation loss; ReduceLROnPlateau guarded against plateauing. Regularisation combined with dropout in the classifier head, L2 weight decay on convolutional kernels, and stochastic augmentation at training time. Inference-time ensembling, in terms of test-time augmentation and snapshot averaging, was used to stabilise predictions, consistent with ensemble strategies reported for microscopic fungi classification. To enhance interpretability and align predictions

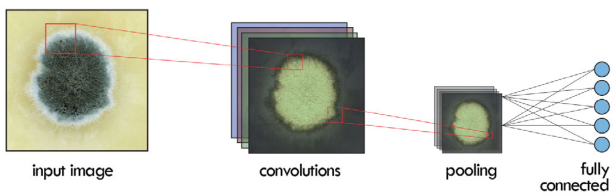

Figure 8. CNN architecture and training workflow. The convolution and pooling layers are fine-tuned in terms of hyperparameters, specifically for convolution: the number of filters, kernel size, stride, and padding; and for pooling: the window size and stride. Cross-validation is used to choose hyperparameters that maximise performance while reducing overfitting. The *Crisalide* platform utilizes the classifier's probabilistic output as dynamic biological risk layers to provide early warning and decision support.

with morphological cues, the model adopted Grad-CAM and Score-CAM via PyTorch to visualise class-discriminative regions, supporting expert validation of network attention against known morphological markers (conidiophore geometry, spore ornamentation). Performance reporting included accuracy, macro-averaged F1 score, per-class sensitivity and specificity, and confusion matrices; while calibration was assessed with reliability diagrams and expected calibration error.

The pipeline orchestration used the OmegaConf library in Hydra framework for experiment configuration, fixed random seeds for determinism, and TensorBoard for experiment tracking and logging. Trained models, designed for adaptability, were exported to ONNX for runtime portability and seamlessly integrated into the *Crisalide* inference service as a gRPC microservice. This integration allowed for batched scoring of aerobiological frames on both CPU and GPU, demonstrating the versatility of the models. When Matlab was the preferred tool in literature studies (Koo et al., 2021; Rahman et al., 2023), interoperability was ensured by exporting trained TensorFlow and PyTorch weights and reproducing preprocessing with Matlab's Image Processing and Deep Learning Toolboxes to validate cross-platform consistency. The resulting approach demonstrated strong performance in distinguishing between closely related fungal genera and species, confirming the viability of the automated fungal identification process. The framework's interpretability was further improved using Gradient-weighted Class Activation Mapping visualisation, which highlighted the image regions that contributed the most to classification decisions, connecting computational predictions with observable morphological qualities. This combined methodological pathway demonstrates the potential of bridging traditional microbiology with artificial intelligence. The recognition of biodeteriogenic taxa can be automated, and the results can be integrated into broader environmental surveillance frameworks by converting microscopic images of fungal structures into structured digital datasets that are suitable for CNN training.

The approach not only preserves the depth and reliability of culture-based methods but also introduces the scalability and predictive power of machine learning, paving the way towards adaptive and proactive conservation strategies, a framework that has the potential to transform the way biodeterioration risks are managed in heritage environments.

Hence, combining biodiversity-derived features, real-time environmental datasets, and adaptive machine learning, it becomes possible to establish a system capable of providing early warnings and supporting preventive conservation strategies. This paradigm shift, from descriptive to predictive and from static to adaptive, justifies the transition towards a digital twin specifically designed for the two pilot sites. Such a twin should not merely replicate environmental conditions but also function as a predictive and adaptive model, continuously refined by incoming data, allowing for a proactive approach to the conservation of biological artefacts and archival collections.

4. The digital twin as a predictive decision support for planned conservation

The integration of heterogeneous datasets (e.g., microscopic images, environmental measurements, and molecular outputs) paired with CNNs, transfer learning, and ensemble modelling, offers a strategic pathway toward programmed and truly preventive conservation in archival and museum sites. Within this paradigm, predictive analytics are not an end in themselves but the computational substrate of a decision-support system capable of simulating degradation scenarios and optimising conservation strategies before damage manifests. CNNs, now a consolidated class of algorithms with mature software stacks and validated performance across adjacent domains, can be embedded as modular diagnostic components inside a complex infrastructure such as the digital twin of a collection or an entire building (Giuliani et al., 2024).

The digital twin evolves from a static digital replica into a predictive and adaptive ecosystem that guides curatorial decisions, plans maintenance, and coordinates low-impact interventions in a way that is auditable, explicable, and compliant with conservation ethics, combining sensing streams with learnt priors and periodic bio-diagnostic inputs.

4.1 From diagnosis to a predictive environment

An effective way to frame this approach is by analogy with clinical practice, where a patient's condition is assessed through a layered diagnostic process and longitudinal records. The two pilot sites and their enclosures were conceptualised as "digital patients", whose states are inferred from multimodal evidence and continuously updated through time. In this analogy, CNNs operate as imaging diagnosticians for bioaerosol and microscopy data, turning heterogeneous visual inputs into quantitative indicators of biological threat (Figure 9-10). Culture-based characterisation and molecular assays extend the diagnostic spectrum by identifying taxa and strain-level signals associated with biodeterioration propensity. At the same time, environmental monitoring contextualises these findings in terms of thermo-hygrometric stress and particulate-mediated transport. The digital twin becomes the patient chart and simulation engine, aggregating historical trajectories from artefact and room-level nodes, linking them with current sensor observations, and projecting near-term risk states conditioned on seasonal cycles, occupancy patterns, and known susceptibilities of materials, such as parchment artefacts in the case study. In this configuration, the digital replica is not merely a repository of measurements; it is conceived as a proactive, predictive ecosystem where environmental, microbiological, and genetic layers are co-registered, queried, and used to propose mitigation actions with explicit uncertainty quantification and traceable rationales (Hosamo and Mazzetto, 2025), thereby providing control over potential risks.

4.2 Implementing continuous risk monitoring and early warnings within *Crisalide*'s multilayer platform

The *Crisalide* platform has been implemented to ingest and harmonise continuous data streams and periodic diagnostics, enabling early-warning capabilities grounded in the logic of stratified risk. In the pilot configuration, periodic diagnostics follow a fixed cadence: culture-based surface and air sampling is performed weekly to provide actionable ground truth, targeted quantitative Polymerase Chain Reaction (i.e., qPCR) screens are run monthly to detect non-cultivable taxa and low-abundance signals, and amplicon sequencing campaigns are executed quarterly to refresh the genomic baseline and track community shifts. At the environmental tier, temperature, relative humidity, and airborne particulate matter are sampled at 1-minute intervals and aggregated into 10-minute intervals, with automatic hourly/daily roll-ups to capture diurnal cycles, seasonal variability, ventilation regimes, and visitor-driven microclimatic perturbations. At the microbiological tier, bioaerosol frames acquired continuously from automated collectors are classified by CNNs into probability distributions over relevant taxa or morphotypes at sub-minute latency, allowing the system to track shifts in airborne biological loads over time rather than relying on single-point counts. At the molecular and genomic tiers, qPCR targets and sequence-based

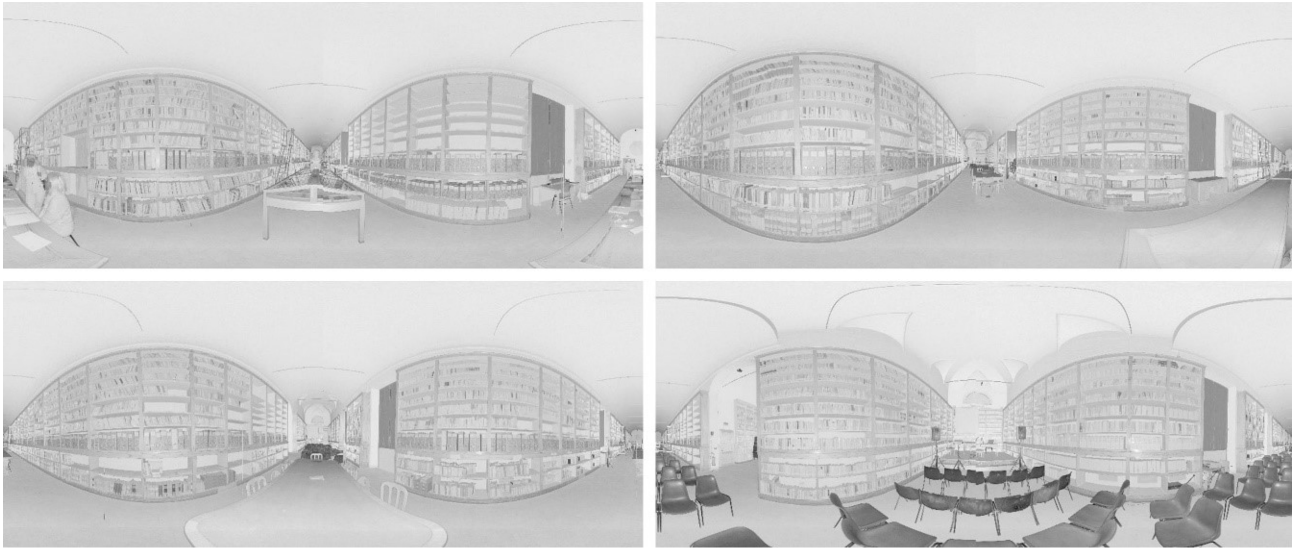

Figure 9. The Planisphere Room at the *Panizzi Library*, Reggio Emilia. The terrestrial laser scanner campaign implemented to support the digital twin development for the risk monitoring multilayer platform.

markers provide sensitivity to non-cultivable organisms and strain-level traits that may not be discernible morphologically, acting as early signals even when visible colonisation is absent. These tiers are integrated within the platform as dynamic risk layers: sensor-level data can be queried continuously via the platform GUI by interrogating individual sensors. The dashboard is refreshed every 10 minutes and spatially maps the layers to rooms, storage zones, and display cases across the pilot sites.

On-site automation closes the latency gap between sampling and response: sustained increases in particulate loads co-occurring with elevated CNN-inferred probabilities of problematic spores trigger graded alerts, while molecular confirmations adjust thresholds and reweight model priors. The platform detects drifts in indoor sensor behaviour and seasonality, retrains models when new labelled data are available, and recalibrates alarm rules to minimise nuisance triggers. Temperature and relative humidity thresholds are applied to indoor environments and display-case sensors. Outdoor registrations are ingested only as boundary conditions to anticipate indoor drifts and schedule preventive heating, ventilation, and air conditioning actions. In the current configuration, illuminance thresholds for light-sensitive holdings (e.g., parchment, paper and organic artefacts in general) are set at: *warning* > 50 lux (sustained ≥10 min), *alert* > 80 lux (≥10 min), and *critical* > 100 lux (≥5 min); case-level limits can be tightened by ~20% for highly sensitive objects. Indoor temperature targets low-energy stability with: *warning* outside 18–22 °C (sustained ≥30 min), *alert* outside 16–24 °C (≥30 min), and *critical* outside 14–26 °C or when the indoor air–surface dew-point margin at the showcase drops below 3 °C. Indoor relative humidity adopts a conservation band with: *warning* outside 40–50 % RH or a 24-h drift > ±5 % RH, *alert* outside 35–55 % RH or 24-h drift > ±10 % RH, and *critical* outside 30–60 % RH or upon dew-point risk; for case-level microclimates, drift limits are tightened by almost 50% relative to ambient (e.g., warning if 24-h drift exceeds ±2–3 % RH). Occupancy, estimated by doorway entries, uses rolling 15-minute windows referenced to ventilation capacity: *warning* > 30 persons/15 min, *alert* > 45 persons/15 min, and *critical* > 60 persons/15 min, or earlier if co-occurring with RH/temperature excursions. All thresholds are site-tuneable after baseline characterisation and can be tightened for highly sensitive rooms or relaxed for robust spaces. The resulting outputs are rendered as predictive risk maps and contamination probability surfaces, accessible through an immersive dashboard for conservators and facility managers. These maps reveal current hotspots and forecast their evolution under observed trends, making anomalies and emerging patterns intelligible at a glance. Because each layer contributes complementary evidence, the system reduces over-reliance on any single modality and provides a secure basis for escalating actions, from microclimate tuning to targeted inspections and surface sampling. The platform's ability to generate concordant signals (e.g., a sustained RH rise co-occurring with elevated particulate loads, CNN-inferred spore probabilities, and subsequent qPCR positivity) not only increases confidence but also suppresses false alarms. Most importantly, it justifies proportionate, documented interventions with quantified uncertainty, instilling a sense of confidence in the decision-making process.

4.3 Scenario-driven decision support and adaptive control in an "adaptive archive and museum environment"

Decision support in *Crisalide* platform is anchored in scenario simulation and predictive control. CNN outputs, especially when combined through ensembles, feed the digital twin with probabilistic, noise-robust indicators of biological risk. Transfer learning further accelerates deployment by allowing models pre-trained in archive contexts to be adapted to museum environments with limited additional annotation, preserving domain-invariant morphological cues while fine-tuning to site-specific backgrounds and optics. *Crisalide* platform's ability to provide early warnings is not just a feature, but a crucial aspect of its functionality. These probabilistic layers drive what-if analyses that explore counterfactual futures: the dashboard projects how risk maps would shift with a change in ventilation schedules, a planned increase in visitor flow, or a revised setpoint for relative humidity (Walther, Molinari and Voss, 2025). The approach facilitates logical compromise between conservation requirements and practical limitations, revealing the sensitivity of risk to controllable parameters. When predictive thresholds are crossed or rapid upward trends are detected, the *Crisalide* platform issues early warnings and proposes interventions whose expected impact is computed from the twins' learned dynamics. In pilot deployments,

Figure 10. The Rare Manuscripts Room at the *Archiginnasio Library*, Bologna. The photosphere campaign addressed the implementation of the monitoring platform immersive user interface.

particulate exceedances have been linked to dynamic alerts that escalate if accompanied by consistent CNN-inferred spore probabilities, guiding short, reversible actions such as localised ventilation adjustments, filtration checks, or the temporary restriction of access in sensitive rooms. Crucially, the platform does not attempt to replace established diagnostic practices; instead, it renders them scalable and timely. Culture-based examinations and expert inspections remain the ground truth for attribution and remediation design. The twins' role is to focus those efforts where they are most needed, compressing the time between onset and response and providing a quantitative trail to justify decisions. As additional molecular and genomic information becomes available, especially from targeted assays that reveal taxa not captured in culture, the platform updates its belief state and revises forecasts, treating genetic signals as early indicators that can predate visible growth. This tight loop between sensing, inference, and action, together with the capacity to simulate the effects of candidate responses, embodies an "adaptive archive and museum environment" in which conditions are continually optimised to suppress biodeterioration drivers with minimal disruption.

Operationally, the integration of CNN modules into the platform framework enables real-time control support. Classification probabilities are ingested as event streams that the decision logic correlates with environmental kinetics; when risk accumulates beyond site-specific envelopes, the system is set to recommend or automatically trigger low-intensity control actions within pre-approved bounds. Over time, archived streams are mined to refine site baselines and seasonally re-parameterise the models, strengthening the predictive horizon

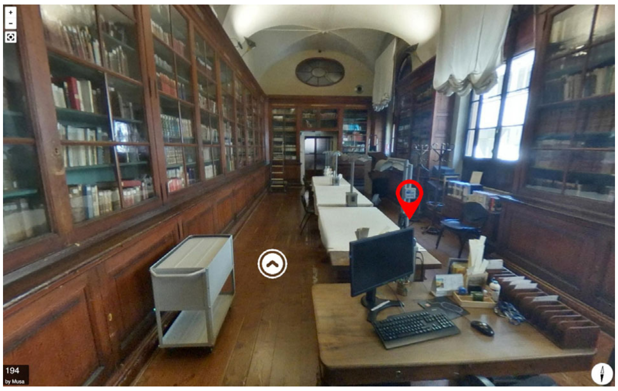

Figure 11. The *Crisalide* platform immersive user interface.

and stabilising alert performance (Petrić et al., 2024). Because outputs are presented as uncertainty-aware overlays in the dashboard, with explanatory heatmaps for image-derived inferences, conservators can audit why a specific recommendation was made and calibrate actions accordingly. For example, on an RH alert (e.g., sustained exceedance >55 % RH for ≥30 min with high confidence and a co-occurring rise in particulate, the system recommends a temporary 2–3 % RH set-point reduction) an increased dehumidification duty cycle and extended evening ventilation run-time, short-term limits on occupancy in the affected rooms (Catrambone et al., 2025), insertion of additional buffering materials in display cases, and the scheduling of targeted inspections plus surface/qPCR sampling within 48 h, with automatic rollback of measures once the risk index falls below threshold. The result is a proactive, learning system that anticipates biological risk, orchestrates preventive conservation measures, and documents their efficacy, thereby embedding scientific reasoning into day-to-day stewardship.

5. Discussion and conclusions

Physical change to historic organic materials is often what is noticeble first, as fibres lose cohesion, surfaces craze or powder, and chromatic shifts dull or stain the image plane. On the other hand, a biochemical process is usually indicated by these major symptoms. Fungal and bacterial enzyme suites, including cellulases, proteases, laccase/lignin-modifying enzymes, and low-molecular-weight organic acids, depolymerise proteins and polysaccharides, break binding phases, and mobilise additives and pigments in legacy organics. This leads to a gradual deterioration of mechanical strength and visual impact, both of which are exacerbated by the presence of purely physical stresses. Starting with the observable damage, the analytical path proceeds retrogradely to its enzymatic drivers; on that basis, the operative biodeteriogenic processes are ascertained and, in turn, the environmental conditions that sustain them are delineated, preconditions for any credible mitigation of deterioration.

What makes filamentous fungi troublesome in collection spaces is, first, the way they travel: dry conidia and hyphal fragments detach easily and stay airborne, so even the light air currents from door openings or HVAC diffusers can disperse them across rooms and into cases. Many species will also initiate or sustain growth at relative humidities lower than those typically needed by bacteria, often within bands a museum would otherwise regard as acceptable for mixed holdings (e.g., 45–55% RH). Add to this their capacity to survive intermittent drying and recover quickly when moisture returns, and the result is a disproportionate threat to hygroscopic, organic substrates, which offer thin nutrient films and little buffering once microclimatic control slips. Seen through a preventive lens, the priority is to assess how the environment behaves, not as a backdrop, but as interacting drivers of risk. The chief contamination vectors that trigger biodeterioration on parchment and related substrates are temperature, relative humidity, air movement, and particulate load, which impact surface moisture, particle transport, and the residence time of airborne spores. In libraries, archives, and museums, a consistent array of microbiological agents frequently modifies the chemistry and mechanics of the substrate, hence facilitating subsequent pest colonisation. Under routine operating conditions, the research traces biological shifts in historic parchment and relates them to instrumented microclimates and recurrent microbial taxa, thereby providing the basis for targeted, proportional measures aligned with the principles of preventive conservation (Dalla Mora et al., 2025). Viewed more broadly, the approach establishes normative trajectories of behaviour, time- and space-bounded baselines against which deviations can be recognised early and addressed promptly. In this frame, improving indoor air quality emerges as a priority lever for regulating environmental conditions and moderating biodeterioration risk. (Florian, 1997). Rather than beginning with agents of decay, the discussion starts from the decision-support function required in day-to-day stewardship. CRISALIDE was configured as an integrated monitoring and control environment: wireless sensing nodes, IoT-enabled, streaming thermo-hygrometric and aerobiological telemetry to the platform, which curators can interrogate in real time, remotely and concurrently, through a role-aware interface. Within pre-approved bounds, the system proposes and, where authorised, triggers low-impact stabilisation measures such as brief ventilation cycles or set-point trims, and it learns from outcomes so that recommended actions become progressively better calibrated to the site's behaviour.

The logic behind this architecture is predictive rather than merely descriptive. A paired microclimatic–aerobiological regime is continuously tracked, and departures from established baselines are interpreted in relation to architectural context and preservation status to surface incipient biohazard conditions before they manifest in the fabric. In practice, the platform's coupling of bioaerosol surveillance with environmental analytics allows staff to modulate relative humidity, temperature and air movement in a timely, proportionate manner, reducing the likelihood that transient disturbances harden into risk.

Only at this point is the biological mechanism invoked to explain why such control matters. Quiescent spores are ubiquitous, on object surfaces and in room air, but they are not, in themselves, a guarantee of growth. The moisture availability within materials is the decisive variable: once water activity crosses favourable thresholds, spores germinate, and metabolic activity accelerates. The CRISALIDE workflow reduces microbial rates at their source by containing the microclimate within stable envelopes and slowing the deterioration kinetics. The result is an operational model in which sensing, inference, and measured intervention come together to guide conservation within defined space and time, translating continuous evidence into preventive practices that safeguard parchment and related collections with minimal intrusion.

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