A Data-Driven and Physics-Informed Framework for Cultural Heritage Conservation

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***Abstract*—The conservation of cultural heritage requires increasingly advanced tools to monitor, understand, and predict degradation phenomena affecting artefacts, historical buildings, and archaeological assets. In this context, the integration of the Internet of Things, Artificial Intelligence, physical models, and three-dimensional digital replicas represents a promising direction to support predictive maintenance strategies and informed decision-making by domain experts. This work proposes a framework for cultural heritage conservation based on the integration of sensor data, 3D models, numerical methods, and Scientific Machine Learning. The framework is organized into four functional layers: acquisition, knowledge-base, inference engine, and application. A central component is the employment of Physics-Informed Neural Networks, which make it possible to incorporate physical knowledge into the learning process. Furthermore, the framework integrates Reduced Order Models, particularly methods based on Proper Orthogonal Decomposition, to improve the efficiency of simulations in many-query or real-time scenarios. The proposed approach aims to provide a flexible tool for the analysis of complex geometries, the simulation of physical processes, and the support of predictive maintenance in cultural heritage contexts.**

***Index Terms*—Cultural Heritage Conservation; Internet of Things; Artificial Intelligence; Digital Twin; Physics-Informed Neural Networks; Reduced Order Models; Scientific Machine Learning; Predictive Maintenance.**

I. Introduction

The conservation of cultural heritage is a scientific, technological, and social challenge of primary importance. Monuments, artefacts, historical buildings, and archaeological sites are exposed to several degradation factors, including environmental conditions, pollution, structural phenomena, and the intrinsic properties of materials [1]. The possibility of monitoring these factors and predicting their evolution over time is essential for planning more effective, timely, and sustainable conservation interventions.

In recent years, several digital technologies have transformed the way cultural heritage is documented, analysed, and managed. The Internet of Things (IoT) enables continuous data acquisition through sensor networks [2]; Artificial Intelligence (AI) allows large amounts of information to be processed and meaningful patterns to be identified [3]; three-dimensional digital replicas and Digital Twins (DTs) provide virtual environments in which risk scenarios can be simulated and operational decisions can be supported [4]. However, many existing approaches tend to focus on only one part of this process: some emphasize 3D documentation, others sensor-based monitoring, numerical simulation, or data-driven prediction.

A major limitation of these approaches is often the lack of effective integration among data, digital geometries, physical models, and machine learning tools. In the field of cultural heritage, this integration is particularly relevant because available data may be limited, noisy, or difficult to acquire, while the physical knowledge of degradation phenomena and the expertise of conservation specialists represent fundamental resources. For this reason, a purely data-driven approach may be insufficient, whereas a purely physics-based numerical approach may be computationally expensive and difficult to adapt to dynamic contexts.

This work proposes a framework that combines data, physics, and AI for cultural heritage conservation. The key idea is to exploit the potential of Scientific Machine Learning (SciML), and particularly Physics-Informed Neural Networks (PINNs), to integrate differential equations, sensor data, and three-dimensional geometries within a single architecture [5], [6]. This is complemented by the employment of Reduced Order Models (ROMs), which reduce the computational cost of simulations while preserving an adequate level of accuracy [7]. The proposed framework is intended as a methodological and technological basis for developing decision-support systems for predictive maintenance of cultural heritage assets.

II. The Proposed Framework

The proposed framework is organized into four functional layers: the Acquisition Layer, the Knowledge-Base Layer, the Inference Engine Layer, and the Application Layer. This modular structure separates the different stages of the process, from data collection to result visualization, while preserving strong integration among the components [8].

The Acquisition Layer is responsible for collecting and preparing the information required for the analysis. It includes the management of sensor data, the integration of APIs and open data, and the processing of three-dimensional models of cultural assets. Sensors can collect information related to temperature, humidity, pollution, corrosion, or other phenomena relevant to conservation. These data can be managed through an IoT platform, which enables storage, visualization, and transfer to the other layers of the architecture. At the same time, the 3D model module processes digital replicas obtained, for example, through photogrammetry or laser scanning. A significant feature of the framework is its ability to automatically transform 3D models into information suitable for simulation. To this end, the architecture exploits Blender APIs to extract geometric data. These data are used to generate meshes, collocation points, and boundary data. In this way, the geometry of the cultural asset becomes directly usable in physical simulation and physics-informed learning workflows.

The Knowledge-Base Layer represents the storage and organization core of the framework. It collects sensor data, information extracted from 3D models, external data acquired through APIs and open data services, and intermediate results produced by the computational modules. This layer also supports preprocessing, validation, and organization procedures, reducing the risk of anomalies or inconsistencies before the elaboration phase.

The Inference Engine Layer is the computational core of the framework. It integrates different strategies for the simulation and analysis of physical phenomena. On the one hand, it includes modules based on classical numerical methods, such as the Finite Element Method, which are used to obtain high-fidelity solutions of physical problems. On the other hand, the framework integrates ROMs, particularly methods based on Proper Orthogonal Decomposition (POD), to build reduced models capable of rapidly approximating solutions as functions of physical, material, or environmental parameters.

Another central element of the Inference Engine Layer is the PINN module. PINNs train neural networks by directly incorporating the physical knowledge describing the observed phenomenon into the loss function. As a result, the model learns not only from available data but also from the physical knowledge of the problem. This is especially useful in cultural heritage applications, where data may be scarce or difficult to obtain, but where consolidated knowledge of physical and material processes is often available.

PINNs can be used for both direct and inverse problems. In direct problems, the objective is to estimate the evolution of a physical field, such as temperature, humidity, or pollutant concentration, starting from known parameters and available data. In inverse problems, the system aims to identify unknown physical parameters from observations or measurements. This second possibility is particularly relevant for conservation, since it enables the estimation of properties that are difficult to measure directly, such as material parameters or conditions influencing degradation.

Finally, the Application Layer makes the results available to end users, including conservation experts, restorers, researchers, and decision-makers. Through dashboards, simulation modules, and upload/download tools, users can upload 3D models, access data, launch simulations, and visualize results. The visualization may include simulated physical fields directly mapped onto the geometry of the cultural asset, supporting a more immediate understanding of its condition and possible future scenarios.

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