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A 3D digitisation workflow for architecture-specific annotation of built heritage

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A R T I C L E I N F O

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A B S T R A C T

Contemporary discourse points to the central role that heritage plays in the process of enabling groups of various cultural or ethnic background to strengthen their feeling of belonging and sharing in society. Safeguarding heritage is also valued highly in the priorities of the European Commission. As a result, there have been several long-term initiatives involving the digitisation, annotation and cataloguing of tangible cultural heritage in museums and collections. Specifically, for built heritage, a pressing challenge is that historical monuments such as buildings, temples, churches or city fortification infrastructures are hard to document due to their historic palimpsest; spatial transformations, actions of destruction, reuse of material, or continuous urban development that covers traces and changes the formal integrity and identity of a cultural heritage site. The ability to reason about a monument's form is crucial for efficient documentation and cataloguing. This paper presents a 3D digitisation workflow through the involvement of reality capture technologies for the annotation and structure analysis of built heritage with the use of 3D Convolutional Neural Networks (3D CNNs) for classification purposes. The presented workflow contributes a new approach to the identification of a building's architectural components (e.g., arch, dome) and to the study of the stylistic influences (e.g., Gothic, Byzantine) of building parts. In doing so this workflow can assist in tracking a building's history, identifying its construction period and comparing it to other buildings of the same period. This process can contribute to educational and research activities, as well as facilitate the automated classification of datasets in digital repositories for scholarly research in digital humanities.

1. Introduction

One of the most widely used applications of computational methods in human sciences is the automatic annotation and classification of large datasets (of text, images, etc.) in digital libraries that otherwise would require a highly laborious annotation process by trained and skilled users (Canul-Ku et al., 2018; Engel et al., 2019; Dhali et al., 2020). In the case of image-based datasets, computer vision methods have been used to analyse and annotate photos, e.g., the geo-reference of series of aerial photos (Cantoro, 2014), the semantic analysis of a digital library of museum artefacts, or a collection of old photographs for the semantic categorisation of content (Eramian et al., 2017).

Datasets generated by European efforts in digitising cultural heritage content for preservation purposes and online access, in response to European Commission's 2011 recommendations (https://ec.europa.eu/digital-single-market/en/digitisation-digital-preservation), have been growing and have started to include not only 2D information about cultural artefacts of museums and collections but also 3D models and

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digital assets. This effort is exemplified by many EUROPEANA (https://pro.europeana.eu/project/3d-content-in-europeana) actions and its 3D repository, various Horizon 2020 projects occupied with the development of a publication of relevant APIs, standards, and metadata schemata in 3D linked datasets (https://share3d.eu/, https://www.inception-project.eu/en), as well as by centralized online repositories for semantically enriched 3D representations of cultural assets (https://sketchfab.com/tags/europeana) used by museums.

In this paper, we present a 3D digitisation workflow that was specifically designed to assist scholars and researchers in the humanities and architecture with the process of historic annotation and the analysis of cultural heritage monuments. The presented work is part of ANNFASS (An Artificial Neural Network Framework for understanding historical monuments Architectural Structure and Style, http://annfass.cs.ucy.ac.cy), a project funded by Research & Innovation Foundation (https://www.research.org.cy/en/).

The competitive Call through which ANNFASS was funded encourages local research and technological innovation, focusing on fields and societal challenges such as the safeguarding and promotion of the cultural heritage of Cyprus. ANNFASS responds to this challenge by developing an online platform and framework for digital humanities, that utilises 3D CNNs for the classification of architectural elements of Cypriot monuments. In addition to the criteria of the Call of the funding agency, another reason for choosing Cypriot architecture as a test case for the project platform was that arguably these examples of built heritage are rich in complex combinations of structural and architecture stylistic elements, and therefore would serve as a challenging test scenario of the platform's performance and possible limitations.

2. Related Work

Recently researchers and scholars in the humanities have started to share and exchange 3D datasets of cultural heritage assets that are larger in scale than what was considered until recently as a typical application of digital methods in heritage, i.e., museum objects and collection artefacts. For example, datasets comprised of assets of architectural scale (e.g., buildings) are now being exchanged online, and often digital 3D models of whole excavated archaeological sites (Prasomphan and Jung, 2017), generated with the support of the appropriate computational tools, are accessible through online visualization technologies. Beyond the management, accessibility, and the FAIRification (Harrower et al., 2020) of these unstructured 3D datasets, a major challenge emerges for researchers with regards to their geometric analysis and interpretation in the context of humanities-driven enquiries. However, the sheer number of digitised cultural heritage assets, their complexity and the sophisticated computational interfaces that are required to be used by humanities scholars require new tools and techniques that would aid and accelerate research, as well as enable cross-disciplinary enquiries (Charalambous and Artopoulos, 2018). In addition, these big datasets can only benefit researchers if they are organised in the form of linked data (https://inspire.ec.europa.eu/training/introduction-linked-data) that can be mined for the identification of patterns, trends and macroscopic mapping of cultural production in time (Fiorucci et al., 2020).

These efforts in digitising the content of humanities studies led the cross-disciplinary field of Digital Humanities to enquire for the automatic semantic analysis of visual content. Arguably this process is more complex than solely the annotation of a cultural object's, e.g., a vase or a column, provenance and general description (Dallas, 2003). One of the fundamental essential classification operations in humanities and archaeological research is the periodisation, i.e., to classify artefacts based on the historical period (Jimenez-Badillo et al., 2010). This is typically done by experts, who classify artefacts chronologically based on spatial and social context, the technique of their production as identified through visual study, its provenance, style and geometric or material features (Baratin et al., 2012). In these practices, and up until recently, it has been very difficult to apply these digital process of unsupervised visual analysis in the case of large-scale cultural products, such as buildings or monumental structures, due to their inherent geometric and architectural complexity, a limitation that resulted in posing new challenges to the data management of these objects collections. However, the exponential growth of Machine Learning (ML) algorithms, combined with the large size of 3D datasets being generated in digital humanities and cultural heritage, recently enabled researchers to apply ML techniques in their practice for the interpretation of 3D spatial data at both buildings (Grilli and Remondino, 2019) and urban scales (Dirk et al., 2018).

Until recently, most of the research in architecture style analysis has been done with 2D data, e.g., images, architectural drawings, or floor plan configurations (Hillier et al., 1987), but advances in neural networks have allowed researchers to handle more complex and bigger datasets, drawing from developments in other fields, cf. 2D image-based retrieval of information by means of Convolutional Neural Networks (CNN) (Llamas et al., 2017). CNN's were first introduced in the 1980s, (LeCun et al., 1989), but were popularized more recently (Krizhevsky et al., 2012), because of their successful application in image and video recognition, recommendation systems, image classification, and medical image analysis. CNN's draw inspiration from biological processes in that the connectivity pattern between neurons resembles the organization of animals' visual cortex. Individual cortical neurons respond to stimuli only in a restricted region of the visual field known as the receptive field. Each neuron or node in a CNN depending on the layer it is located has different functionality. Input layer nodes are responsible for receiving data/patterns from the environment (analogous to human senses) and pass them to the next layer to be processed. Finally, the output layer assesses the extracted features to classify the network's input, e.g., whether the input represents a door or a window (da Silva et al.,2017).

In parallel, technological developments - both in spatial 3D documentation equipment as well as in computer vision, e.g., photogrammetry - enabled the acquisition of high resolution and precision 3D data, e.g., point clouds and meshes (Georgopoulos and Ioannidis, 2004), which naturally capture more information than 2D images of building façades and floor plans, as previously used in architecture history for didactic purposes. These developments and new research opportunities, together with the evolution of deep learning methods in processing 3D data, such as 3D point cloud classification for object identification and semantic annotation (Qi et al., 2017; Wang et al., 2017, 2018; Kalogerakis et al., 2017; Su et al., 2018; Bassier et al., 2019; Poux et al., 2017; Messaoudi et al., 2018; Malinverni et al., 2019; Feng et al., 2020; Pierdicca et al., 2020; Morbidoni et al., 2020), have been the source of inspiration for the authors in applying 3D CNNs in 3D architectural elements and whole building scale heritage to facilitate historical study and interpretation, involving annotation and classification processes. To do so the ANNFASS project aims to develop an online platform and software tool that will classify architectural styles and the relevant historical period that examples of built heritage drew inspiration from based on a 3D analytical operation, instead of 2D image-based analysis (Mathias et al., 2012).

3. Dataset generation pipeline

The professional, traditional practices of measuring and documenting heritage buildings require highly developed skills and precision and at the same time are time-consuming. However, many of the activities involved in these methodologies, which are manual/supervised, often result in data loss during the transfer of information from the building site into 2D measurements, in order to create 3D representations of the surveyed site. It is not rare that important details for the conversion would be missed or neglected, as physical observation by an expert is required, especially because of the difficulty of capturing and representing the physical complexity of a heritage building site that involves a lot of irregular components through 2D drawings (Dallas, 2003).

Typical classification workflows of building elements and architectural style of heritage comprise of the following steps:

- Production of 2D plans and diagrams.
- Literature review for the monument based on cross-referencing literature and onsite findings and,
- Interpretation based on facts and assumptions, as stated by the architect.

A classification workflow involves the analysis of individual architectonic elements of the building under study in great resolution and detail. Through this analytical process, an architect is able to map and interpret singular human interventions on the building structure, or the stylistic influences the designer or its mason drew inspiration from, in order to arrive at the classification of distinct elements.

Nowadays it is common for built heritage and monuments to be documented in 3D through terrestrial laser scanning or photogrammetric techniques for conservation and geometric analysis purposes. This is enabled by advanced software that becomes increasingly accessible to the market, as well as by the advancement in computing power available to researchers and professionals in the field. ANNFASS exploits these developments and adapts to the current best practices of architecture and archaeology. Thus, its experimental methodology starts with the 3D documentation of the architectural heritage under study.

ANNFASS' state of the art pipeline involves the use of reality capturing technology, like 3D scanning technology and photogrammetric techniques, as an exercise in integrating state-of-the-art archaeological and built heritage documentation practices in its methodology when completed this methodology will be offered as a tool that could be used by practitioners, scholars and educators who work with 3D reconstructions of buildings. Apart from the objective to create this pipeline based on current techniques of 3D documentation and reconstruction of the complex geometry of heritage buildings, other reasons for the authors' choice to use reality capture-based 3D models of monuments for training and testing the algorithms were to (a) avoid simplified manually modelled representations of heritage buildings, and (b) assess the limitations and challenges of developing a tool that in future versions would allow the public to upload 3D models of structures documented in the wild by non-experts via reality capture tools (e.g., recently mobile devices started integrating lidar sensors for 3D capture of real-world environments).

In ANNFASS the architectural study of the surveyed monuments was complemented with the theoretical documentation and classification of each building through the analysis of its various characteristics, such as building façade, form, shape, structure, material, colour, openings, ornamentation, roof type, as well as localised factors, including environmental conditions, site topography or cultural aspects.

Stathopoulou and Remondino (2019) trained CNNs on 3D datasets of historic building façades in Italian cities which were created with a photogrammetry-based documentation pipeline, for the generation of labelled 3D datasets. Contributing to this inquiry, the ongoing research of ANNFASS explores the use of 3D CNNs trained on 3D point cloud datasets generated by means of photogrammetry and aims to develop an integrated interface for researchers and scholars in digital humanities for the guided annotation and classification (in terms of architectural style, typology and period) of heritage buildings, in three dimensions. Using historic buildings and monuments of Cypriot architecture, which distinct from typical central European historic cities often are located outside a continuous urban fabric, and therefore have more than two elevations exposed, in addition to a courtyard, to train the 3D CNNs, is helping the authors to develop a flexible integrated tool for the labelling and classification of all the 3D mass of a built structure, in addition to its façade.

The authors expect that, when the project is completed and the 3D CNNs will be trained with a large enough 3D building dataset, the ANNFASS tool will enable for a more accurate classification of the building typology, based not only on architectonic features but also on the whole building components (e.g., its roof). The authors expect that the capacity of the tool for analysing the building as a whole, combined with the annotation of the style and period of the architectural features and decoration of the facade, will contribute more information to the architect-user of the tool than other existing methods in the literature. The 3D CNNs of ANNFASS were trained using architecture 3D datasets (specifically, a labelled dataset of 2000 buildings, of different types - an ongoing effort at the University of Massachusetts) and is currently further employed in labelling the many architectural features of Cypriot heritage, listed below.

Partial results of the ongoing research of ANNFASS are presented below. Specifically, the theoretical considerations and practical challenges related to the development of a 3D documentation workflow (which represents the first step of the presented workflow) that is customized and adapted to the needs of reconstructing objects of architectural scale, involving 3D mesh adaptation (3.1), as well as the parameters of the annotation process (3.2). These two steps of the process are essential in generating the necessary input that can be used to train the 3D CNNs of the presented methodology.

The authors note that the heritage buildings used in the annotation process were chosen because of their historical and cultural significance for Cyprus, with the aim to cover as many historical architectural periods as possible. Also, all monuments under study are located in Nicosia, as the authors wanted to focus on exemplar cases situated in a historically complex location, where significant hybridisation/exchanges of stylistic features are identified by experts and literature. It is worth mentioning that the historic city of Nicosia is ideal for accessing and identifying architectural monuments from various time periods, as it has a history of thousands of years and has been at the crossroads of many empires and civilisations who would introduce their influences to the local architecture, for cultural or political reasons (Michaelides, 2012). A summary of the selected buildings per period/architectural style can be seen in Table 1. In order to test the developed workflow with the particularities of more contemporary architecture comprised of different geometric characteristics, the authors included in the dataset examples of the built heritage of the recent past and, in particular, select buildings of Modernist architecture. The following section explains in detail the challenges of annotating the selected examples and presents the results of the workflow.

Table 1
List of selected monuments, categorised by period/architectural style.

Lusignan - Gothic Architecture	**Ottoman Architecture**
Armenian Church	Buyuk Han
Cathedral of Our Lady Hodegetria	Bayraktar Mosque
Augustinian Hermits	Ayios Michael Tripiotis
St. Catherine's Church	Axiothea House
	Hadjigeorgakis Kornesios Mansion
Venetian Architecture	**British - Colonial architecture**
Famagusta gate	Pafos Gate
Kyrenia Gate	English school
Stavros tou Misericou	The club of the British Cavalry
Neo-classicism - Greek-revival architectural style	**Vernacular construction methods**
Faneromeni Church	Townhouses in Ayioi Omologites
Parthenagogio of Faneromeni	Townhouses in Strovolos
Pancyprian Gymnasium in Nicosia	
The Severios Library	
Archaeological Research Unit (ARU) Building	
Cyprus Archaeological Museum portico	
Modernist architecture principles	
Stavrou Economou Building	
Lefkaritis Building	
Nicolaou Building	

3.1. Building scale 3D documentation

The online 3D visualisation of heritage buildings and monuments in the ANNFASS workflow extends typical vector-based and orthophotography visualisation methods. This online interface allows the user of the tool to have a photo-realistic 3D representation of the structure that enables both expert and non-expert audiences to study and compare architectural elements, stylistic variations, and their integration in the form of the building. The steps of the hybrid 3D documentation process, which involves terrestrial photogrammetry methods and manual 3D modeling, are described below. An integrated photogrammetry method is defined as a hardware/software configuration that produces photogrammetric products from digital imagery using manual and automatic techniques. Close range photogrammetry is a measurement technology that can be used for the extraction of 3D points from the images, and by extension, these points are useful for accurate 3D modelling and visualisation. Digital photogrammetry derives all the appropriate measurements from the images themselves rather than taking measurements directly from the objects (Lachambre et al., 2017).

In ANNFASS, the architectural structure 3D documentation process involves the following steps:

3.1.1. On-site collection of data

The result of this procedure is a complete dataset of 3D models of the selected heritage building, including geometry and texture. In the documentation step, the aim is to gather multiple photos of the monument from various angles, along with the basic external measurements. In some monuments, it is necessary to have a more detailed geometry and texture, in combination with the main geometry, of different architectural elements of the building, such as doorways, ornaments, pilasters. For example, an ornament's texture which covers a large area of a model might be enhanced by adding a higher-resolution detail texture at a much smaller scale which shows small details and imperfections in the ornament. The documentation process of the geometry and texture of architectural details was the same followed for regular, plain building surfaces, except that shots were taken more closely to the building, focusing on a small area. Typically, in photogrammetric methods, the part of the building that was documented in order to produce the texture had to be as generic as possible, as detail textures are typically tiled many times across an object. In practice, these shots were taken at the closest focus limit of the camera and lens combination used for the documentation process.

Lastly, due to the lack of access to privately owned properties, in some cases, there were parts of the building that were covered from plants or civic equipment, while due to the location of the buildings in the densely built-up medieval historic core of Nicosia, the aerial recording was at the time not an option for 3D documentation of roofs. These restrictions resulted in relying on terrestrial photogrammetric techniques that produced partial 3D models of the selected buildings rather than complete 3D documentation of them in terms of geometry and texture (Fig. 1). As stated above, this limitation was incorporated in the ANNFASS project and was considered by the authors as a real-world challenge that many researchers and humanities scholars would face if they were to 3D document built heritage in densely populated areas where access to LiDAR data is not possible.

In ANNFASS, the survey equipment used consisted of a Canon EOS6D (self-calibration was used) and a tripod for image stabilisation (see Table 2).

3.1.2. Generation of dense 3D point-clouds

The next step of the documentation process was the generation of dense 3D point clouds. The photographs acquired were imported into photogrammetric modeling software, Agisoft Metashape. Reference points were selected on the monument, e.g., the corners of the building which are easily identifiable and separable. This process is known as orientation. Furthermore, the reconstruction application compares the shapes in the photos (Alignment) to generate a high-resolution 3D point could and by extension the mesh model. The color contained in the pictures is then transferred to either the point cloud and mesh vertex colors (Colourise) or textures used on the surface of the mesh.

(a)

(b)

Fig. 1. Examples of processing the collected data: (α) ARU Building, Alignment of the collected data, (b) ARU Building, Dense 3D Point cloud data.

Table 2
Rectified photography properties.

Property	Value
Dimensions	5472 × 3648
ISO speed	ISO-100
F-stop	f/7.1
Exposure time	1/250 sec.
Flash mode	No Flash
Focal Length	35 mm
Output	.CR2(raw) & .JPEG

As expected, the photogrammetric software generated an extremely high-resolution point cloud and mesh model. This was not suitable for use in 3D modeling software and the online annotation tool because rendering, processing and interaction with its geometry were prohibitively slow. To overcome this limitation the generated 3D models had to be decimated with photogrammetric software (see Table 3). In this process, the important architectural details for the architectural classification of the building were preserved from the high-resolution 3D mesh. The texture transfer from the original mesh model to the decimated one was done with a texture baking process.

In detail, texture baking generally refers to the process of recording as an image, some aspects of the texture or mesh characteristics of a 3D model. The baking tool starts with a low-resolution model and casts rays inwards towards the high-resolution mesh model. When a ray intersects the high-resolution mesh model, it records the surface detail and saves that into a texture map, using the first model's Texture Coordinates. In other words, with texture baking, what is originally a procedural texture can be recorded as an image. Sometimes various "channels" (properties) of a material can be consolidated into a single image, simplifying the number of texture images used. In normal baking, the mesh normal can

Table 3
Statistics of Modeling Procedure.

Monuments 3D documentation	Cameras	Point Cloud	Mesh model	Final Model
Colonial / Hybrid architectural style				
English school	596 / 650	440,971,995	88,209,900	1,555,196
Neo-classicism / Greek-revival architectural style				
Severios Library	333 / 357	100,285,759	20,057,150	1,293,236
ARU Building	915/ 930	422,123,606	101,435,980	1,427,309
Cyprus Archaeological Museum	486 / 487	108,395,083	21,679,015	1,089,696
Vernacular construction methods				
Townhouses in Ayioi Omologites	242 / 255	77,773,370	158,554,674	441,804
Townhouses in Strovolos	234 / 234	256,645,209	51,329,037	1,248,625

be recorded – this results in specialized types of images, with RGB values based on normal vectors. Usually, baking requires having the model UV unwrapped and -mapped, so the resulting image is properly fit to the model (Fig. 2).

Due to the fact that the mesh quality and resolution may vary significantly, depending on the algorithms involved during the decimation, this process required several iterations, in order to decimate the generated 3D meshes appropriately, so as to maintain the geometric features and architectural details of the building (and the original 3D model), but at the same time to produce a 3D model that would meet the constraints and specifications of the annotation digital platform (Fig. 3). The main constraints were computer memory and processing time, which resulted in a trade-off between the model resolution/detail and loading time (proportional to model size). This led to the presented ANNFASS methodology, creating hybrid models with enough detail to resemble closely the original while reducing memory consumption (especially for mobile devices) and loading/rendering time to the minimum.

Table 3 lists the details of the original photogrammetric models of some of the buildings in the list, the points of which range from 422,123,606 points, in the case of the Archaeological Research Unit Building, to 77,773,370 points for the townhouses in Ayioi Omologites, while the poly-counts that consisted the mesh models range from 158,554,674 (Townhouses in Ayioi Omologites) to 20,057,150 (Severios Library). After the decimation of the original 3D mesh models, the final low poly-count model of the monuments was limited to a range between 441,804 (for the Townhouses in Ayioi Omologites) and 1,555,196 (English School). In detail, the process of the mesh model decimation was done in the photogrammetric modeling software Agisoft Metashape, the re-meshing and the mesh smoothing steps were done with Autodesk's Mesh Mixer open-source software, while the final processing and synthesis of all 3D models were completed on Autodesk's Maya design software.

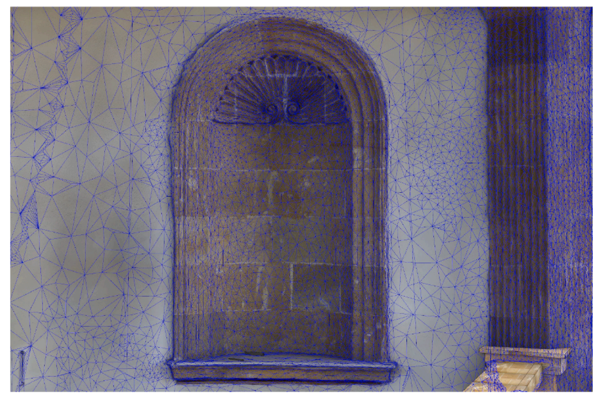
3.1.3. *Post-processing of the produced 3D mesh and manual 3D modellings*

All the above limitations in the resolution of the 3D models forced the authors to create a hybrid method (partly automated and semi-supervised) for the production of the monuments' 3D models. So for each building in the list, this process involved the creation of a 3D model that combined high mesh quality of the period-relevant and style-characteristic architectural features (e.g., windows, doors, pilasters) identified through expert visual inspection on-site, with a reduced resolution of the 3D mesh of the not so distinct elements (e.g., walls, roof, etc.), some of which were even modelled manually (Fig. 4).

3.1.4. *Segmentation of the 3D model into elements*

The last step of the modelling process proved more challenging than the original estimations, due to the required segmentation of each building's 3D model into its elements, in order for the user of the ANNFASS annotation tool to be able to easily annotate the architectural parts. In order to respond to this requirement, the process had to be developed in a supervised way, as follows: as soon as the final 3D model of a building was produced, a series of segmentation on the generated final surfaces needed to be created, be named and grouped together with all the relevant architectural elements (e.g., other windows), that is, semantically structuring the elements of the building manually. The goal of this step in the production process was to allow the future users of the final product of ANNFASS, to easily select architectural elements on the (ANNFASS) tool, and to enable them to add into their selection list new elements of the same architectural characteristics, as the already selected elements, through the use of the command < EXPAND> (Fig. 9). The following sections present details related to the factors that were integrated into the online ANNFASS tool for the proposed function of monument classification for the purposes of the project (Fig. 5).

(a)



(b)

(c)

Fig. 2. Examples of monuments' detailed geometry and texture: (a) Townhouses in Ayioi Omologites, Detailed mesh model of the fanlight, (b) ARU, Detailed mesh model of entrance ornamentation, (c) Cyprus Archaeological Museum portico, Detailed mesh model of the entrance.

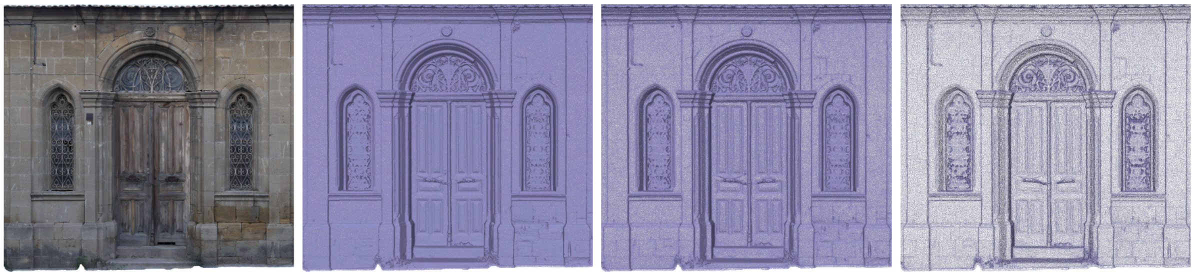


Fig. 3. Mesh model decimation: (a) Townhouses in Ayioi Omologites, (b) Townhouses in Ayioi Omologites, High poly-count 3D mesh model, 15.000.000 triangles, (c) Townhouses in Ayioi Omologites, Medium poly-count 3D mesh model, 6.000.000 triangles, (d) Townhouses in Ayioi Omologites, Lowpoly-count 3D mesh model, 1.000.000 triangles.

Fig. 4. Hybrid 3D model of townhouses in Ayioi Omologites.

3.2. Building classification and stylistic definition factors

In ANNFASS, the period and architecture style classification operations are based on a building's main architectural parts (e.g., tower, roof type, courtyard, openings), as well as the architectonic features on its elevations. "Architectonic" is used here to refer to architecture, formal and structural aspects of a building feature. The building elevations are divided into two sets of features, i.e., structural parts and decoration. The selected heritage buildings were formally analysed and compared according to the indicators of their elevations, such as:

- Form and shape: in terms of the main form, geometric or irregular and dimension;
- Building structure: in terms of the type of structure (skeletal frame, load-bearing), type of column, material and shape of brackets and material of balustrade;
- Building Material: in terms of usage, color, function;
- Openings: in terms of size, shape, position on the building façade;
- Door, Entrance, Window: in terms of height, width, position;
- Balcony / Bay window / Semi-open space: in terms of location, function, size;
- Ornamentation: in terms of period, style, date; and,
- Proportions and plan space configuration.

The methodology of building classification included the factor of visual analysis, such as onsite observation and 3D documentation, as well as the study of the literature of historical sources, in order to understand all the elements and the details that compose the selected monuments. The main aim was to analyse the design of the buildings in terms of morphological characteristics. In this context, the buildings in the list were selected as exemplar cases of historic architecture in Cyprus to train the algorithms (as briefly discussed in Section 4.2 below) and allow users of the ANNFASS platform to make a comparative assessment between different buildings of many important historical periods of Cypriot architecture.

The list of architectural components and stylistic factors, along with the corresponding labels used for the building annotation purposes can be found in Table 4.

The authors note that the selected heritage buildings were used as a set of pilot cases to assess the performance of algorithms with the arguably geometrically and historically complex construction of select Cypriot heritage. These structures presented probably some of the most challenging examples of architectural constructions to classify. This is due to the irregular and variable combination of decoration and features borrowed by their builders from multiple historical periods as documented in the literature (Chrysochou, 2014).

This difficulty was tackled by dividing them into separate objects per architectural part and engaging groups of experts to guide the classification process, as presented below. Thus, the classification would regard individual building parts and not the whole monument. The authors' motivation was to use these difficult examples in order to showcase the value of the ANNFASS tool in educational environments.

4. Features of the ANNFASS framework

In the previous section (section 3 Dataset), the procedure of creating the hybrid 3D models of monuments was described (Fig. 6), and here the functionalities and purpose of the annotation tool and platform will be discussed, as the next step in the workflow presented by the article.

It is worth mentioning that prior to the development of the annotation tool and ANNFASS platform, the authors sought digital tools developed for similar scope and research purpose aimed to be used in digital humanities by scholars and cultural heritage experts in comparative, analytical studies. As it was difficult to identify tools that offer similar functionalities to ANNFASS', the authors had to assess the needs of experts through primary research, in this case, participatory methods such as focus groups and workshops.

In doing so, several meetings with a group of history of Cypriot architecture experts were held, introducing the group of stakeholders to the objectives of the ANNFASS, and discussing the needs, challenges, and particularities of their research. Those meetings were necessary and helpful for the development of a platform tailored to their requirements.

4.1. Annotation tool

In these meetings, the architecture experts had the chance to use an annotation tool inspired by the annotation tool of the BuildingNet platform (Selvaraju et al.,2020) and further developed based on the objectives of ANNFASS. Each stakeholder meeting consisted of a short demonstration of the tool's essential functionalities, followed by an annotation session where the experts were asked to annotate structural components (wall, door, etc.) of the select monuments. This process not only offered to the target user group a hands-on experience of the tool but also allowed the authors to collect valid labels for their dataset of monuments and buildings. Feedback from the experts was collected by means of a previously validated questionnaire that captured input

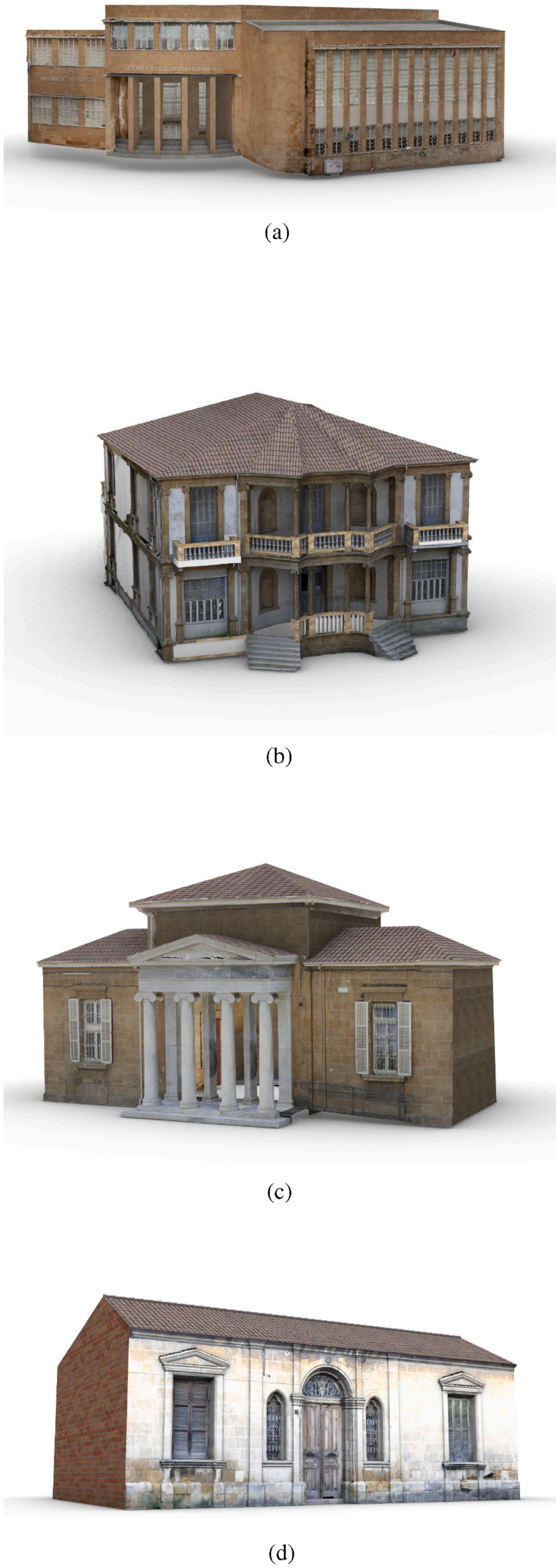


Fig. 5. 3D mesh models of selected historical monuments:(a) Severios Library, (b) Archaeological Research Unit Building, (c) Cyprus Archaeological Museum portico, (d) Townhouses in Ayioi Omologites.

Table 4
List of labels used to name the architectural components.

Architectural Components		
Arch bay	Balcony	Bay window
Beam	Belltower	Canopy
Column	Chimney	Door
Doorway	Fanlight	Keystone
Minaret	Ornamentation	Pilaster
Railing	Roof	

specifically on the user interface of the online ANNFASS tool, accessibility, friendliness and usefulness/purpose of the tool for specialists.

In detail, the user experience involves the following steps: once a user accesses the annotation tool, a monument is loaded in two visualisation forms, the 3D model (stripped from any textures) and its textured twin (Fig. 7). The model to be annotated appears on the left side of the screen, but since sometimes architectural features cannot easily be distinguished in the plain model, the textured version of the 3D model is also presented next to it in order to enhance the user's perception and allow for detailed observation. Through this interface, a building 3D model can be observed by rotating it 360∘ in any direction and zooming in/out to provide the user a better look at the different elements of the building.

For the annotation process to start, the user must click on the component of interest and assign it a label. A label can be chosen in one of the following ways: by navigating to the desired label on the upper right corner of the screen or pressing the < View all labels > button, for the entire list of labels to appear between the two building model views, and selecting the desired one. The authors are well aware that an architectural element might appear in a variety of configurations and designations, thus to eliminate confusions and mislabelling, a set of example images (Fig. 8) for each label is provided by clicking on the link below the label in question. The extent and specificity of the labels are limited to the most frequently found architectural elements, in order to cover the majority of buildings on the platform while avoiding overwhelming the user. In the event of lacking a corresponding label for a component, it can remain unlabelled or the user can select the label "cannot label".

Furthermore, to speed up the annotation process, similar elements were grouped semantically based on function/operation during the subdivision step in the modeling process, so that when the < EXPAND > button is selected, all similar elements will be selected and labelled at once. The selected item(s) turn white on the plain model to be distinguished from the rest of the components, while a floating, highlighted bounding box appears surrounding the item on the textured model, to help the user of the tool identify it faster. Once a component is labelled it will be given the corresponding colour of its label so that it is differentiated from those elements that remain unlabelled. To avoid relabelling when an annotated element is picked, a message will appear to the user stating the current label of the element (Fig. 9). Naturally, an architectural element can be relabelled if the user deems it necessary.

Finally, when the user is satisfied with the annotation completion and accuracy, she/he can select the < Done - Submit task > button in order to continue to the annotation of another building or exit the tool. In case a user is given a monument that is not of their interest, she/he can click on < skip this building > to load the next monument in the list. On the submission of a building, the annotation choices are saved and used in the next stage of the workflow which includes the development and testing of the platform's automated functionality briefly mentioned in the following section, and currently under development.

4.2. Platform

Following the demonstration of the ANNFASS platform for heritage annotation in the expert group meetings, feedback was received from

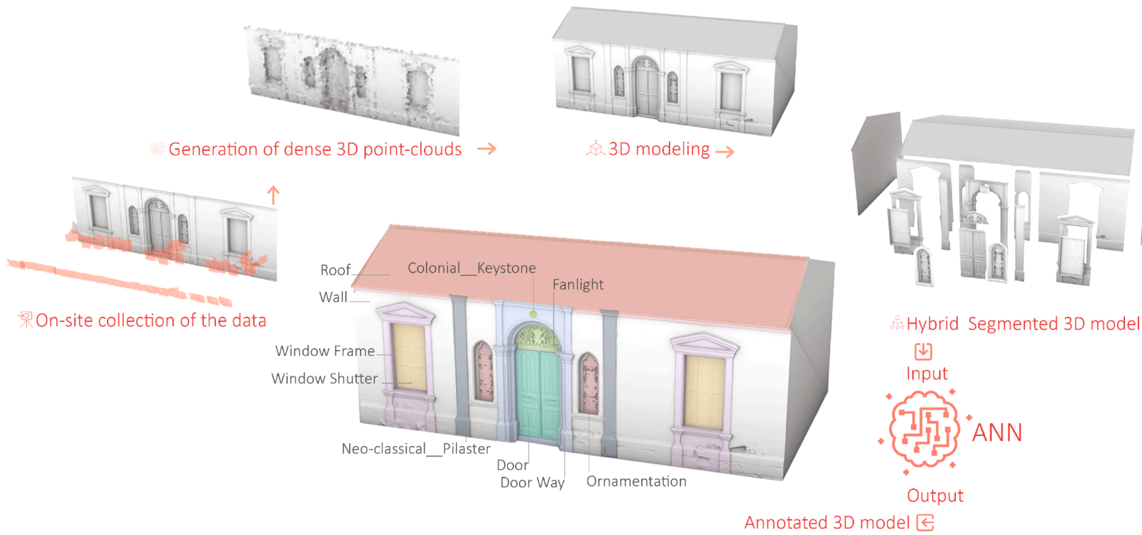


Fig. 6. 3D digitisation workflow for architecture-specific annotation of built heritage.

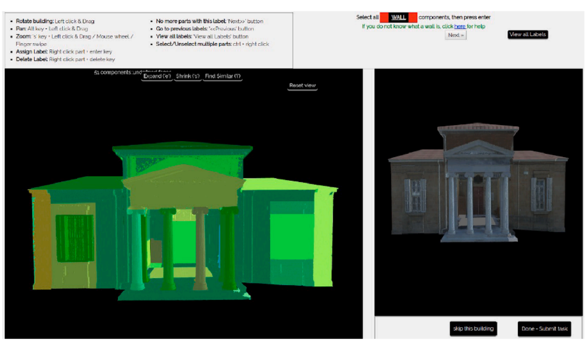


Fig. 7. 3D model in annotation tool: (a) Geometry of the model, (b) textured monument.

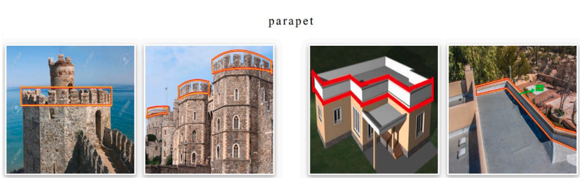


Fig. 8. Explanatory images for the label “parapet”.

the participants, regarding their experience with the tool, including suggestions about improving the user interface and the need for other desirable functionalities of the platform. These served as design and development guidelines for the final platform that will be delivered to the architecture history experts to be used, e.g., in education activities, at the end of the ANNFASS project.

The primary outcome of the questionnaires collected was that this tool is much needed to the education community in particular, since it modernises, automates and speeds up the currently used methods and procedures in scholarly analysis in architecture. Responding to this feedback, the final ANNFASS platform, currently under development, will consist of both essential features for the visualisation of the 3D model of the building, as well as automated modules for comparative analysis. Essential tool features and functionalities include: viewing a monument’s 3D model or displaying its description and historical information.

Specifically, every model in the platform is accompanied with the following information: monument name, brief description /chronicle, architectural style(s)/stylistic influences, location (country and geographic position), the 3D model and lastly, a cover photo for preview purposes. During the expert group meetings, it was indicated that this is the minimal information needed to perceive the main context. More information can be added, if available, to enrich this perception, such as the architect(s)’ name and details, construction start and end period, and a photo gallery of the monument (archival and contemporary). The ANNFASS tool addresses didactic needs in educational environments and the main purpose is not to automatically determine the construction period of the monument under study but rather to assist in identifying the historical references of decorative and architectural features of the building. In addition to the visualisation features, the platform will also be equipped with the following automated modules:

- Architectural Component Recognition
- Construction Period Recognition

4.2.1. Architectural component recognition 3D CNN

Analysing and identifying the various architectural elements and components (e.g., roof, door) is a necessary step in the process of studying a building’s structure and style, which is also a time consuming and tedious procedure. The current advances in the field of machine learning allow the automation of this procedure, with the use of 3D CNNs, and specifically the employment of deep learning methods. The success of neural networks in image-based tasks, induced by the introduction of convolutional layers, inspired researchers to develop convolutional layers that can operate on 3D data through the use of convolutions in 3D space (3D CNNs) (Wu et al.,2015); Wang et al., 2017, 2020; Choy et al., 2019). ANNFASS’ architectural component recognition relies on a 3D CNN with sparse 3D convolutional layers, called MinkowskiNet (Choy et al.,2019), adopted in our case to learn how to identify the various components of 3D building models.

In detail, the network is trained in a supervised manner, taking as input a set of 3D models and their ground truth labels (expert annotations), in order to learn patterns and extract features that appear frequently (Fig. 10). The authors are aware that deep neural networks require a large number of data to learn effecting representations for part labelling. The Cypriot dataset on its own is not sufficient for this task. For this reason, another much larger 3D building dataset was developed at UMass, called BuildingNet (Selvaraju et al.,2020), which consists of 513,087 annotated building mesh components across 2000 building models of different types (e.g., residential, religious), and 31 unique semantic labels (e.g., tower, wall).

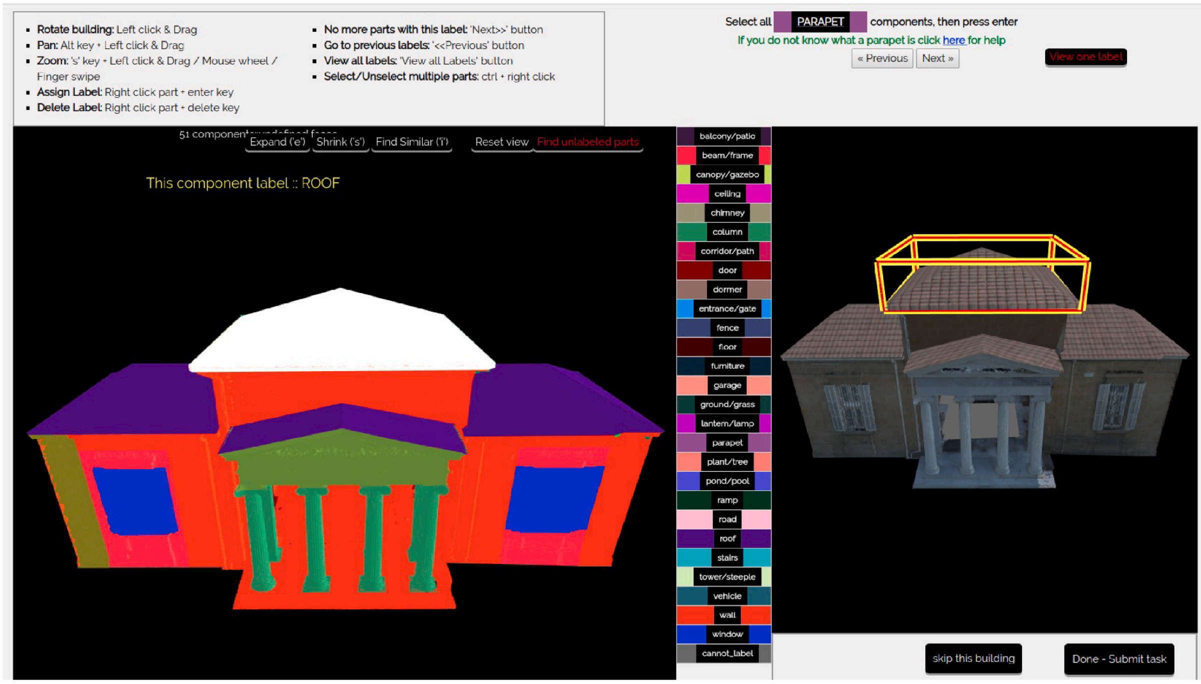


Fig. 9. Partially annotated monument.

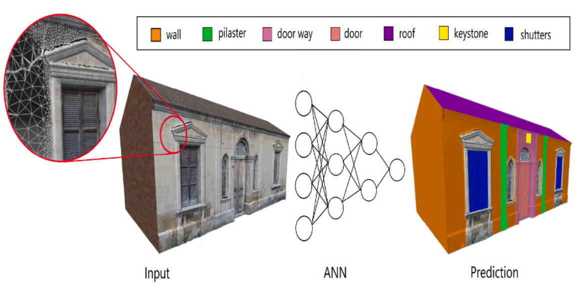


Fig. 10. Architectural component recognition 3D CNN.

The aforementioned dataset is used to train the 3D CNN on recognising the different structural components of buildings. Once the network is adequately trained on Building Net, a representative subset of the Cypriot monuments will be used for fine-tuning the network parameters. The fine-tuning phase aims to help the network identify specific to the Cypriot building labels (e.g., keystone) since only a few training examples are available in the training dataset. The remaining data will serve as test cases to evaluate the network's abilities on unseen data. In the end, the trained network will apply the acquired knowledge (learned features) to classify components of 3D models uploaded by the platform users. It is not required for the uploaded models to be pre-segmented to components, as the used 3D CNN produces annotations using only the geometry information and textures of a model. Though, for purely aesthetic reasons, having this additional information can be used in post-processing steps to produce smoother results. An example case is illustrated in Fig. 11, where a toy example model (square) consists of a single component with four faces (f1 − f4) coloured based on two annotation strategies (face-based vs component-based labeling). In the first case, labels are derived for each mesh face, with facesf1 − f3 annotated as label-1 (orange) andf4 as label-2 (blue), resulting in an inhomogeneous component annotation. However, for the component-level481labelling, an additional step is taken, that of averaging all component child faces label probabilities and assigning the predominant one to the whole component i.e., in this case, label-1 (orange). Note that the only given information for this additional step was the component a

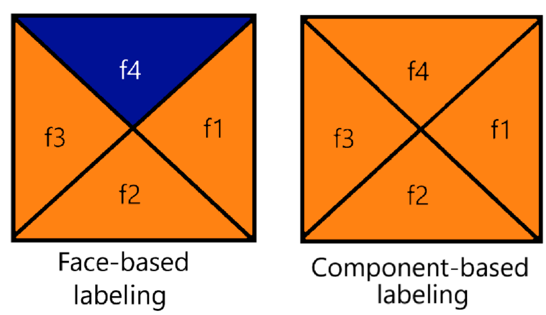


Fig. 11. 3D CNN prediction projections on mesh on face and component level.

face belongs to.

The inclusion of the 3D CNN in the platform allows a digital humanities expert to extract the architectural components of a building with minimal effort and in much less time since the network will largely automate the classification task.

4.2.2. Automated suggestion of stylistic influences at building component / architectural feature level

The process of studying and understanding a heritage building in the context of the development and completion of the ANNFASS platform continues after the steps presented by this article, with the detection of its stylistic influences. This task is proven to be more challenging than the architectural component labelling and recognition, since several styles can be concurrently present on a building - a common occurrence in the case of Cypriot heritage, with its characteristic hybridised architectural style. To tackle this issue, a similar approach to the previous task is pursued by the authors. That is, having another 3D CNN trained to recognise the architectural style influences of each component (if any) based on its appearance, and at the end of the process to present the various possible stylistic influences of the building identified by the tool to the user. Once again, for the training of the 3D CNN, a set of buildings with style-based annotations is required as input to the tool. In the context of this ongoing research, another expert group session with the architecture historians was conducted to acquire this information. This time though, the authors added further complexity to the process, and specifically, a period categorisation (Lusignan, Ottoman, etc.) was assigned to classify the various architectural components based on their appearance, instead of their functional aspects and type of architectural object (door, window, etc.). At the end of this process, and after the collection of historic architectural style labels and the training of the 3D CNN is completed, the user can load a new 3D model on the ANNFASS platform and have the 3D CNN recognise its stylistic influences by means of percentages (Fig. 6). As this is an ongoing task, a number of methods are being tested to determine the better-performing ones, before finalising the style recognition pipeline.

5. Conclusion

As stated before, this work is part of an ongoing project (ANNFASS). The collection of data for the 3D model generation is currently completed, having 3D models for all selected Cypriot heritage buildings ready to be used for the training of the 3D CNNs. A variety of computation methods have been developed, tested and assessed regarding the reliability of the automated modules, which will be hosted on a server for better communication with the ANNFASS platform. The ANNFASS platform will be updated with multi-period monuments, built-in Cyprus under different cultural influences, which in turn will be used to enrich the feature learning for the structure and style recognition 3D CNNs. A fundamental aspect of the classification process of architectural elements is first to identify a building's stylistic influences and function by finding similarities that are common between monuments of the same historical period. By extension, the mapping of similarities makes it easier to identify the uncommon and the rarest samples that can be found in cultural heritage monuments. Monuments that are not able to be classified in a specific large group of canonical examples of a historical period can be viewed as uncommon or exquisite cases of architecture outside the norm/standard and established styles and could be examined as unique/ non-standard cases. In a sense, the ANNFASS platform strives to provide the capacity to identify what is hidden and uncommon in many examples of architectural elements, styles and buildings, contributing to scientific excellence in architectural history, education and research.

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