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AUTOMATIC RECOGNITION OF BIO-COLONIZATION PROCESSES ON HISTORIC FAÇADES: APPLICATION ON CASE STUDIES

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Abstract

Many factors (physical, chemical, natural, and human activities) contribute to the degradation of historic buildings. Preventive conservation is a cost-effective approach international preservation bodies recommend to mitigate risks to built cultural heritage. A substantial challenge is bio-colonization, especially by microalgae, which affects brick-facing masonry surfaces due to environmental factors (i.e., temperature and moisture), leading to progressively increasing deterioration. Early detection systems could be useful to reduce damage from these organisms. Advances in computer vision and machine learning, such as convolutional neural networks, offer promising solutions for automating the identification of building pathologies using image collection. This research focuses on developing predictive models using convolutional neural networks to monitor bio-deterioration on historic façades, specifically targeting early-stage microalgae colonization. After a training phase using laboratory-induced bio-colonization on brick samples, the method was applied to real case studies of architecturally significant buildings affected by bio-colonization. In fact, a substantial number of digital images of these buildings, even if taken for other purposes, are available. The work shows that analyzing these images with the trained network facilitates the early detection of bio-colonization, providing a contribution to the field of built cultural heritage conservation.

Keywords

Microalgae, Bio-colonization, Historical buildings, Convolutional neural network, Monitoring.

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1. INTRODUCTION

The deterioration of historic building heritage is driven by a combination of physical, chemical, natural, and human-induced factors [1]. It is recognized that preventive conservation is one of the most cost-effective approaches, also recommended by international institutions involved in preservation [2], and consists of «a set of actions useful for reducing risk situations concerning cultural assets in their context» [3]. Bio-colonization (growth of living microorganisms) is one of the several pathologies affecting historical heritage that should be paid attention to. Historical buildings could be affected by primary (microalgae), secondary (molds and lichens), or tertiary (plants) colonizers, and the restoration of the affected surfaces can be costly. The colonization process by microalgae (primary colonizers) starts from an interaction between environmental factors and the physical and chemical properties of clay brick [4]. In the case of buildings of cultural value, the growth of these organisms could cause severe losses in original materials [5]. Adequate temperature and availability of water can indulge the growth of microalgae and, therefore, the degradation of the material, contributing to the creation of a suitable environment for the growth of other colonizers [4, 6, 7].

Furthermore, porosity and roughness of the substrate can promote algae growth [8, 9]. In this context, the availability of early detection systems based on data collection and images can help limit the aesthetic, chemical, and physical degradation of building surfaces due to bio-colonizers. The topic of computer vision-based automated building pathologies identification (using image processing and machine learning techniques) has attracted research attention in recent years, particularly about crack detection [10] on concrete [11] and masonry structures [12]. A convolutional neural network is a specialized type of deep learning model designed to process and analyze structured grid-like data, such as images. It is particularly effective in tasks involving image recognition and classification because it can automatically learn spatial hierarchies of features through convolutional layers. In the field of architectural heritage, convolutional neural network classification techniques have been used to identify and locate several types of damage (i.e., stain, efflorescence, cracks, and spalling) in masonry buildings [13, 14]. The issue of bio-colonizers on existing buildings has been addressed in [15] about tertiary colonizers (plants).

Regarding the specific problem of microalgae, in literature, there are available works focused on digital images acquired during the growth of microalgae strains in water solution but not on building façades [16]. In this work, to fill the lack of existing literature, the development of predictive models using a convolutional neural network useful to automatically monitor the bio-deterioration status of historic building heritage with facing-masonry façades is proposed. Given that digital images of historical building façades are constantly being captured and collected for various purposes (e.g., photographic documentation and tourist information), as well as automatically provided by surveillance cameras, there is a substantial amount of material available to assess the condition of these surfaces using the proposed method. The findings of this work serve as a preliminary step toward developing tools for the early detection of damage to building façades, particularly biodeterioration.

2. METHODOLOGY

2.1. RESEARCH FRAMEWORK

To reach the proposed goal, the research process was set up as follows: first, an experimental activity has been developed to follow, in controlled conditions, the microalgae growth, considering diverse types of clay bricks and various exposure conditions (temperature, RH%, rain). Then, digital images collected during the experimental campaign were resized and cropped to generate a dataset of about 12.000 sub-images representing the various stages of the bio-deterioration process. A convolutional neural network was trained using the digital images dataset that was obtained. Finally, the method was tested on case studies with brick-facing masonry to verify its applicability as an early detection system.

2.2. EXPERIMENTAL CAMPAIGN

The digital images to be used to train the convolutional neural network were obtained from an experimental campaign in which five types of clay bricks (designated as AH, AL, B, CH, and CL) were selected and tested in five different environmental conditions, reproduced using climatic chambers to accelerate the growth process. Clay bricks differ by color, porosity, and roughness. Considering that bio-colonization causes a shift of the original color towards green-blue nuances, and the initial color spectrum is influenced due to the transition between wetted and unwetted conditions, were chosen three different brick colors: light-red (AH and AL types), dark-red (B type), yellow (CH and CL types). Because the "shape" of the bio-colonization (e.g., spots, lines, areas) is influenced by the surface features and the water retention characteristic of the clay bricks, different microstructures were considered. Different environmental conditions were considered and characterized by different temperatures, RH%, and wetting processes to include a wide range of expected environmental conditions. Surface properties like porosity (according to ASTM D4404-10 [17]) and roughness (according to UNI EN ISO 4287:2009 [18]) of the tested clay bricks were measured. A green alga (Chlorella mirabilis strain ALCP 221B) and a cyanobacterium (Chroococcidiopsis fissurarum strain IPPAS B445) were used to reproduce the bio-colonization process [7]. Microbial strains were cultivated in a Bold's Basal Medium (BBM), formulated following ASTM D5589-09 prescriptions [19]. To reduce testing times, the tests were conducted under accelerated conditions (a visible biological degradation mostly begins after at least one year of natural environmental exposure). Five distinct environmental conditions were chosen to take into account a wide variety of potential real exposures. To find out how changing relative humidity (RH) levels affected algae growth on clay brick surfaces, three distinct RH conditions were replicated in three different climatic chambers.

Saturated solutions were used to condition the indoor environment, as recommended by EN ISO 12571:2013 [20]. The first RH condition (RH1, around 75%) was obtained using a saturated solution of NaCl; the second RH condition (RH2, around 87%) was obtained using a saturated solution of Na_2CO_3; the third RH condition (RH3, about 98%) was obtained using only deionized water. Tests were conducted at constant temperature (27.5 ± 2.5°C) in order to examine the impact of RH only. Each sample had nine distinct locations on its surface that were inoculated with 5µl of the mixed culture at the start of the test. After that, samples were placed, with an inclination of 45°, on aluminum-glass racks inside the climatic chambers, front-to-front along the chamber's long length. In order to protect the test equipment from outside influences such as light, temperature, and relative humidity, it was housed in a closed room. Two neon lights (Sylvania TopLife 39W) able to faithfully reproduce natural light conditions were installed in each growth chamber with the aim of recreating day/night cycles 14/10 h (Fig. 1a). The impact of temperature on algae growth was investigated in the wake of previous studies available in the literature [8, 9]. Until the stagnation phase was reached, accelerated tests were conducted using periodic water sprays on the material's surface (Fig. 1b). Growth chambers (100 × 40 × 53 cm^3) containing 35 liters of BBM inoculated with the mixed cultures represent the test apparatus for this phase of the work. Algal suspension was applied (sprayed) to sample surfaces (8 × 8 cm^2) situated on two 45°-inclined racks made of aluminum and glass. Run/off cycles were programmed to occur every 15 minutes for a total of 6 hours a day (3 hours of run time and 3 hours of rest time). Two 39W neon lights (Sylvania TopLife) have been used to reproduce a day/night lighting cycle of 14/10 hours. Following existing literature [21, 22], two distinct temperatures were chosen for the accelerated tests: 27.5 ± 2.5°C, which falls within the range of ideal growth values (which span from 20°C to 30°C), and a lower value of 10 ± 2.5°C, which falls within the range of suitable growth. A properly modi-

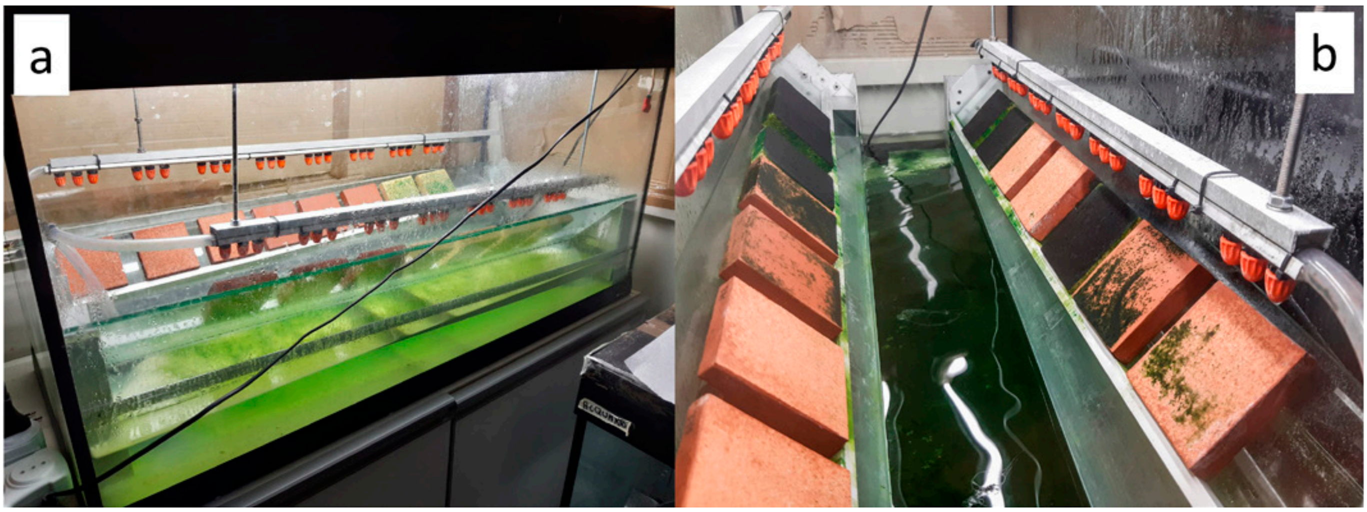

Fig. 1. *The test setup used to evaluate the effects of relative humidity on microalgae growth development (a) and the one used to investigate the impact of temperature (b).*

fied refrigerator (Electrolux RC 5200 AOW2) was utilized to set the lower test temperature. The presence of the wetting cycles makes it reasonable to assume that the relative humidity was always 100%. Temperature and relative humidity sensors (Sensirion SHT31-D) were used to monitor all test settings, with data taken every 10 minutes. During each accelerated growth test, specific analyses were performed to evaluate the algal extent and the biofouling process on the samples' surface [8]. First, colorimetric analysis was done to check how the color changed over time. A spectrophotometer (Konika Minolta CM-2600dD) was used to quantify the chromatic variation (ΔE*) [17]. According to UNI EN 15886:2010 [23] and UNI 11721:2018 [24], the CIELAB color space was used to represent the results. Equation (1) was used to determine color variation in terms of total color difference (ΔE*)

$$\Delta E^* = \sqrt{(L_0^* - L^*)^2 + (a_0^* - a^*)^2 + (b_0^* - b^*)^2} \qquad (1)$$

where L^*_0, a_0^*, b_0^* are the color coordinates of samples before the test (time zero), and L^*, a^*, b^* are those evaluated during the accelerated growth phase. The value has been measured on nine different spots on each sample surface every week.

2.3. DIGITAL IMAGE ACQUISITION AND DIVISION

A high-resolution scanner (HP Scanjet G3010) was used weekly to collect digital images to train the convolutional neural network. Previous works [8] have proven the effectiveness of this technique. As mentioned in the following part, the obtained images were elaborated using ImageMagick software. The ImageMagick software (rel.7.1.1-20) allowed the scaling of the images to 1780 x 1780 pixels; these were then cropped to create 256 x 256 sub-images: 49 sub-images were produced from each image. The name and order of every sub-image were changed randomly, and after that, a manual annotation procedure was carried out. Matlab software (rel. 2023a) was used to filter the image's R, G, and B channels in order to make the annotation process easier and take into account the fact that microalgae growth results in a color shift towards green values. Images with microalgal presence traces were labeled as *algae*, while the others were labeled as *no_algae*. Finally, the 13.120 sub-images that composed the annotated picture dataset were split equally into two sections: *train* and *test*. There are 1780 *no_algae* and 4780 *algae* photos in each dataset segment. No filtering was applied to the output images to evaluate the trained and tested convolutional neural network's capacity to operate directly with real pictures [25].

2.4. CONVOLUTIONAL NEURAL NETWORK DESIGN AND TRAINING

A convolutional neural network is called a feed-forward neural network with many convolutional layers layered on top of one another, each one able to recognize increasingly complex forms. Pooling layers (subsampling layers) are included. By calculating a summary statistic from the outputs in the vicinity, the pooling layer substitutes the network's output at specific points. This reduces the spatial dimensions of the representation, which in turn decreases the amount of computation required and leads to more efficient and faster model performance. Following a hyper-tuning procedure, a two-convolution layer was selected to maximize the convolutional neural network's layer count. The first convolutional layer has dimension [32, (3,3)]. The second convolutional layer has the dimension [64, (3,3)]. In order to turn the final matrix into a single array, two pooling layers, two dense layers (256,1), and a flatten layer were added. The first dense layer and the second convolutional layers use the *Relu* activation function. The second "dense" layer has been designated for the *Sigmoid* activation function. RMSprop optimizer (learning rate = 0.001) has been considered. The accuracy measure was displayed because our challenge is binary classification. The ratio of accurate forecasts to total predictions made by the model is known as accuracy. For the training procedure, batch sizes of 20 and 50 epochs were considered. The convolutional neural network has been trained and tested using a Python script (rel 3.9). The convolutional neural network was trained and tested using the *Tensorflow* and *Keras* libraries; then, it was hyper-tuned (parameter optimized) using the *Keras-tuner* library.

2.5. APPLICATION TO CASE STUDIES

Two specific case studies have been selected to demonstrate the practical applicability of the proposed model: the Mole Vanvitelliana and the Rocca Roveresca, two historical buildings of high architectural value that exhibit evident bio-colonization problems.

The Mole Vanvitelliana (Fig. 2) is a large, pentagonal architectural complex from the 18th century, located by the sea in the port area of Ancona (Marche region, Italy). This structure, also known as the Lazzaretto, originally served as a quarantine station for those arriving by sea in Ancona (a precautionary measure to monitor and control the spread of contagious diseases). Over the years, the building has been repurposed for various uses, including military and commercial functions, and today, it operates as a multifunctional cultural center. Designed in the 18th century by the architect Luigi Vanvitelli, the Mole Vanvitelliana is a unique example of architecture and a notable symbol of the city of Ancona. The main building of the complex is enclosed within a perimeter wall. Both the primary structure and the surrounding wall are constructed with brick-facing masonry. Notably, the sloped, rain-exposed perimeter walls show significant signs of bio-colonization, whereas the vertical walls of the main building, which are sheltered from the rain, do not exhibit such issues.

The Rocca di Senigallia, also known as Rocca Roveresca after the Della Rovere family who commissioned its construction (Fig. 3), is located in Senigallia (Marche region, Italy), and it stands as one of the most significant

Fig. 2. *The Mole Vanvitelliana, Ancona, Marche Region, Italy.*

Fig. 3. *The Rocca Roveresca, Senigallia, Marche Region, Italy.*

monuments of both the city and the region. As it appears today, the fortress is the result of centuries of transformation. Originally built during the Roman era as a defensive tower, it evolved into a medieval fortress in the 14th century and eventually took its current form as a typical Renaissance fortified residence in the 15th century. The monument consists of two interconnected structures: the central body, intended as a noble residence, is surrounded by a military defensive structure. The noble residence is encircled by a highly regular structure: a quadrilateral enclosure with four low circular towers at the corners, all connected to each other and the central building by an integrated system of vertical and horizontal communication routes. As in the previous case, the perimeter walls are made of brick-facing masonry. As shown in the figure, some portions of the structure, particularly those with a sloped configuration that makes them more exposed to weather conditions, exhibit signs of bio-colonization (specifically, the lower parts of the perimeter walls). In contrast, other areas are more protected and do not suffer from this issue.

Two different datasets of images were collected from the two case studies. Firstly, digital images extracted from video surveillance HD cameras were collected to evaluate the model's applicability to this type of data source. The second dataset consisted of images of brick-facing masonry façades captured manually using an HQ resolution camera. All the images were resized to the same dimension (1780 x 1780) using the ImageMagick tool, rel.7.1.1-20, and cropped to obtain ca. 1,550 256 x 256 pixels sub-images coming from video surveillance cameras and ca. 500 sub-images of 256 x 256 pixels from the HQ resolution camera images.

3. RESULTS

3.1. CONVOLUTIONAL NEURAL NETWORK TRAINING AND TEST

A trained, tested, and validated convolutional neural network has been used to determine the beginnings of the microalgae development process. The plot of the historical training and test procedure is displayed in Figure 4. The accuracy using the "training" and "test" datasets has been displayed after each epoch (iteration on the whole dataset). When the final accuracy or the ratio of accurate predictions to all predictions produced by the model is 0.83, meaning that 83% of the photos, whether they included microalgae or not, were identified correctly.

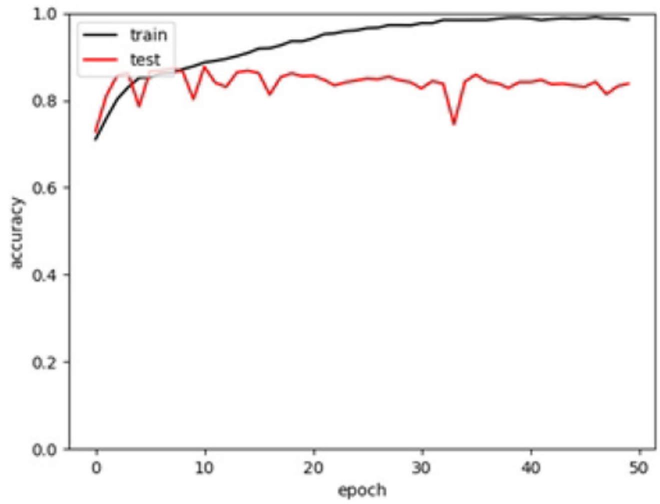

Fig. 4. *Plot of the "training and test" history process. The black line represents the accuracy obtained at the end of each epoch during the training process. The red line represents the accuracy obtained at the end of each epoch during the test process.*

3.2. AUTOMATIC DETECTION OF BIO-COLONIZATION ON CASE STUDIES

The trained model was applied iteratively to verify its recognition ability in real cases. The trained network was first used to detect bio-colonization presence in images collected by security HD cameras. The application of the method to this group of images highlighted that the ability to recognize bio-colonization on the brick-facing masonry façades is affected by several factors. Dividing images from surveillance cameras results in low-resolution sub-images, reducing recognition effectiveness. Moreover, images acquired from security cameras include other elements (ground, grass, roads, roofs, stone, metallic elements, etc.) that were not included in the original dataset. If the cropped image contains objects different from the bricks, convolutional neural networks frequently fail, reducing total accuracy to unacceptable values. This clearly highlights two things. First, there is a need for higher resolution images, and second, there is a necessity to expand the dataset used to train the convolutional neural networks by including images of the brick

Fig. 5. *Some examples of images extracted from HD security cameras installed at the Mole Vanvitelliana and the Rocca Roveresca.*

Fig. 6. *Some examples of images collected with HQ resolution cameras at the Mole Vanvitelliana and the Rocca Roveresca.*

surface and images featuring all elements present on and around building façades (Fig. 5).

Then, the trained network was used to detect bio-colonization presence in the second group of images, those directly collected near the building façades, which include only bricks with and without bio-colonization (Fig. 6). In this scenario, accuracy improves to 0.68 but remains below the one achieved after the training and testing phases (0.83). Thus, enhancing resolution and excluding non-brick elements improved the recognition performance of the trained convolutional neural networks.

However, the not-perfect matching among the colors of the bricks used to train the convolutional neural networks and the color of the historical clay bricks of the case studies, along with the potential presence of other types of bio-colonizers and/or stains, reduced the accuracy achieved with real images.

It is important to note that no image filtering was conducted to evaluate the performance of the trained and tested convolutional neural networks to work directly with real images.

4. CONCLUSIONS

Architectural heritage is subjected to many deterioration problems; one of these is the phenomenon of bio-deterioration and, in particular, microalgae growth. Following the preventive conservation approach, this work aims to provide a tool for "early" damage detection in order to reduce major invasive interventions, moving from restoration (intended as those activities needed to repair serious deteriorations) to a more inclusive approach based on continuous care and supported by data collection, regular monitoring, inspections, control of environmental factors and maintenance activities. In this context, predictive models based on convolutional neural networks that can detect microalgae growth on facing-masonry surfaces were studied and developed. The convolutional neural network has been trained with images collected during an experimental campaign. The model obtained after the training phase is able to recognize the beginnings of the bio-colonization process on several types of clay bricks and can rely on an accuracy of 83%. The initial results from applying the described procedure to a case study were promising but nonetheless highlighted some issues. While automatically obtained images from surveillance systems proved less effective (due to their low quality and the inclusion of contextual elements that interfere with the recognition system), using high-quality images, even those taken for other purposes, yielded significantly better outcomes. However, the application to case studies has not yet achieved results comparable to those obtained in laboratory samples, indicating that further refinement is still needed. To address the primary limitation identified, it will be necessary to extend this study by expanding the dataset through additional experimental activities and incorporating real-world images that capture all elements found on building façades and their surroundings, as well as images of various types of bio-colonizers, into the training process.

Authors contribution

The paper was elaborated as a team, but M.D. designed and directed the project and developed the neural network; A.G. and E.Q. designed and performed the experimental phases, and F.M. contributed to data collection and case-study-related activities. Writing, original draft and writing, review and editing are realized by the authors unless otherwise specified.

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