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Automatic Determination of Damage to Cultural Assets by Means of Artificial Intelligence

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Automatische Bestimmung von Schäden an Kulturgütern in Echtzeit mit Hilfe von künstlicher Intelligenz – Zusammenfassung

Im vorliegenden Beitrag wird ein neues Verfahren vorgestellt, welches Schäden an Kulturgütern automatisch erkennt und den Anwender darüber informiert. Das Verfahren basiert auf Methoden der künstlichen Intelligenz (KI). Zur Erkennung von Schäden werden verschiedene Sensortypen wie berührungslose Temperatur- und Luftfeuchtemessung mit einem Kamera-System kombiniert. Aus den Daten werden dann mit Hilfe von Convolutional Neural Networks (CNN) automatisch die Zustände des zu beobachtenden Objektes ermittelt.

Die automatische Erkennung von Schäden an Kulturgütern ist besonders dann sinnvoll, wenn diese nicht direkt von einer Person überwacht werden können, bzw. wenn die permanente Schadensüberwachung durch Menschen zu aufwendig und kostspielig ist. Ein Beispiel dafür sind die Fenster von Kathedralen, die meist in großen Höhen eingebaut sind. Ein weiteres Beispiel sind Kirchenorgeln, wo die permanente Schimmelüberwachung auch innerhalb der Orgel einfach realisiert werden kann.

Automatic Determination of Damage to Cultural Assets by Means of Artificial Intelligence – Abstract

This paper presents a new procedure that automatically detects damage to cultural objects and informs the user about it. The procedure is based on artificial intelligence (AI) methods. To detect damage, various sensor types such as non-contact temperature and humidity measurement are combined with a camera system. Convolutional neural networks (CNN) are then used to automatically determine the states of the object to be observed from the data.

The automatic detection of damage to cultural assets is particularly useful when they cannot be directly monitored by a person, or when permanent damage monitoring by humans is too time-consuming and costly. Examples of this are the windows of cathedrals, which are usually installed at great heights. Another example is church organs, where permanent mold monitoring can also be easily realized inside the organ.

Introduction

With a novel, innovative approach based on artificial intelligence (AI) algorithms, this article presents a procedure that automatically informs the user in real time about the development of damage to cultural property. For this purpose, a system platform was developed whose results can be understood without expert knowledge and which can be installed with minimal effort. This aspect of the simple applicability of a complex system has already led to very positive feedback from users in the Custos Aeris project (Sander 2017).

The basis of the system platform (fig. 1.) is formed by microcontroller-based electronics, called real-time controller in the following, and a cloud server. The real-time controller, which is installed close to the object to be observed, combines a digital camera with illumination techniques in the visible light range. By evaluating the images with AI algorithms on the real-time controller, a system is created that enables automatic damage detection in situ and in real time. The system is supplemented with interfaces and sensors for recording temperature and relative humidity in the near field of the object to be monitored. In this way, the environmental conditions that led to the damage are also directly documented. The determined data is sent to the cloud server via LTE-connection. The cloud server takes over the data storage, the visualization of the data and informs the user in case of damage. The AI algorithms are also trained on the server.

The following objectives are to be achieved with the system:

- Autonomous detection and assessment of damage in the early stages of visibility – *in situ* and in real time
- Detection of different types of damage, e.g. damage due to condensation, cracking or mould
- Automatic generation of a warning message to the user
- Cloud-based data storage and data visualization
- Documentation of the history of the damage by recording the environmental conditions in the near field of the object to be observed.
- Detected sensor data and camera images can be used as the basis for a knowledge database to develop new algorithms for the early detection of damage.

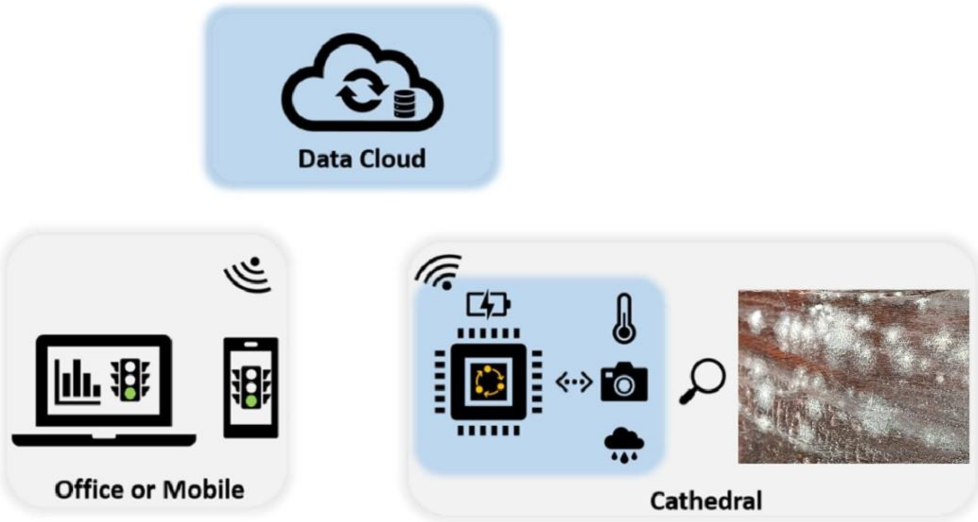

Fig. 1. System Architecture of the mold camera 2021 © iXtronics-Hajuveda.

As part of a DBU 35604 project funded by the Deutsche Bundesstiftung Umwelt (DBU), such a system platform for the automatic detection of damage to cultural assets was developed (DAAMS 2020). The aim of the DBU project is initially to detect the development of mold. However, the system platform is planned to be so general that it can also detect damage to historical windows, such as condensation or cracks. The necessary flexibility of the system platform results from the AI algorithms, which are trained to recognize a wide variety of damage through appropriate training with sufficient image material. In the case of cracks, the system platform can also be supplemented with acceleration sensors for vibration measurement via existing interfaces. In this way, the causes of crack formation can also be documented in this case.

State of the art

The use of digital systems for the protection and preservation of cultural heritage is becoming increasingly widespread, as evidenced, for example, by the EuroMed 2018 conference (IOANNIDES et al. 2018). The applications and methods described include numerical analyses using computer simulation models, 3D digitization and reconstruction, and virtual and augmented reality methods. Currently, artificial intelligence methods are also increasingly being used for the 3-D digitization of cultural assets. The starting point for these methods was the management of very large amounts of data during digitization, e.g. by laser scanners (BRUMANA et al. 2019, SANTOS 2017). To simplify data handling, artificial intelligence techniques such as Convolutional Neural Networks (CNNs) are used to automatically classify cultural objects (BELHI et al. 2018, LLAMAS 2017, PAOLANTI 2019). As a result, it is now possible to automatically catalogue extensive image databases and define more detailed criteria that lead to quick and reliable results for subsequent searches.

In recent publications (CHAIYASARN et al. 2018, KWON & YU 2019), CNNs are also used for damage detection in the cultural property sector. This is university research that uses CNNs for automatic damage detection of, for example, cracks in historical buildings, masonry or sculptures. The data is recorded by camera and subjected to subsequent analysis. However, according to current research, the use of AI methods for preventive damage detection in situ and in real time is uncharted territory in the field of cultural heritage.

This is precisely the innovative character of the project. Based on CNN algorithms, a system is being developed that can detect damage to cultural objects in situ and in real time. By combining digital image recognition using CNN algorithms and sensors for recording the environmental conditions in the near field of the objects to be monitored, it will not only be possible to detect damage to cultural property, but also to directly document the environmental conditions that led to the damage. As an outlook, the data obtained in this way can be further developed into a knowledge database in follow-up projects.

Solution concept and realisation

The solution concept of the system platform is based on the components shown in fig. 1 and the cloud server. The cloud server forms the interface to the user by providing the data of the real-time controller via web server and informing the user about the status of the object to be monitored. The real-time controller collects all the necessary data on site in real time to assess whether there is damage or not and sends it to the cloud server via mobile radio.

Real-time controller functionality

The core component of the real-time controller is a microcontroller on which the peripheral components are managed. A sensor interface to non-contact temperature and humidity sensors is available for measuring the environmental conditions in the near field of the objects to be observed.

The camera interface makes it possible to couple a digital camera with the real-time controller. The camera is supplemented with a ring of LEDs in the visible range, which is controlled by the controller.

The real-time controller is equipped with an energy management system and a power supply based on primary cells in order to be able to work energy-autonomously and without interruption for at least 6 months. With the memory components flash memory and SD card, the data of the cameras and the sensors are temporarily stored. The function of the Real Time Clock is to wake up the microcontroller from the energy-saving mode at defined times and to provide the measurement data with a time stamp.

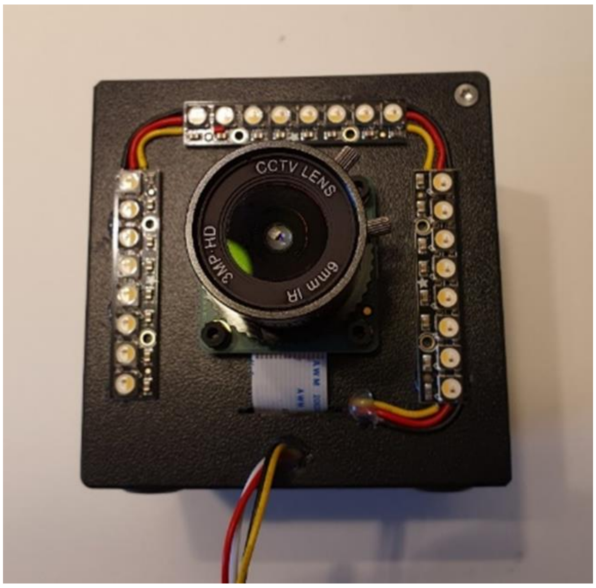

Fig. 2. Front view of mold camera 2021.
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Since the system is intended to be energy-autonomous, the time intervals in which a measurement will be taken and the time intervals in which the data will be transmitted to the cloud server via LTE are synchronized. Due to intensive research on mold growth in churches, the time interval is set to once a day to once every 3 days at midnight.

Fig. 2 shows the front view of the mold camera including LED-bars for illumination and camera-objective. All electronic components are integrated in the housing. The temperature and relative humidity sensor is connected via a cable (hanging down in the picture).

Cloud server functionality

The cloud server forms the system interface to the user. By means of a web server and a user administration, the object data assigned to the user can be accessed and visualized on the system platform in an uncomplicated way by means of username and password via a web browser. The cloud server is also used to automatically notify the user of possible mold growth. The user can choose, for example, whether he wants to be informed by SMS or email.

The database of the cloud server contains the user data, the object data and additional image data for the AI training. The user data includes, for example, the user name and the assigned object data. The object data stores information such as the object name, the object location and all data determined via real-time controller at the object.

The AI algorithms are also initially developed, trained and tested on the cloud server. Through a downstream automatic analysis of all data from the real-time controllers in the field, the cloud server decides during operation whether the AI algorithms need to be retrained.

AI algorithms

The AI algorithms belonging to the central solution concept can only be described here in principle due to their complexity. A detailed description of the topic can be found, for example, in (SCHWAIGER 2019 or CHOLLET 2018). The core of the planned AI algorithms is a special neural network, a so-called Convolutional Neural Network (CNN), which was developed for image processing.

The principle of a CNN, as with all neural networks, is to reproduce the brain of living beings and thus their pattern recognition abilities in the computer. Fig. 3a shows the structure of a CNN, which consists of a detection and an identification part. The identification part typically corresponds to a conventional neural network. The input image to be recognized is filtered in stages in the detection part and broken down into its features from simple to complex to extract the features to be recognized from the image at the end. The actual recognition of the features takes place in the identification part.

Just like the human brain, neural networks must also be trained. To do this, the network must be fed as much data as possible in the so-called training phase. In the case of optical pattern recognition, the neural network receives a correspondingly large number of images for learning. The definition of what a damage image looks like is determined by the user. In the learning phase, labels with the properties to be recognized are assigned to the image data in the database.

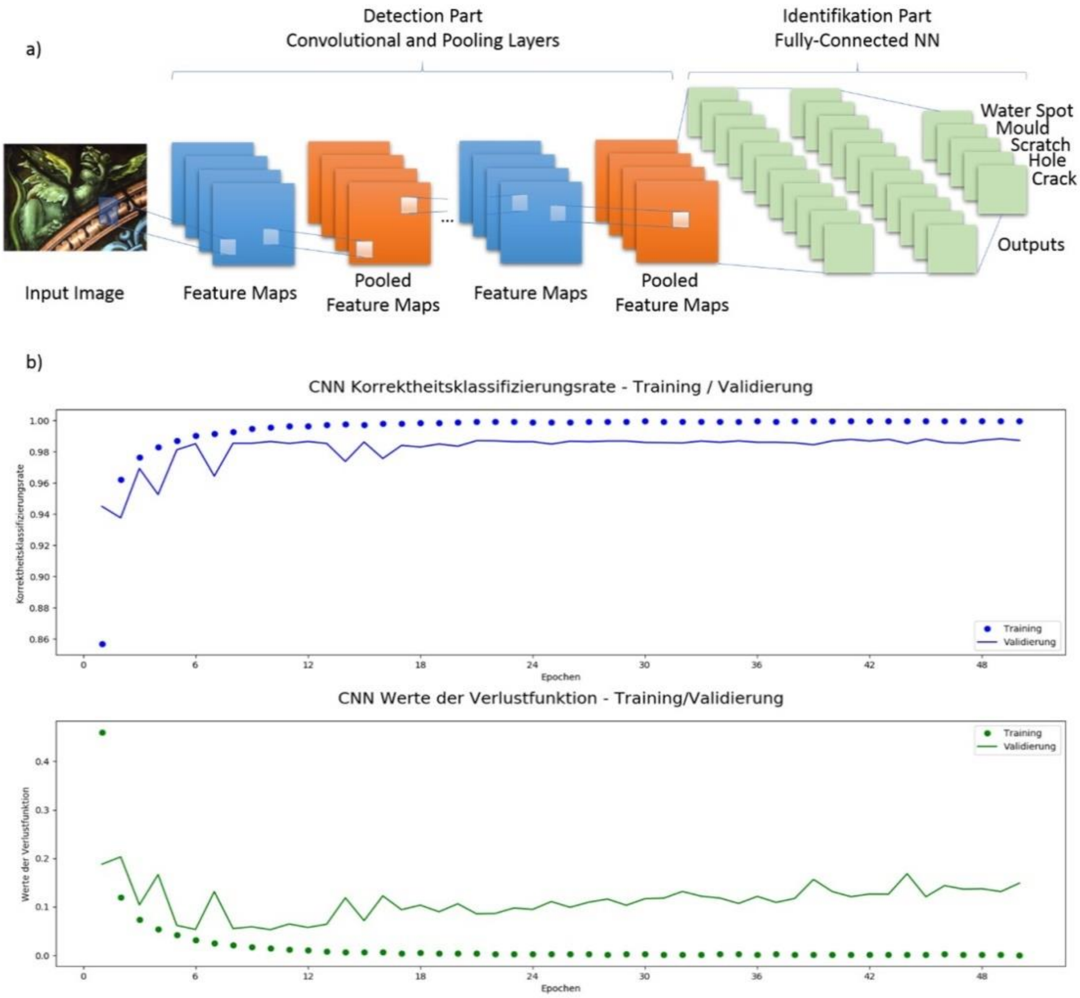

Fig. 3. Structure of a CNNs (a) and process of a Training (b) 2021. © iXtronics-Hajuveda.

Fig. 3 shows the development of the classification rate and the so-called loss function during a training phase for a CNN. The training is divided into so-called epochs. In each epoch, all training data, or training images, are fed into the CNN and optimization functions are used to change the parameters of the CNN in such a way that the recognition of the image information corresponds as closely as possible to the desired result. The optimum is a correctness classification rate of 1, which corresponds to a recognition rate of the images of 100 %. From the diagrams it can be seen that after several epochs the recognition rate for the test data approaches more and more the value 1. The recognition value for the validation data calculated simultaneously after each epoch also increases at first, but then stagnates at about 99 %. Theoretically, the CNN can be trained until a recognition rate of 100 % is reached for the training data. However, it quickly becomes apparent that the CNN achieves a lower recognition rate for new data, such as the validation data. This effect is also reflected in the loss function. For the training data, this numerical value drops towards zero over the epochs. For the validation data, it initially drops and then rises again. This is an indication that the CNN has been optimized too much for the training data and the flexibility to recognize unknown data sets is lost. In this case, the CNN is overtrained. To avoid this, there are various strategies for training a CNN that must be applied in the project.

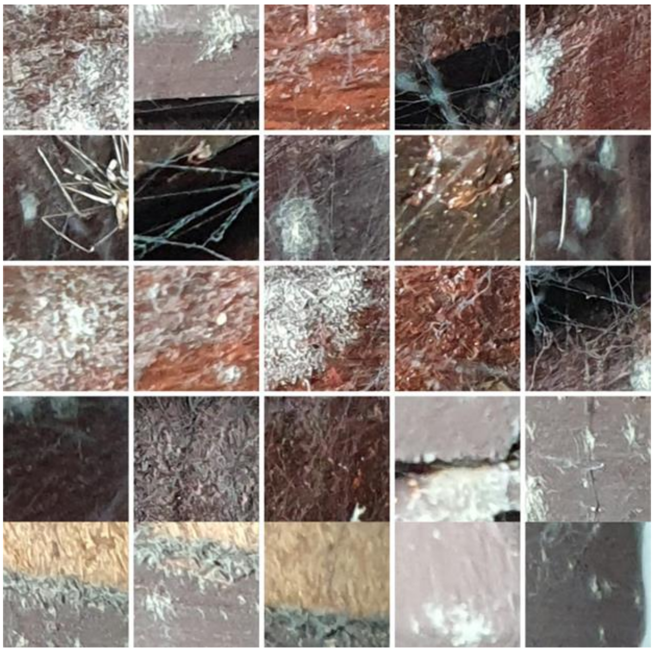

Fig. 4. Cut images from cultural objects, 2021. © iXtronics-Hajuveda.

Practical way for CNN-Training

To be able to train the CNN optimally, many images are initially required. All in all, the support of the project partners and users brought together more than 4000 fotos of mold in cultural objects. Images must be cut for two reasons: first it is necessary to see only one damage feature at a time and second the images should have maximum 250x250 pixels for the CNN to have acceptable computational time.

An example of cut images is shown in Fig. 4. Thanks to the very good support of the project altogether 350000 cut images were finally available for the training.

From this pool, the images for the training for the features mold, dust and "o.k." were then selected. Fig. 5 shows an example for mold:

Data augmentation is also used in the project as another way of obtaining the number of image data required. For this purpose, existing damage images from the database are zoomed, shifted, rotated and mirrored by algorithms in the computer. The training of the CNN is quite time consuming and requires computers with powerful graphic cards. The training was usually stopped after coming to 97% score rating, which means that 97% of the pictures shown were correctly classified to the right features.

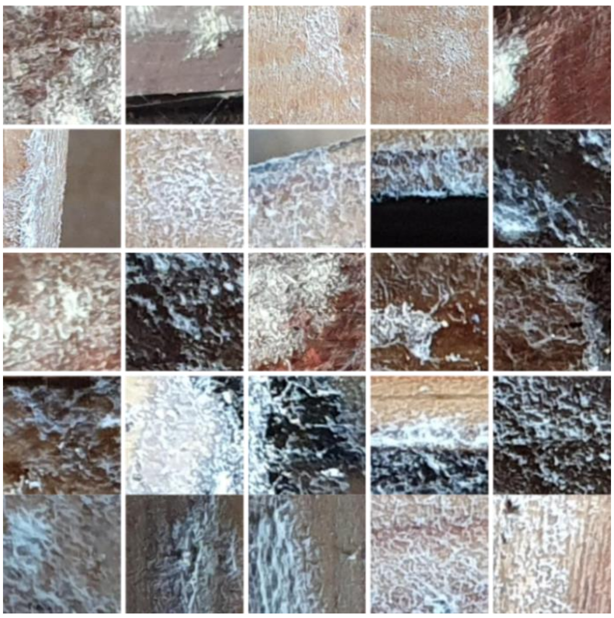

Fig. 5. Images cut of the feature “mold”, 2021. © iXtronics-Hajuveda.

Testing of the technology in the Cathedral of St Victor in Xanten

Fig. 6. The mold camera in a field test in the dome of Xanten, 2021. © iXtronics-Hajuveda.

Many of the training images for the neural networks came from the Xanten Cathedral shortly before mold removal by a team of restorers. In order to detect renewed mold growth as early as possible, a "mold camera - Custos Mucoris" with the real-time controller described here was installed in Xanten Cathedral. Fig. 6. shows the camera looking at the back of an altar. It was suspended with threaded rods from a roof batten which was wedged into the column. The temperature and humidity sensor was stuck with an adhesive pad in the immediate vicinity of the back wall of the altar. The camera has an LTE stick that transmits the camera images and sensor data to the cloud.

Due to the slow growth of mold in churches, the cycle rate of the images was initially set to 1 photo per midnight and later to 1 photo every 3 days at midnight.

During the real-time monitoring of the camera over a period of 5 months, unfortunately no new mold appeared. Therefore, to check the functionality of the concept, 3 mold images were mounted into one camera image. Since the photos are always cropped to a size of approx. 250x250 pixels, the lower mold appears in a total of 4 pictures. Fig. 7. shows a section of the cut images in the back wall of the altar including the mold.

The mold was clearly detected by the neural networks. Based on this evaluation, the user is then informed by email about the occurrence of mold.

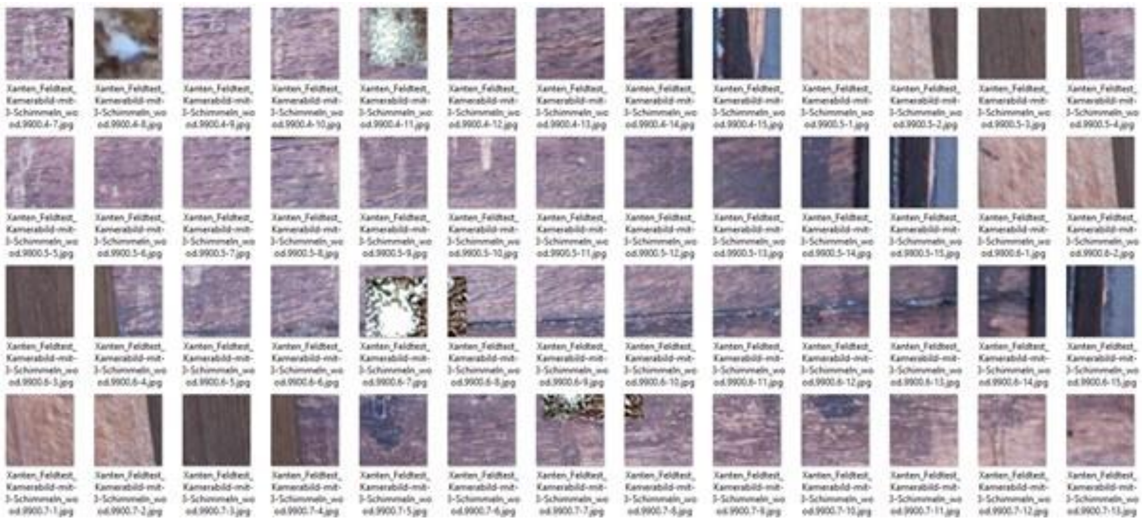

Fig. 7. Spitted image of the back of the altar including mold in Xanten, 2021. © iXtronics-Hajuveda.

Summary and outlook

In the article, the concepts, and the realization of a system platform for the automatic damage detection of cultural assets by means of artificial intelligence were presented using the example of mold. The central components of the system platform are the real-time controller with environmental sensors and the camera system, the cloud server with a database and web server function, and the development of AI algorithms for autonomous damage detection. In the course of development so far, the scripts for image evaluation have been created using CNNs and successfully tested.

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