

Identifying Historical Objects by Using Computer Vision

Walpola Liyanage PERERA, Technische Universität Dresden, Germany

Heike MESSEMER, Universität Würzburg, Germany

Matthias HEINZ, Technische Universität Dresden, Germany

Michael KRETZSCHMAR, Technische Universität Dresden, Germany

Keywords: *Artificial Intelligence — Computer Vision — Art History — Museum — Digital Humanities*

CHNT Reference: Walpola Liyanage Layantha Perera, Heike Messemer, Matthias Heinz, Michael Kretzschmar. 2020. Identifying Historical Objects by Using Computer Vision. W. Börner, S. Uhlirz, and I. Herzog. Artificial Intelligence. New Pathways towards Cultural Heritage (Proceedings of the 25th CHNT). DOI:xxxxxxx.

Introduction

Museums all over the world collect and present an uncountable number of precious objects to preserve the cultural heritage of mankind. These artworks are subject to the study of scholars, students and the general public alike. Advancing information delivery systems to provide data of these objects would be of great value not only to speed up research but also to significantly facilitate students in studying the artworks. To create such systems, it is essential to identify artworks correctly. This can be achieved with the help of computer vision technologies in artificial intelligence (AI).

Aims and Methodology

It will be demonstrated how precious artworks of the museum New Green Vault in Dresden, Germany, are identified with computer vision. Therefore, outstanding artworks of the courtly collection, which date back to the 1560s, were photographed in high resolution. The compiled dataset comprises 105 objects and 70 images.

To identify particular artworks on the images as well as to retrieve images from the dataset, DELF, a neural network model published by Google, and the algorithm RANSAC were used. Furthermore, several libraries (Matplotlib, NumPy, Scipy, Keras) were used in combination with Python code to process the model.

Results

The method used for image retrieval is shown with images of the *Large Display Casket Belonging to Sophia* as an example. How the images were correctly retrieved and incorrect images were skipped is displayed in Fig. 1. Features of the images were detected and key points were selected to match them with other images in the images folder. Inliers were realized so that images with higher inlier counts could be matched with the reference image and be retrieved (Fig. 1). This convolutional neural network-based model is sufficient to obtain both key points and descriptors (Noh et al., 2017).

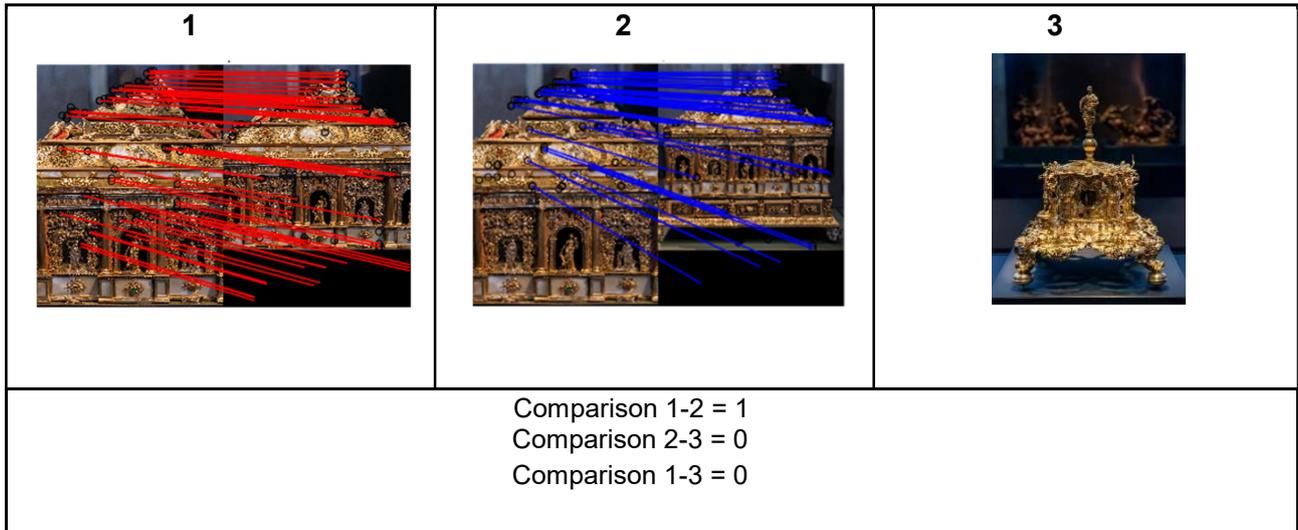


Fig. 1. Retrieving images of the Large Display Casket Belonging to Sophia, Consort of the Elector (ca 1588, Inv.No. IV 115, Staatliche Kunstsammlungen Dresden, Germany; photos: Michael Kretschmar).

For the test displayed in Fig. 1 the desired result is 1,0,0, indicating that image 1 should be matched with image 2 as both depict the *Large Display Casket Belonging to Sophia*. Image 1 and 2 should not be matched with image 3, because image 3 does not represent the *Large Display Casket Belonging to Sophia*.

By using the methodology, which was discussed in the Aims and Methodology section, final tests were performed. The results of the tests were processed through confusion matrix calculations.

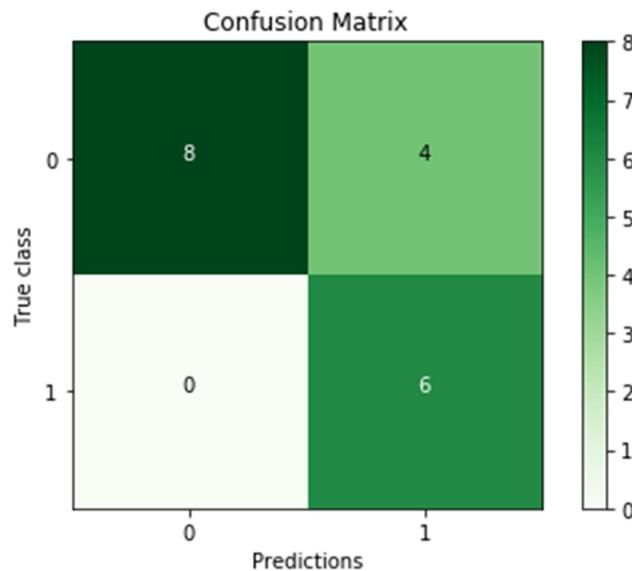


Fig. 2. Confusion Matrix results of image retrieval of the historical objects.

The results of the confusion matrix are: $y_{actual} = 1,0,0, 1,0,0, 1,0,0, 1,0,0, 1,0,0, 1,0,0$ (desired result) and $y_{predicted} = 1,1,1, 1,0,0, 1,1,1, 1,0,0, 1,0,0, 1,0,0$ (predicted result).

In detail this means as shown in Fig. 2:

Number of False Negatives = 0

Number of True Positives = 6

Number of True Negative = 8

Number of False Positives = 4

The results state that the accuracy of the Confusion Matrix calculations is 78% (accuracy = (true positives + true negatives) / (true positives + true negatives + false positive + false negatives)). The precision is 60% (precision = true positives / (true positives + false positives)). The recall score is 100% (recall score = true positives / (true positives + false negatives)) (Manliguez, 2016).

Discussion

As shown the used methods for image retrieval of photographs displaying historical objects were suitable for this task. With the amount of data growing rapidly, AI is getting increasingly important in the field of digital humanities in general. In the field of art history in specific, more and more projects using AI are developed since the 2010s (Bell and Ommer, 2018). This abstract demonstrated that object recognition in computer vision has the potential to be a fruitful research area for the field of art history. AI will also create innovative possibilities in higher education in the long run (Pence, 2019). Especially in the context of large datasets including a growing amount of images and corresponding metadata this technology is necessary to process, to filter, to present and to analyse them as well as to provide correct metadata. "The best arrangement will be a division of labor, AI does what it does best, and humans do what they do best" (Pence, 2019, p. 11).

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