

Identifying Historical Objects by Using Computer Vision

Walpola Liyanage Layantha Perera, Technische Universität Dresden, Heike Messemer, Universität Würzburg, Matthias Heinz, Technische Universität Dresden, Michael Kretzschmar, Technische Universität Dresden, Germany

Introduction

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

Aims and Methodology

In this poster it will be demonstrated how precious art works of the museum New GreenVault, a part of Dresden Castle, are identified with computer vision technologies. Therefore, outstanding art works of the courtly collection displayed in the New Green Vault, which date back to the 1560s, were photographed in high resolution. The compiled dataset (Dresden Treasures Dataset) comprises 105 objects and 70 images. To identify particular art works 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 being used. Furthermore, several libraries (Matplotlib, NumPy, Scipy, Keras) were used in combination with a Python code to process the model.



Discussion

As the amount of data is growing rapidly artificial intelligence is getting increasingly important in the field of digital humanities in general and in the field of art history in specific since in the 2010s more and more projects using AI are developed (Bell & Ommer 2018). The area of application is widening as The Alan Turing Institute indicates in 2020: "The cultural heritage sector is experiencing a digital revolution driven by the growing adoption of non invasive, non destructive imaging and analytical approaches generating multi dimensional data from entire artworks. The ability to interrogate this wealth of data is essential to reveal an artist's creative process, the works' restoration history, inform strategies for its conservation and preservation and, importantly, present artwork in new ways to the public." As shown in this paper, object recognition in computer vision has the potential to be a fruitful research area for the field of art history especially in the context of large datasets. With the growing amount of images and corresponding metadata this technology is necessary to process, to filter, to present and to analyze them as well as to provide correct metadata.

Detecting The Christmas Present from Elector Christian I

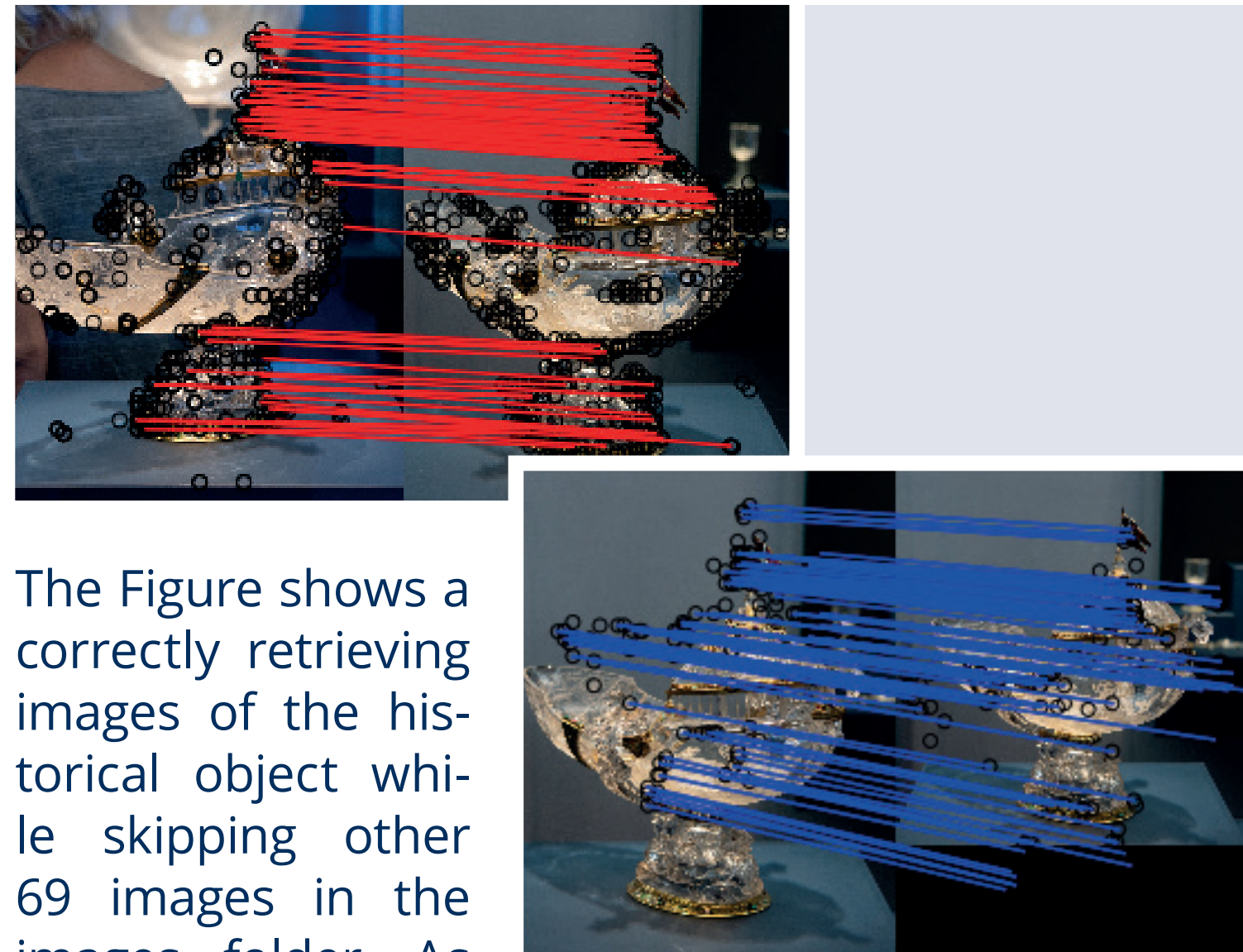


The Figure shows correctly retrieving images of the Christmas Present from Elector Christian I while skipping other images in the images file. Local features of the images were detected and attention based keypoints were selected. Outliers and inliers were realized. In this convolutional neural network based model one-forward pass over the network is sufficient to obtain both key points and descriptors (Noh et al., 2017). After detecting the key points and the descriptors they will be matched with other images in the images folder where the images are retrieved from. The images that have higher inlier counts will be matched with the reference image and retrieved as shown the figure. The desired result for test above is 1,0,0 which means that image 1 should be matched with image two because they show the Christmas Present from Elector Christian I.

References

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- Noh, H., Araujo, A., Sim, J., Weyand, T., & Han, B. (2017). *Large Scale Image Retrieval with Attentive Deep Local Features*. In *IEEE International Conference on Computer Vision, Venice*, pp. 3476-3485. IEEE. doi: 10.1109/ICCV.

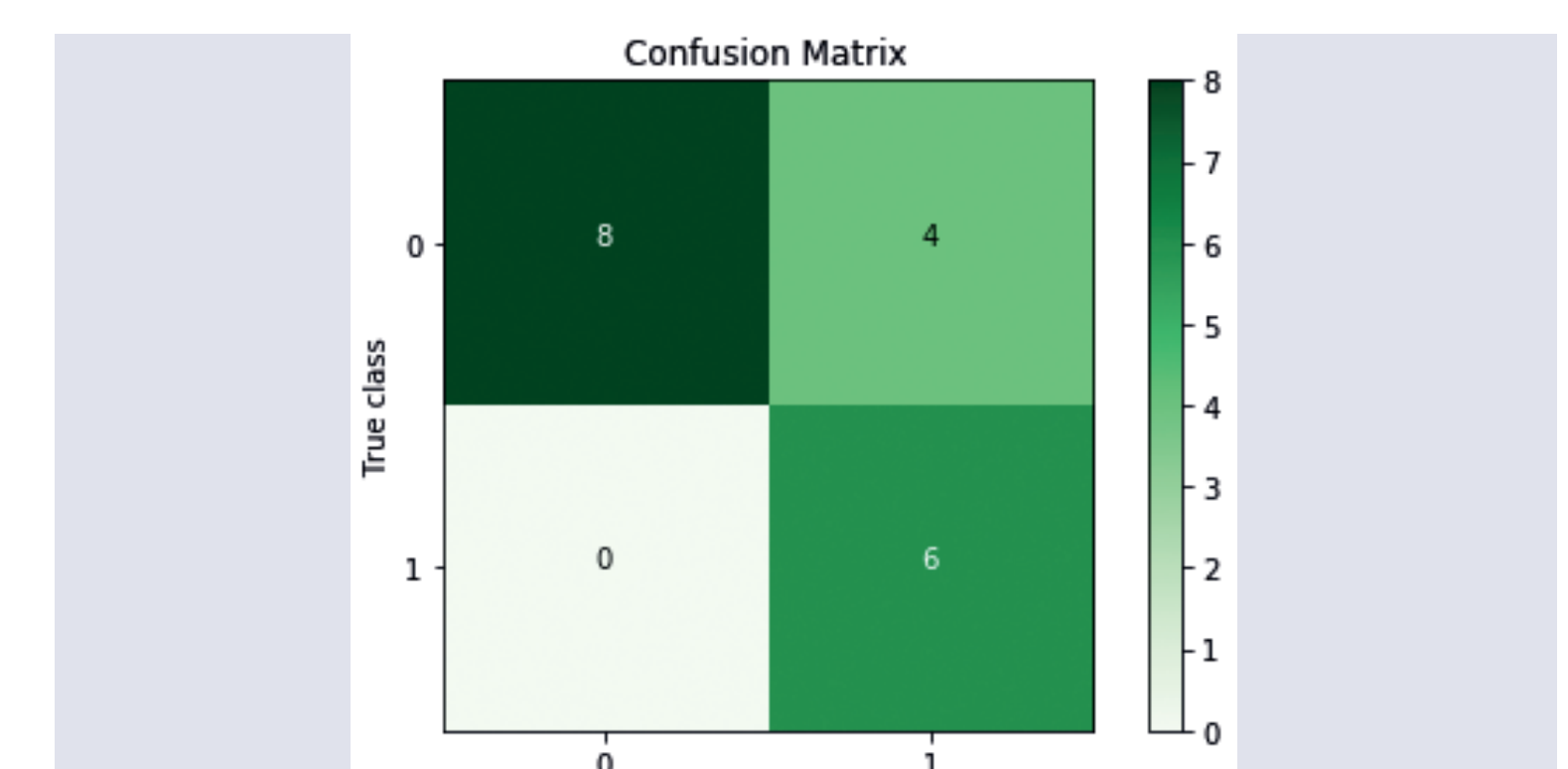
Detecting The Rock Crystal Accompanied



The Figure shows a correctly retrieving images of the historical object while skipping other 69 images in the images folder. As shown in the figure the DELF algorithm with the help of convolutional neural networks is detecting and matching the key points and the image descriptors of the Rock Crystal Accompanied. RANSAC algorithm has been used here to identify inliers and outliers separately. The desired image retrieval result for this test was 1,0,0. The predicted output of the test was 1,0,0. Therefore, in this test the desired output was produced.

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- Retrieved from Keras: <https://keras.io> (01/03/2020).

Confusion matrix of the results



Confusion matrix results of the image retrieval

Number of False Negatives = 0
 Number of False True Positives = 6
 Number of True Negative = 8
 Number of False Positives = 4

Computer code generated KPIs of the Confusion Matrix

According to the results the Confusion Matrix calculations have 78 % accuracy. The accuracy is the ratio of: (true positives + true negatives) / (true positives + true negatives + false positive + false negatives) and indicates the fraction of predictions the used model got right. It also shows that it has 60 % precision, which indicates the proportion of positive identifications that was actually correct. The precision is the ratio of: true positives / (true positives + false positives). The recall score is 100 %. The recall is the ratio of: true positives / (true positives + false negatives) and indicates the fraction of the total amount of relevant classes that were actually retrieved (Manliguez, 2016).