# Buddhist Murals of Kucha on the Northern Silk Road

## An Approach to Semi-Automated Annotation[1]

Erik Radisch

Saxon Academy of Sciences and Humanities in Leipzig, Germany (radisch@saw-leipzig.de)

Sächsische Akademie der Wissenschaften zu Leipzig

## 1. Baseline

Our project has already created around 12,600 annotations on more than 1490 images. The annotations are very unevenly distributed across 800 different categories from our iconography tree. The median is 5 annotations per category. The most populated category (nimbus around the head) has been annotated 679 times. The iconography and our annotations can be viewed on our project homepage: https://kuchatest.saw-leipzig.de/iconography

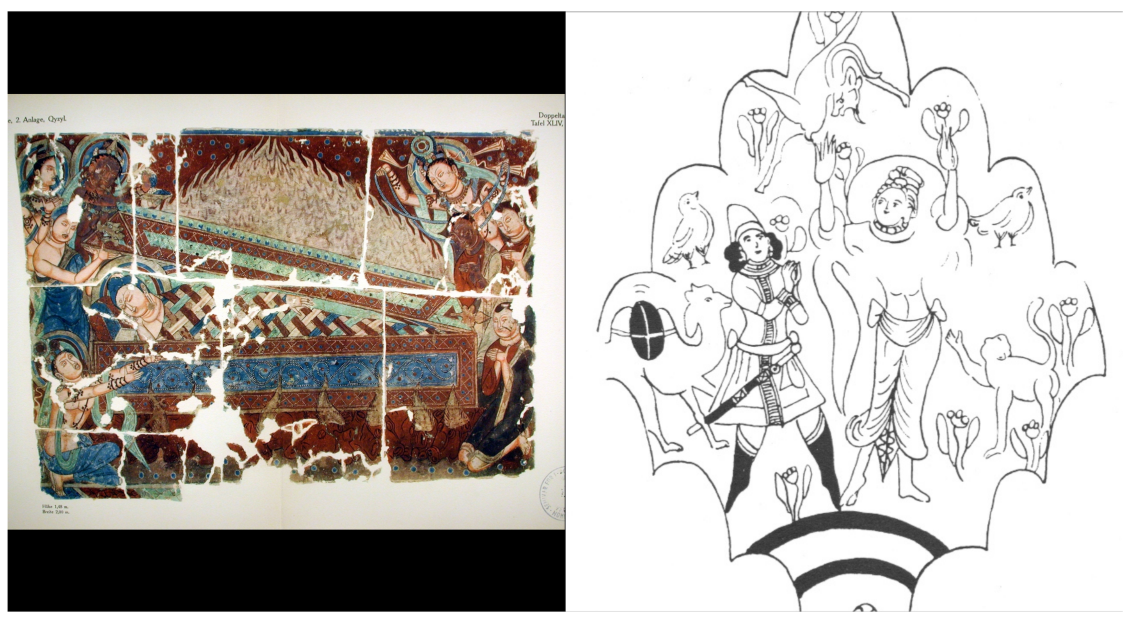
## 2. Aim

Annotating images is very time-consuming. Many categories recur very often (e.g. nimbus around the head) and are easy to recognise. It is therefore worthwhile to check whether these tasks can be semi-automated.

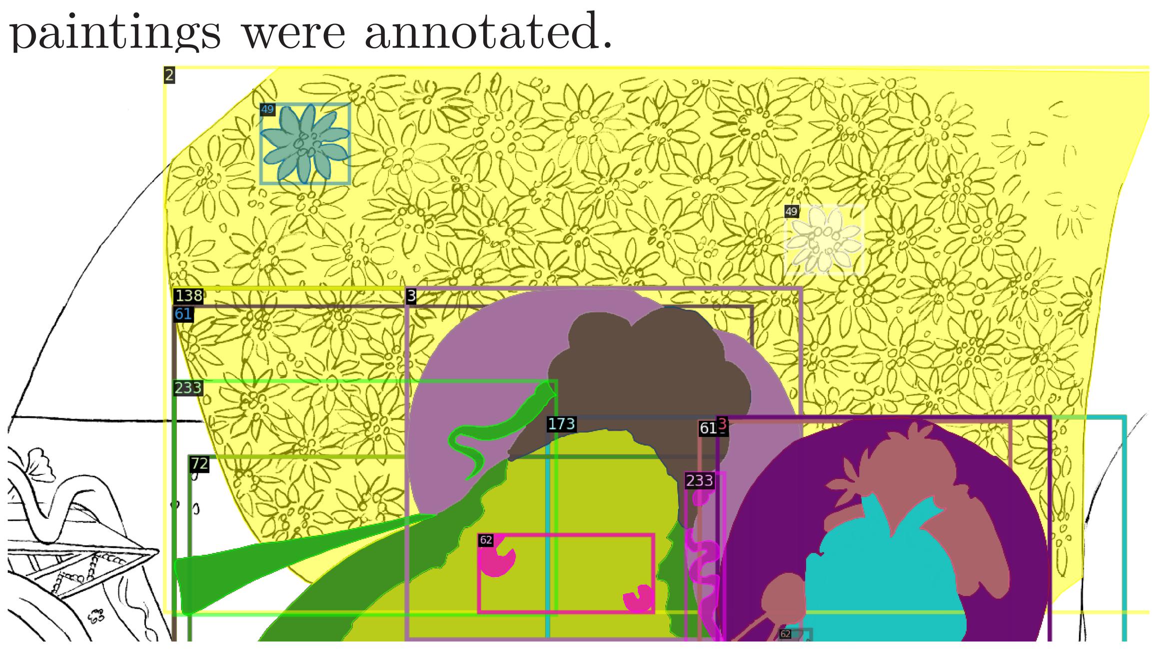
## 3. Obstacles

The large corpus of annotations in our project seems perfect for initialising semi-automated annotation using neural networks. However, there are some obstacles:

**1. Different types of annotated images.** Besides photographs of paintings, there are also drawings that have been used for annotation.

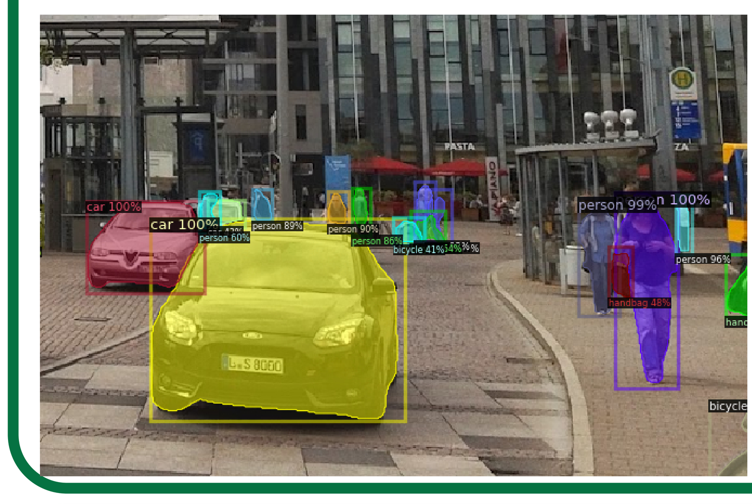


**2. Incomplete annotations.** The focus of the project is not the full annotation of each individual image, but the description of its content. As a result, elements with comparatively little semantic content (e.g. decorative flowers) were not annotated everywhere or only certain areas in the paintings were annotated.



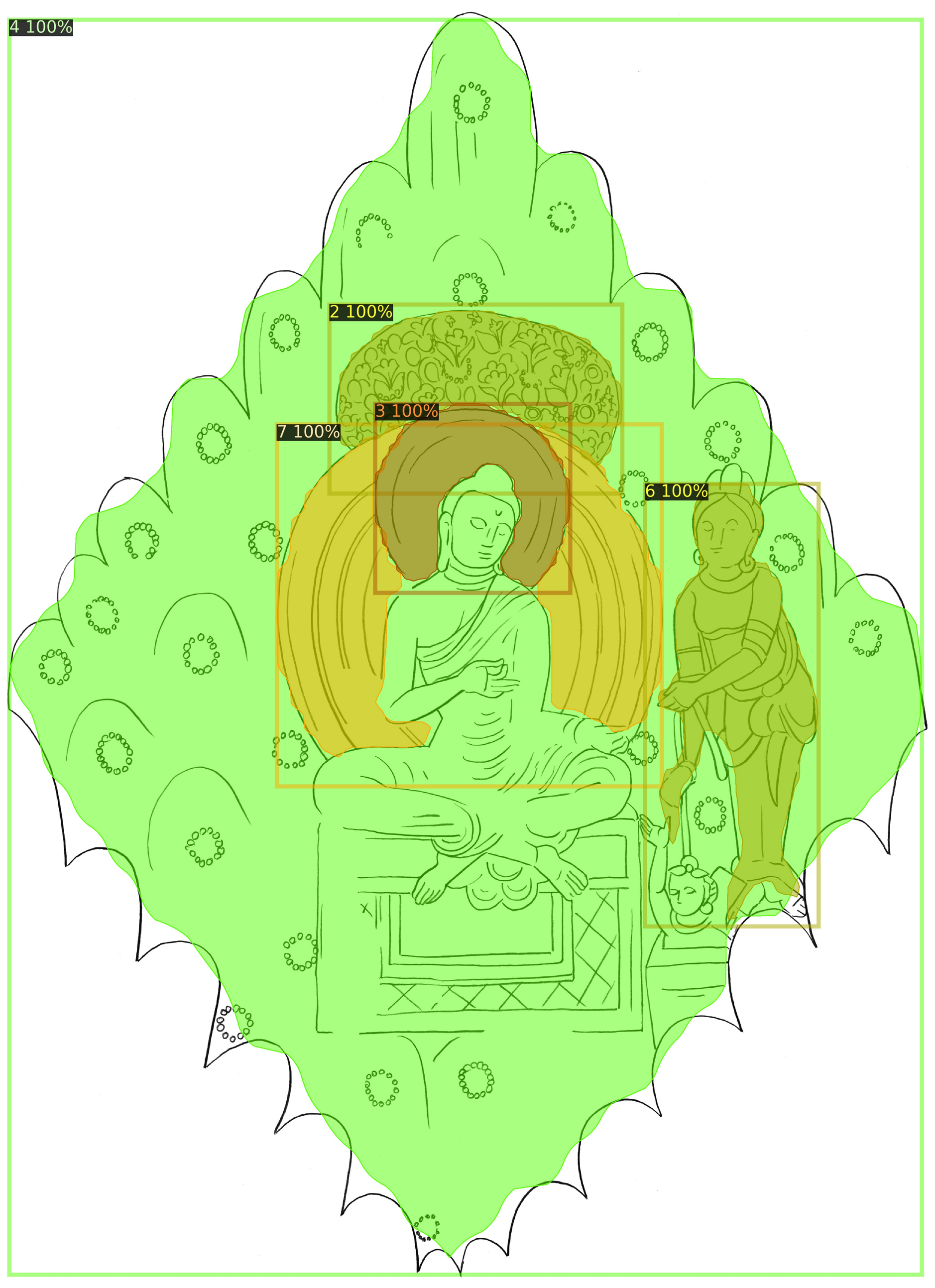
Missing annotations may influence training output and compromise evaluation results. Experiments are to by evaluated visually.

## 4. Framework



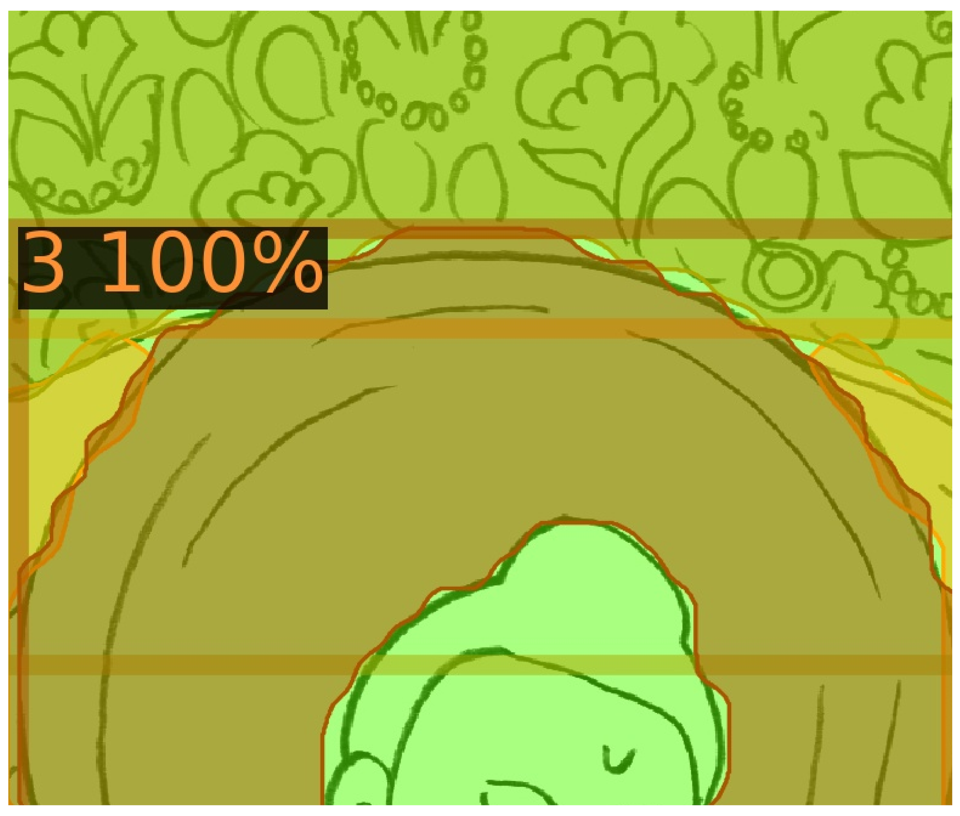
Detectron2 (https://github.com/facebookresearch/detectron2/), a framework for neural networks of many different types, is used for this approach. It allows for easy use of a variety of neural networks. For installation see: https://detectron2.readthedocs.io/en/latest/tutorials/install.html or https://github.com/ghowa/dhd2020 where information can also be found on how to compile individual training data.

## 5. Approach



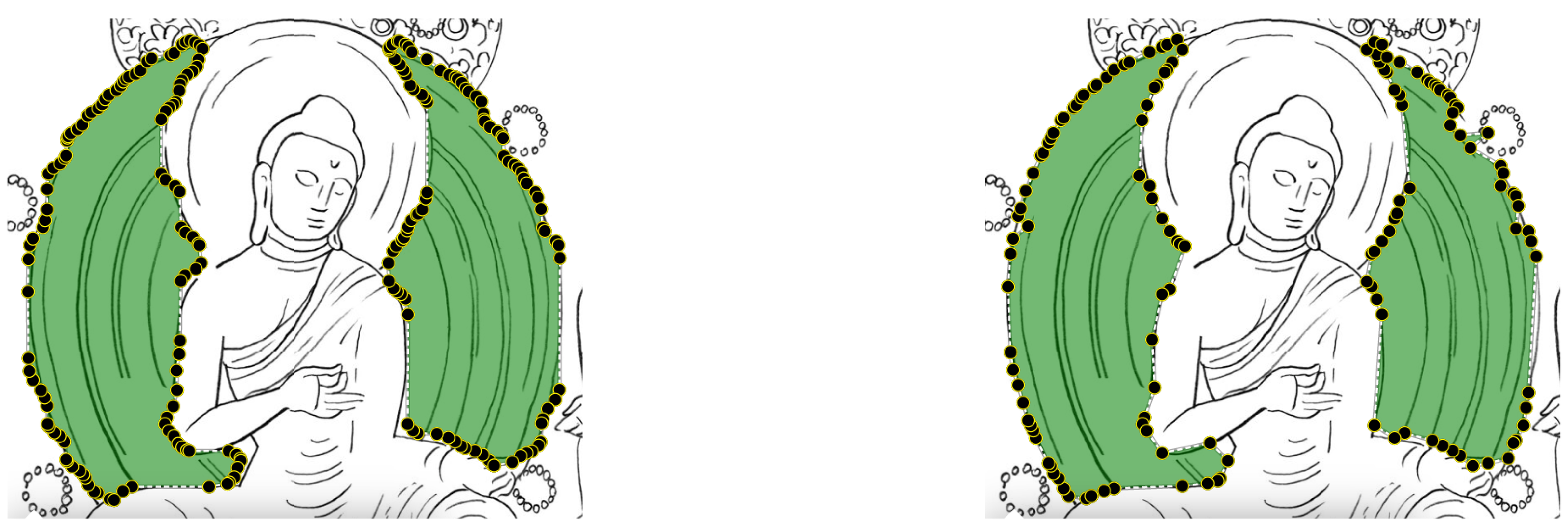
In various experiments a $mAP_{IoU=0.75}$ of 59.9960[2] could be achieved for drawings by merging similar annotation groups and separating photographs from drawings. With this precision, the network produced convenient outputs (see figure on the left).

Further Information on our experiments and additional example images on various experiments can be found here: https://github.com/erikradisch/examplePics/.




**Problem:** However, the proposed annotations cannot be used without a revision, due to very fuzzy edges (see figure to the right). If those revisions were to be done manually, the time saved is likely to be only marginal in many cases, as this is very time-consuming.

**Solution:** Our approach (https://github.com/saw-leipzig/annotorious-openseadragon, https://github.com/saw-leipzig/annotorious-selector-pack) uses OpenCV to detect the contours in the drawings and aligns the points with the nearest contour line. If points coincide in the process, the duplicates are deleted. This can help to speed up the revision process significantly, but the proposed annotations also become somewhat less detailed, since quite a few points are dropped. The revision phase also provides the opportunity to add new points.



(A nimbus before and after contour alignment)

## 6. Conclusions

The workflow of semi-automated annotation proposed here certainly seems to have the potential to speed up the annotation work process. The RCNN has found over 6.000 annotations in currently unannotated drawings. However, how many of those annotations can be accepted is currently being tested in practice.

1 Dieses Forschungsvorhaben ist Teil des Akademienprogramms, das als derzeit größtes geistes- und kulturwissenschaftliches Langfrist-Forschungsprogramm der Bundesrepublik Deutschland von Bund und Ländern getragen wird. Diese Maßnahme wird mitfinanziert durch Steuermittel auf der Grundlage des vom Sächsischen Landtag beschlossenen Haushalts.

2 $mAP_{IoU=0.75}$ indicates the Mean Average Precision at a minimum matching of a region with the gold standard of 75%. In Detectron evaluation, it ranges from 0 to 100.

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