

AI-based Quality Assurance for Electron Beam Welding Processes

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pro-beam GmbH & Co. KGaA
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www.pro-beam.com

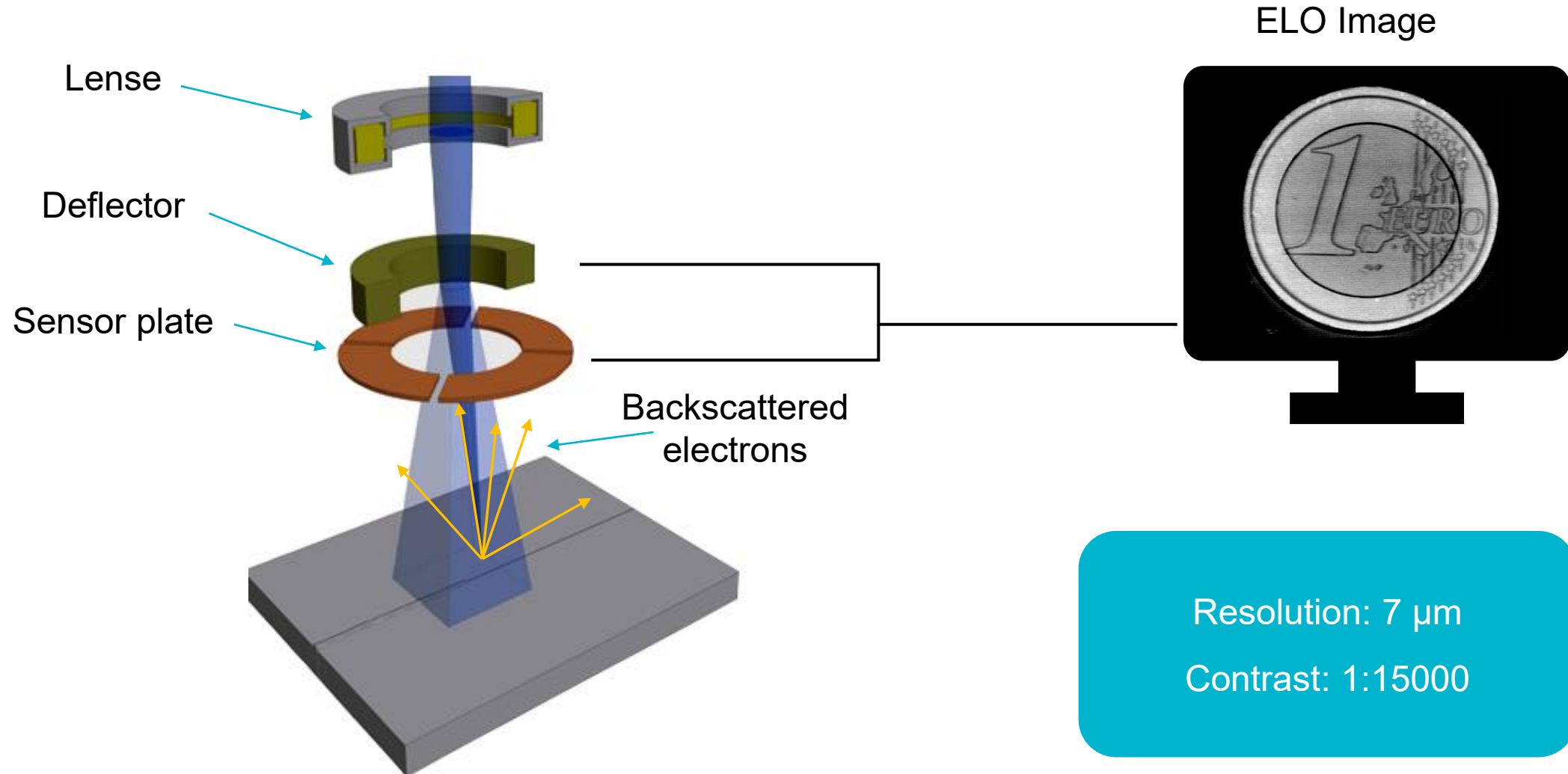
- precision welding process applied in many industries
 - aerospace
 - automotive
 - research
 - ...
- Electron beam in a vacuum can be brought into any shape by magnetic coils
- Many technological advantages:
 - Simple automation, flexibility, high efficiency, precision, high welding speed



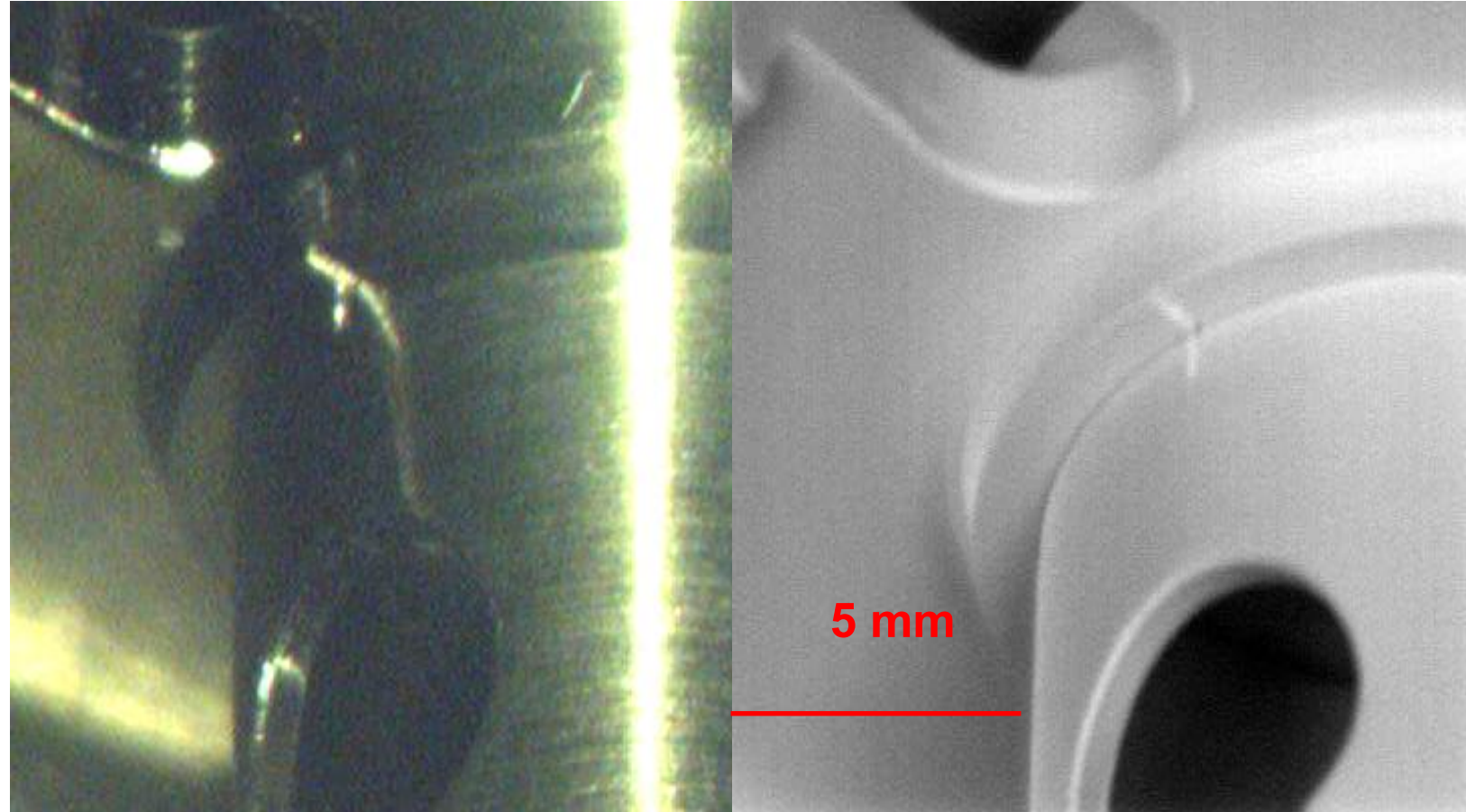
Welding machine WELD110



- Generator (model „Systems“)
- $U = 60-150\text{kV}$
- $P = 45\text{kW}$



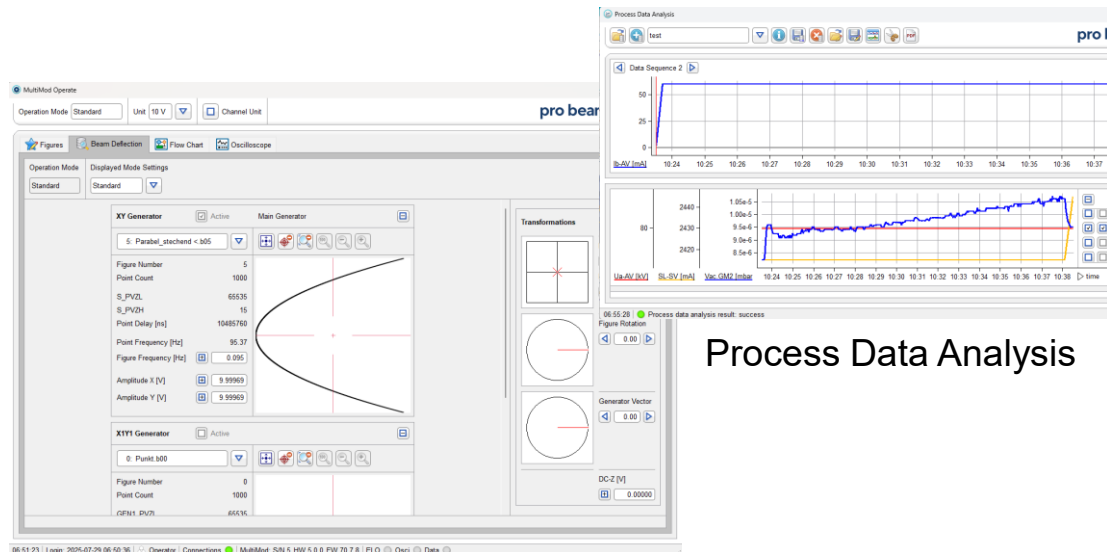
- AI anomaly detection based solely on ELO images



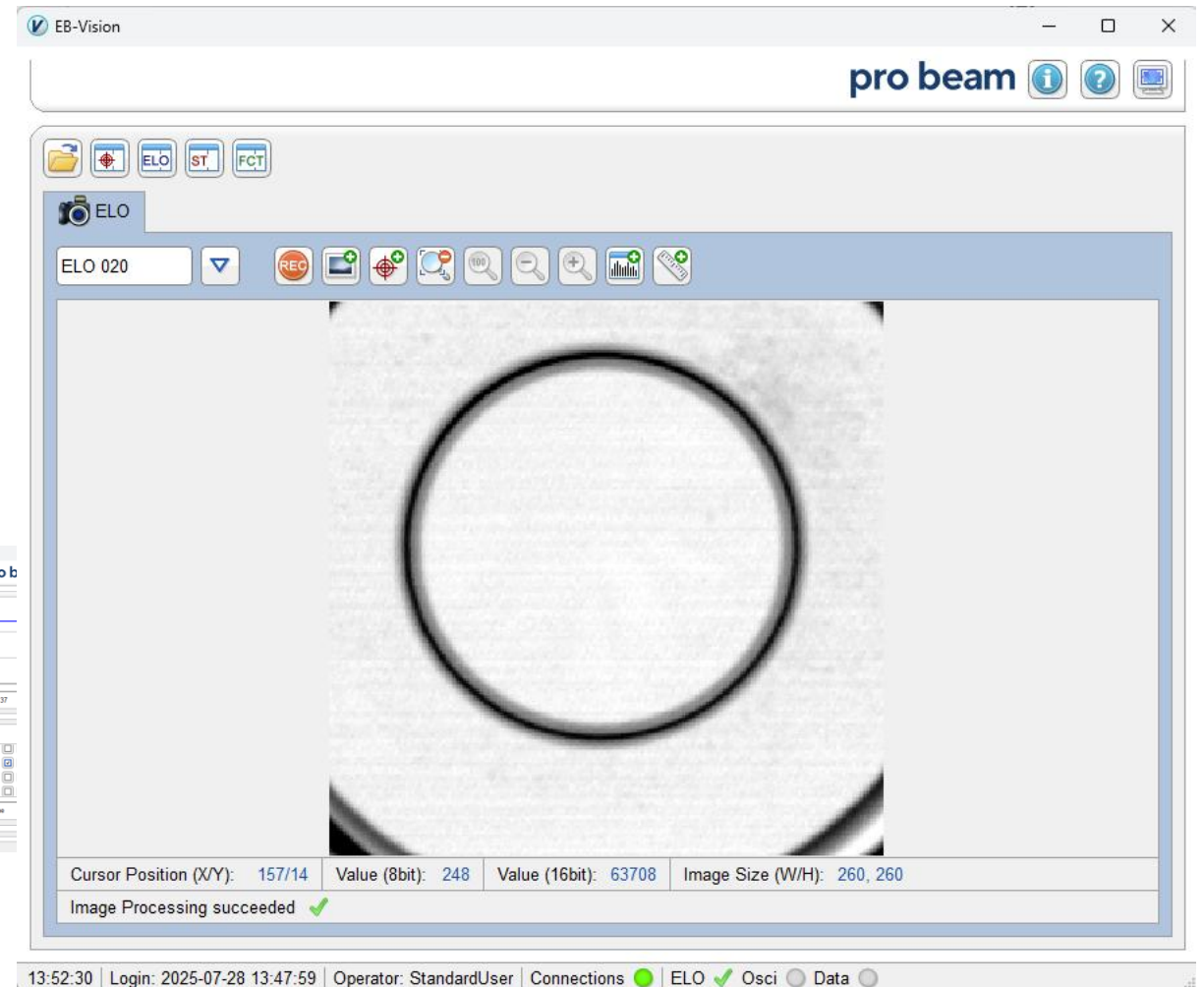
Light optical

Electron optical observation

- Software suite developed by pro-beam, installed on machines computer (MSV-PC)
- Relevant for quality assurance is EB-Vision

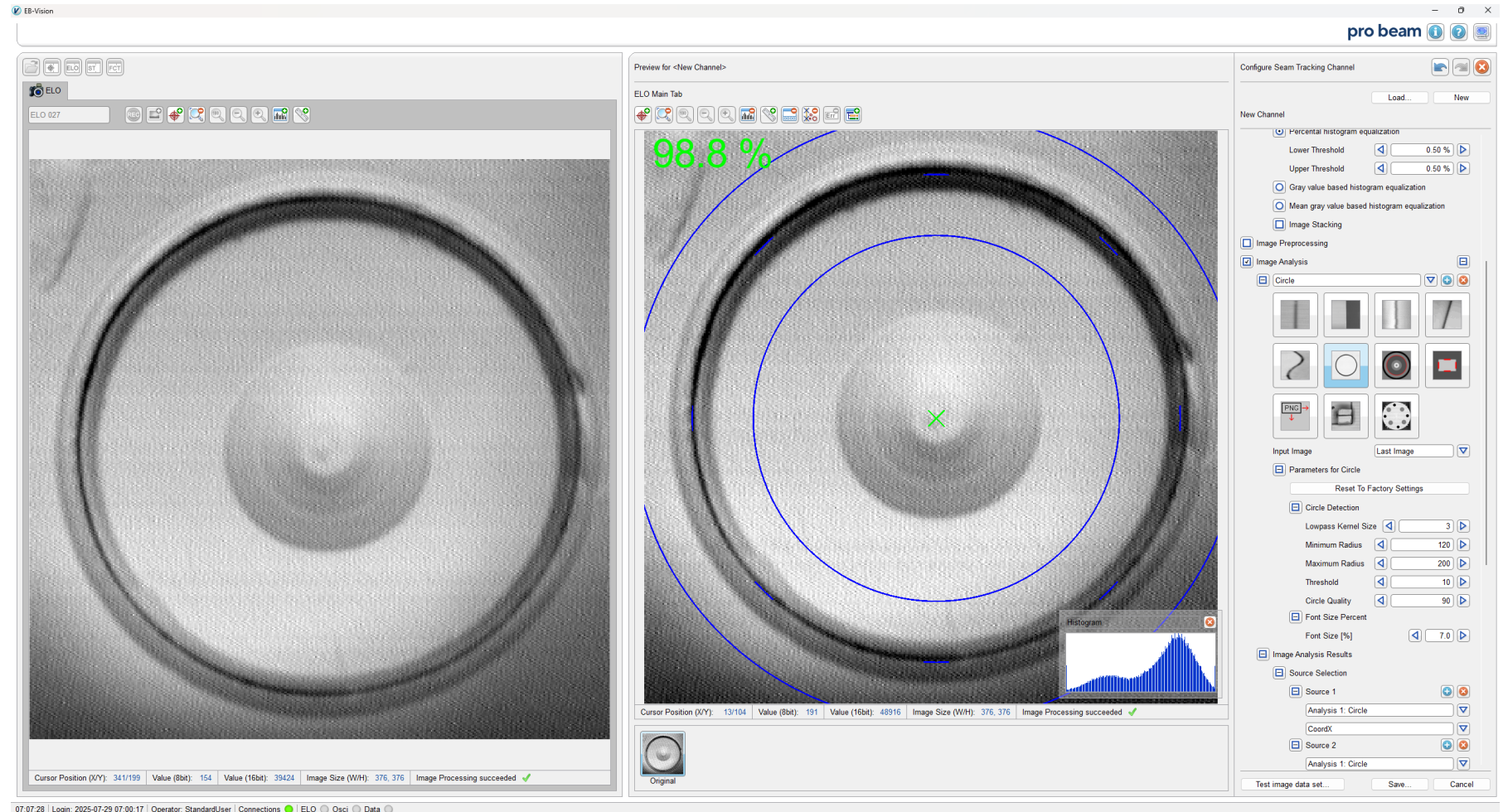


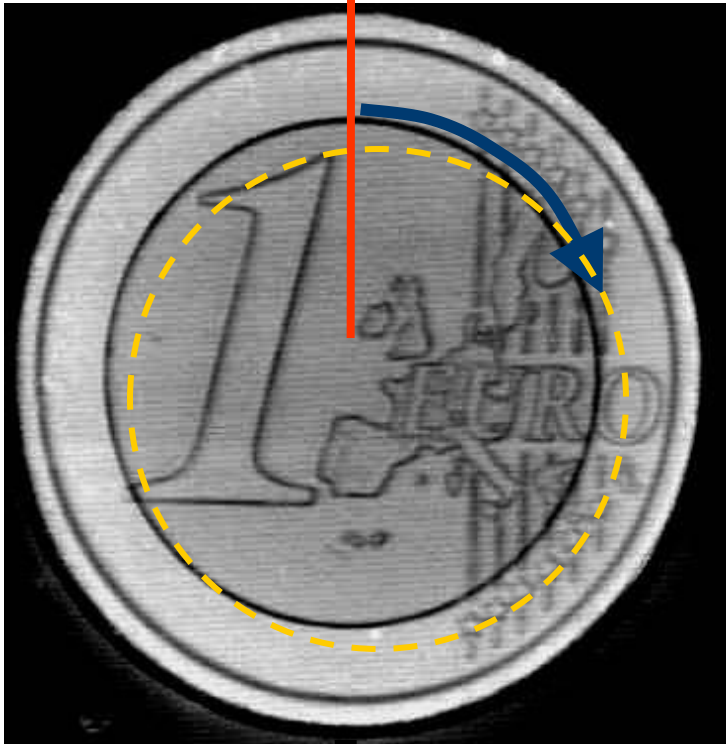
MultiMod Operate



EB-Vision

- Automatic positioning
- Advantageous properties for anomaly detection:
 - Constant image section
 - Preprocessing allows for stable gray values





PATENTED

- Large order volum (>10k components)
 - Palettes are charged with 6x7 Klappentellern
 - High throughput through gate shuttle system
- QA includes visual inspection by operator
 - AI supposed to relieve, not replace operator
- Goal:
 - Reduce visual inspection to about 10% of total charge

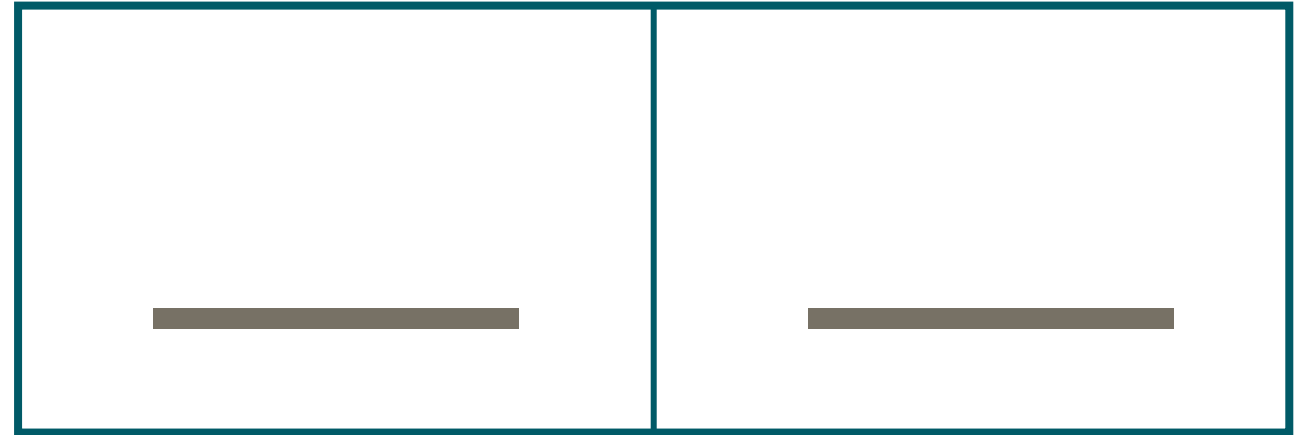
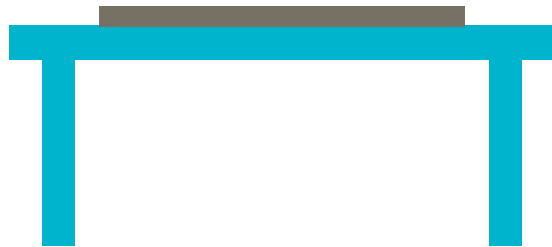


Fully charged palette after welding

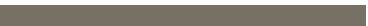
Pre-/postprocessing

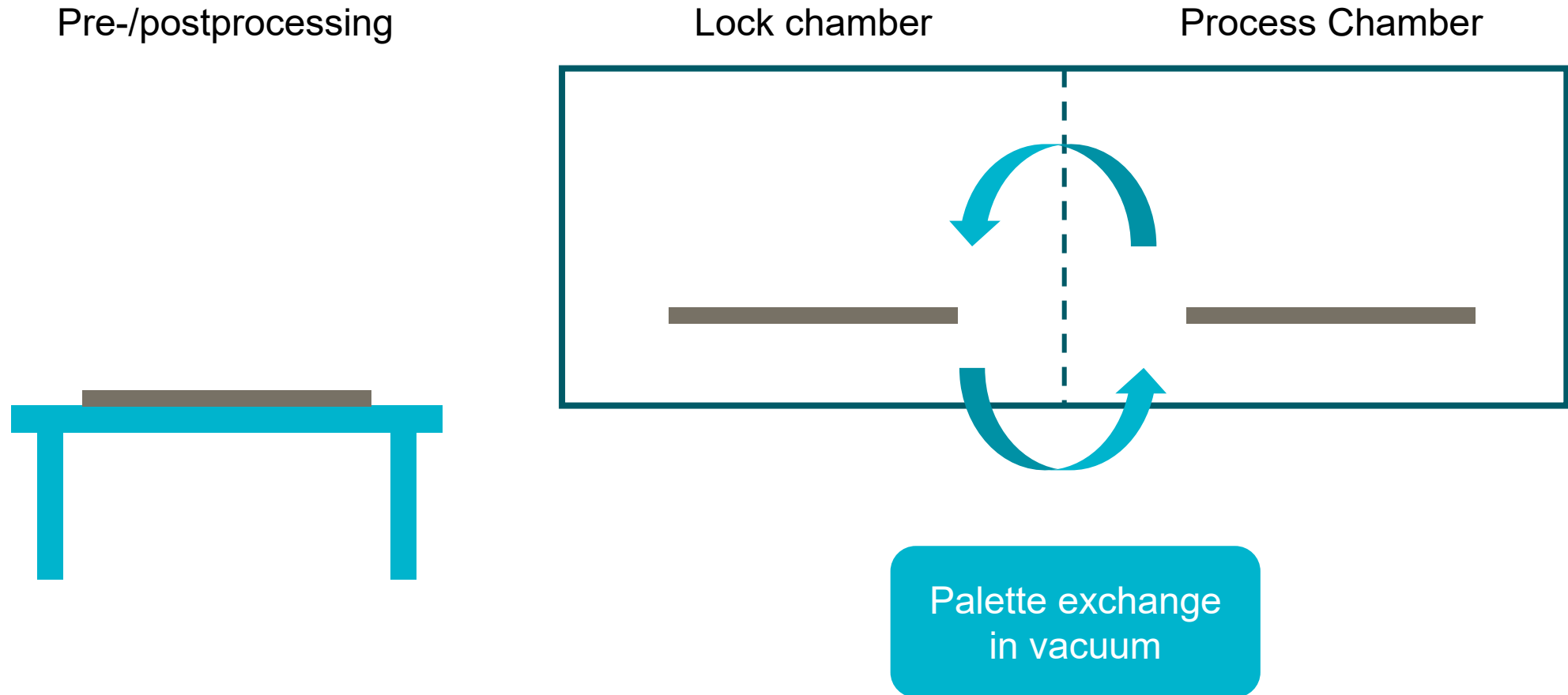
Lock chamber

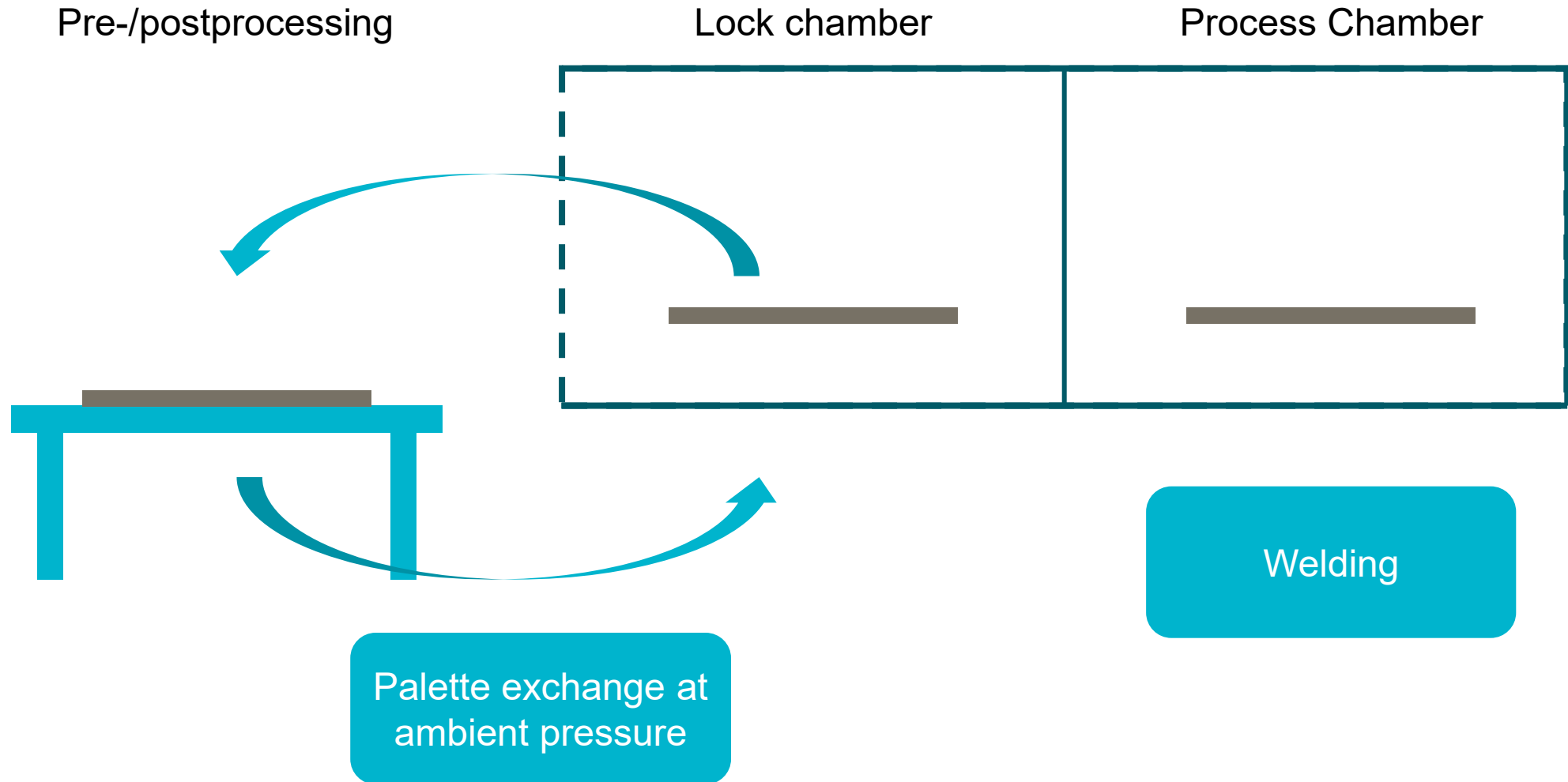
Process Chamber



Welding

 Palette with components

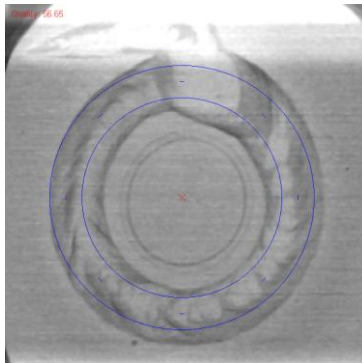




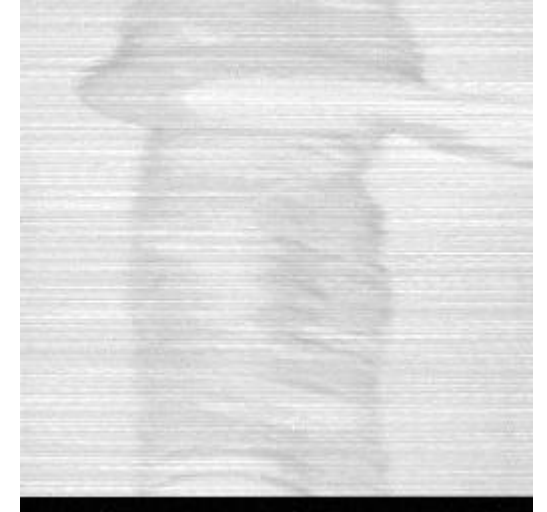


- Rough Klappenteller position on palette is known
- ELO images of the seam inspection are used for AI anomaly detection

- Raw images of seam inspection need to be preprocessed
- Preprocessing steps are identical for training data set and production images
- SLW image (line scan) is used
 - Allows for more universal training compared to standard acquisition



Raw image



- stretched in X
- compressed in Y
- Contrast adjustment

- Joint project with Digitalzentrum Augsburg
- PaDiM chosen for its low complexity combined with good performance
- Anomaly heatmaps show location of anomalies
- Anomaly score represents maximum of heatmap
- No distinction between background and object
 - Our model learns how a normal patch of the image is supposed to look like

PaDiM: a Patch Distribution Modeling Framework for Anomaly Detection and Localization

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Abstract—We present a new framework for Patch Distribution Modeling, PaDiM, to concurrently detect and localize anomalies in images in a one-class learning setting. PaDiM makes use of a pretrained convolutional neural network (CNN) for patch embedding, and of multivariate Gaussian distributions to get a probabilistic representation of the normal class. It also exploits correlations between the different semantic levels of CNN to better localize anomalies. PaDiM outperforms current state-of-the-art approaches for both anomaly detection and localization on the MVTec AD and STC datasets. To match real-world visual industrial inspection, we extend the evaluation protocol to assess performance of anomaly localization algorithms on non-aligned dataset. The state-of-the-art performance and low complexity of PaDiM make it a good candidate for many industrial applications.

I. INTRODUCTION

Humans are able to detect heterogeneous or unexpected patterns in a set of homogeneous natural images. This task is known as anomaly or novelty detection and has a large number of applications, among which visual industrial inspections. However, anomalies are very rare events on manufacturing lines and cumbersome to detect manually. Therefore, anomaly detection automation would enable a constant quality control by avoiding reduced attention span and facilitating human operator work. In this paper, we focus on anomaly detection and, in particular, on anomaly localization, mainly in an

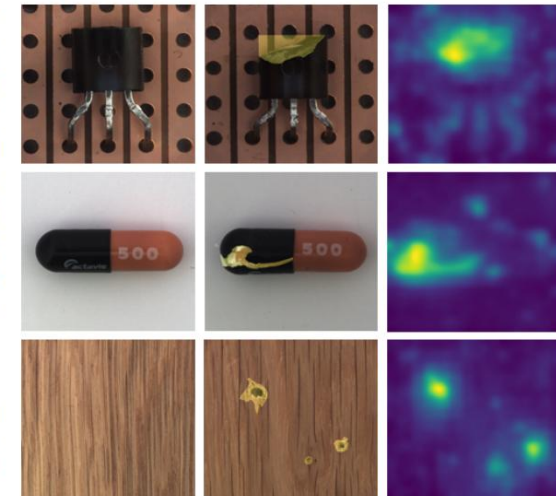
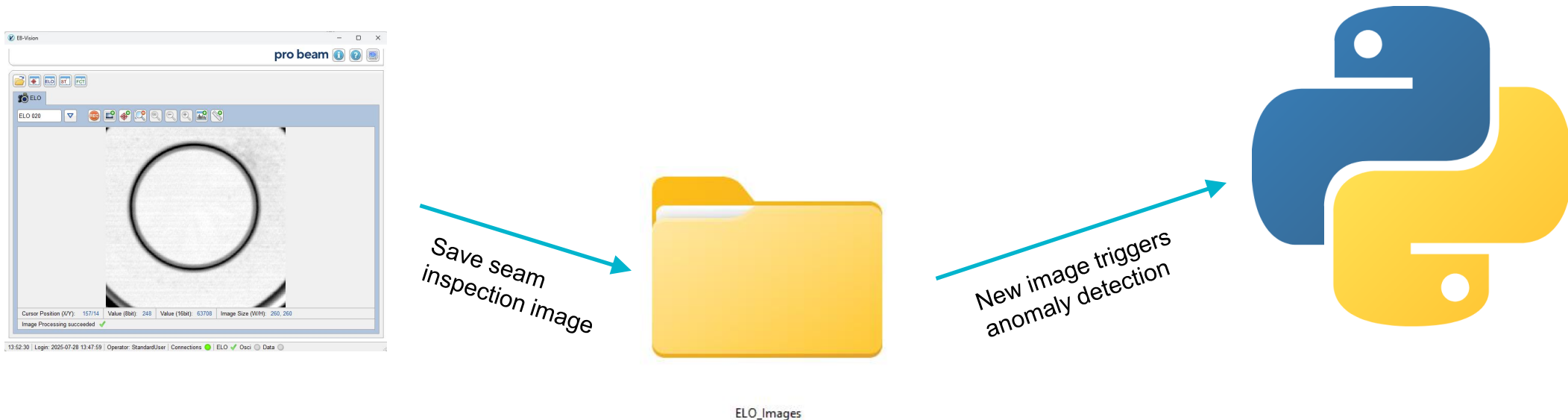


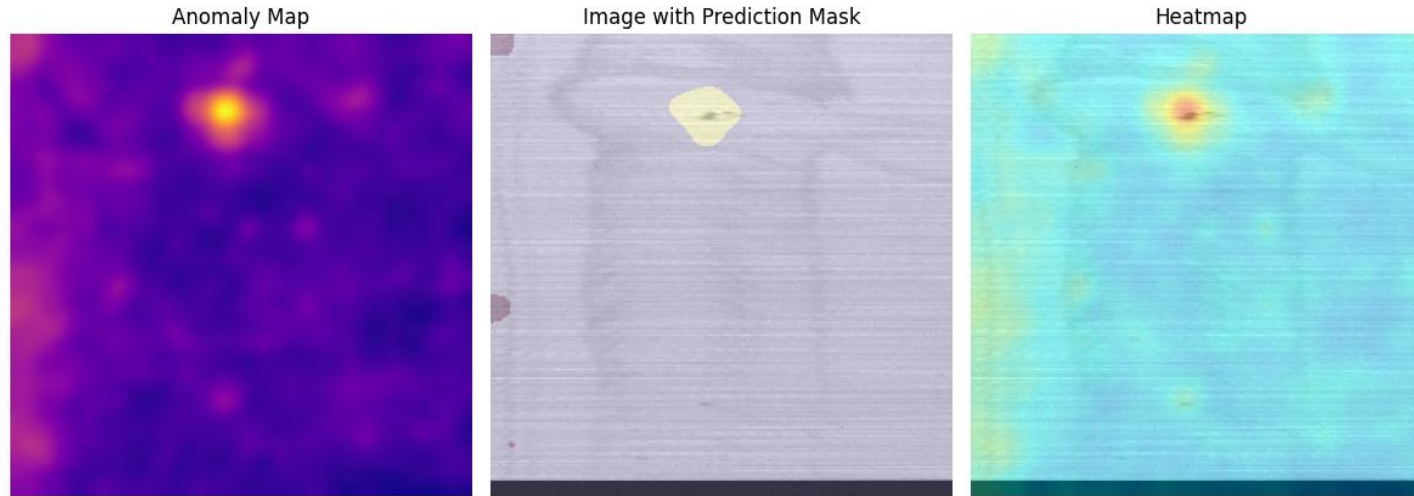
Fig. 1. Image samples from the MVTec AD [1]. Left column: normal images of Transistor, Capsule and Wood classes. Middle column: images of the same classes with the ground truth anomalies highlighted in yellow. Right column: anomaly heatmaps obtained by our PaDiM model. Yellow areas correspond to the detected anomalies, whereas the blue areas indicate the normality zones. Best viewed in color.

785v1 [cs.CV] 17 Nov 2020

- Training of PaDiM model with 3000 images of good components
- Calculation of anomaly score is done using python scripts (not part of EB-Vision)
- Offline analysis of seam inspection images possible after downloading the images from the machine
- Online analysis requires python packages to be installed on the machine
 - We created an executable which contained all dependencies
 - New seam inspection image triggered anomaly score calculation via watchdog

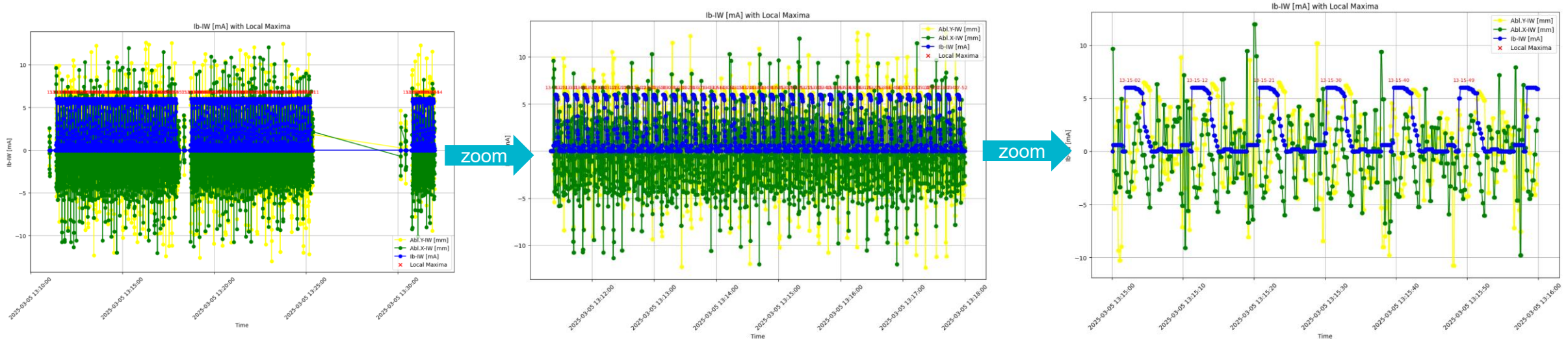


- We save three result images for each analysed image:



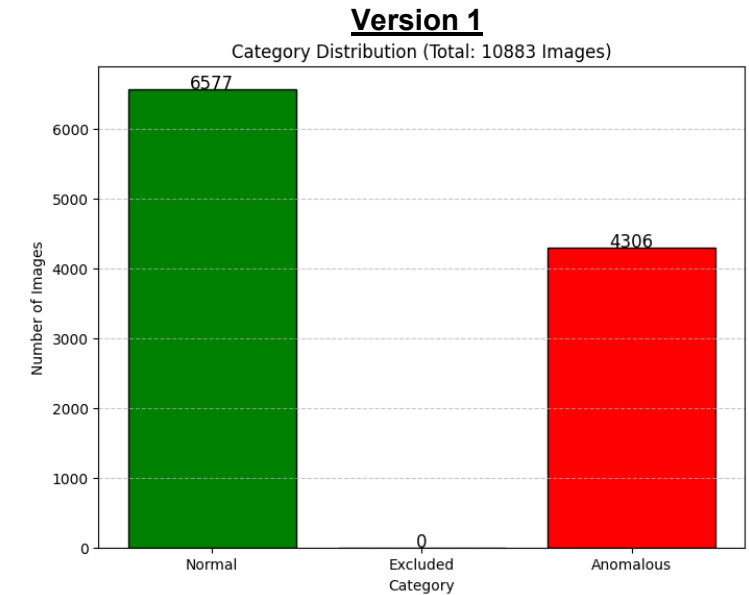
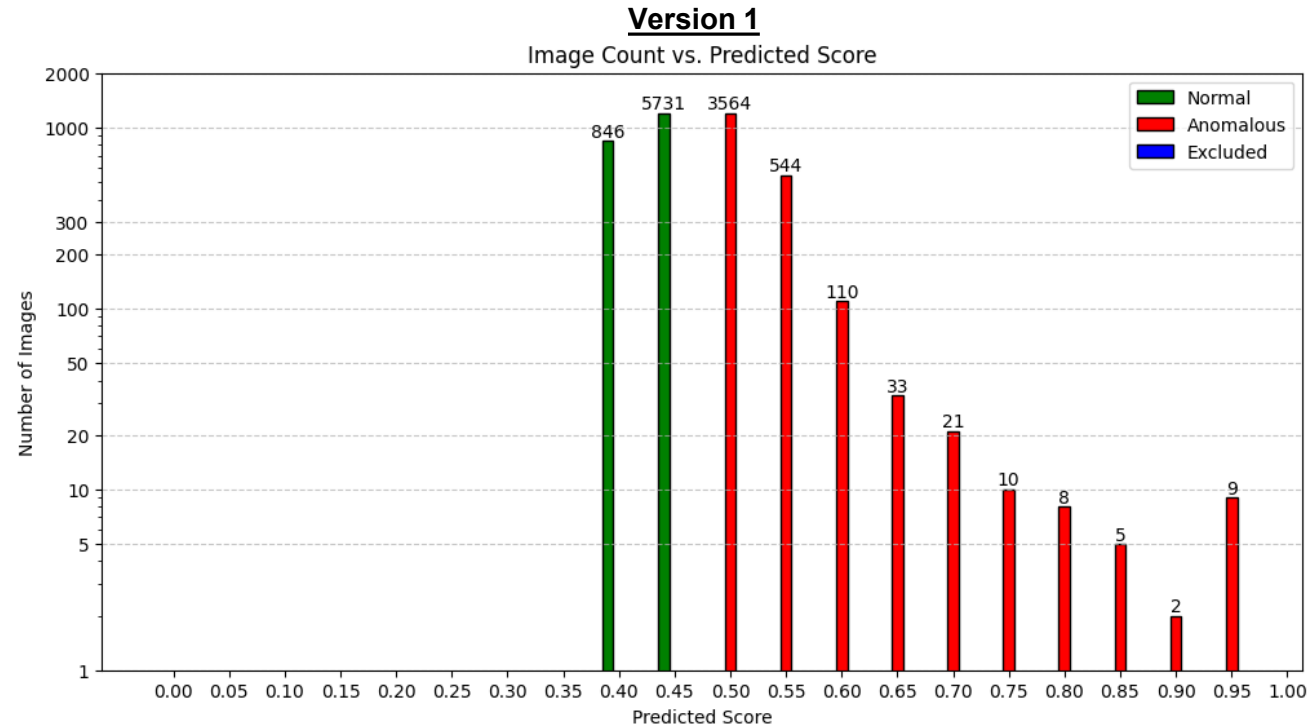
- The anomaly score is written to a log file together with the input image name

- Process data automatically stored by CNC in regular intervals (10 Hz)
 - common machine parameters and EB-specific process values and parameters



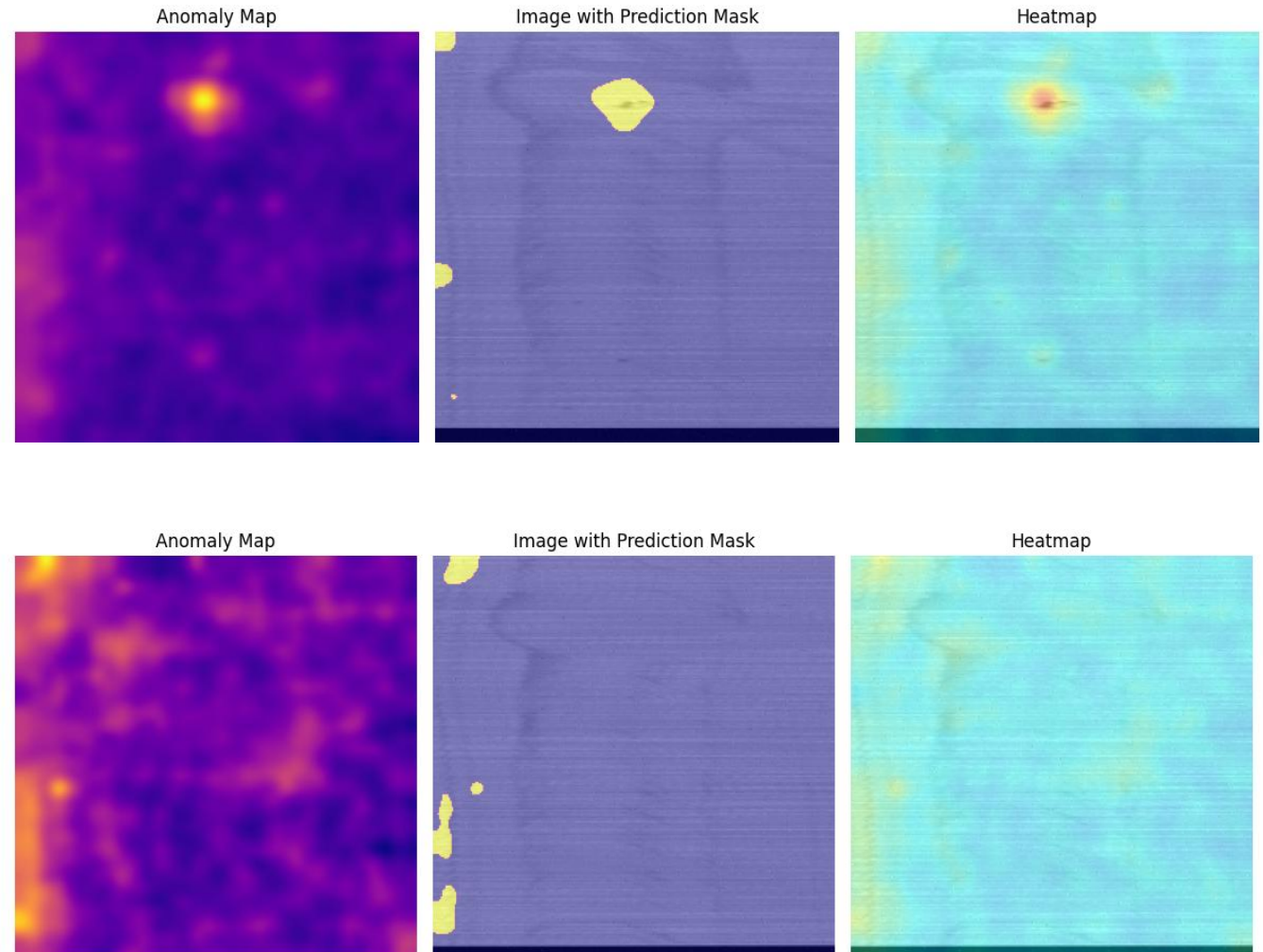
Shown here:

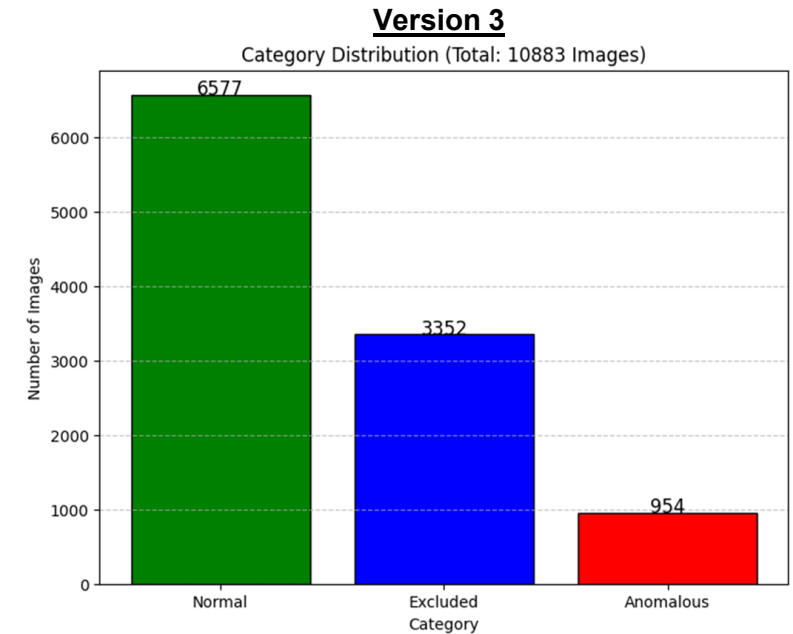
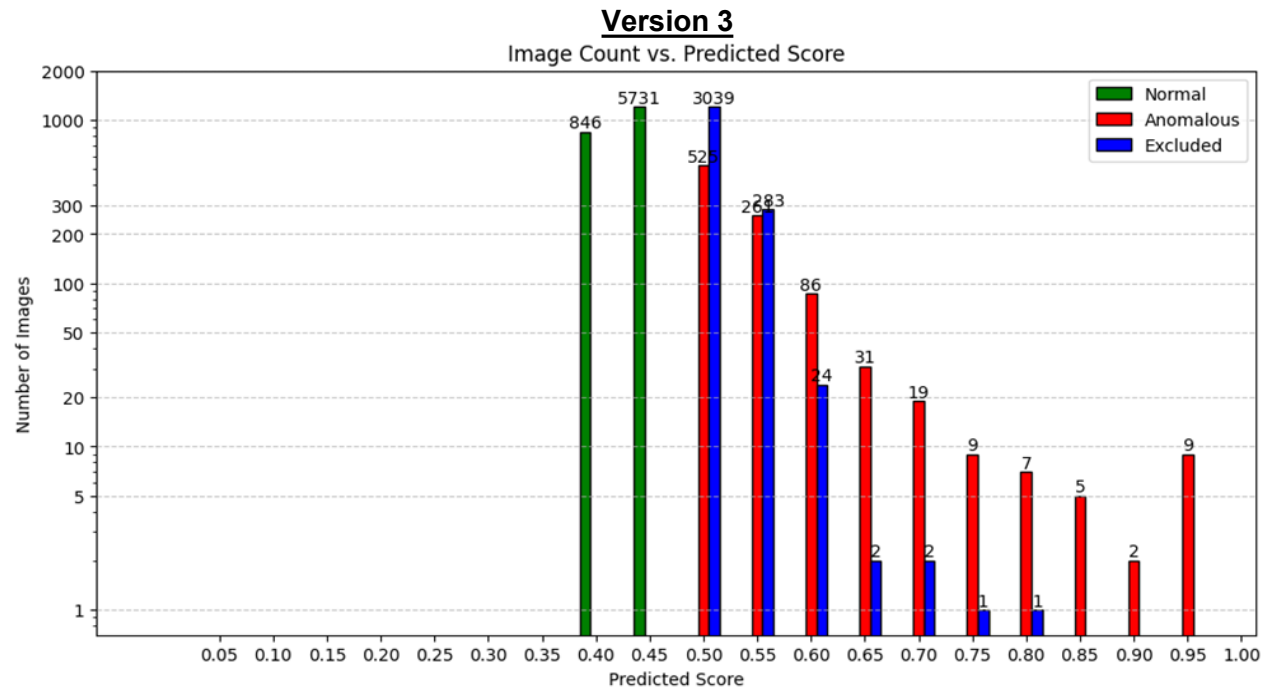
- Deflectors X and Y (green and yellow)
- Beam current (blue)
- Local maxima of beam current (red), used to extract time stamps of individual components



- Components with a predicted score of 0.5 or higher are marked as anomaly
- Almost half of all components labelled as anomalous
- Operator would still need to inspect much more than 10% of all components

- We want to detect anomalies of the surface of the welding seam
- Anomalies are detected on the whole image, often at the edges (see bottom images)
- Anomaly score is simply maximum values within anomaly map
- Solution: ignore non relevant image areas (masking)





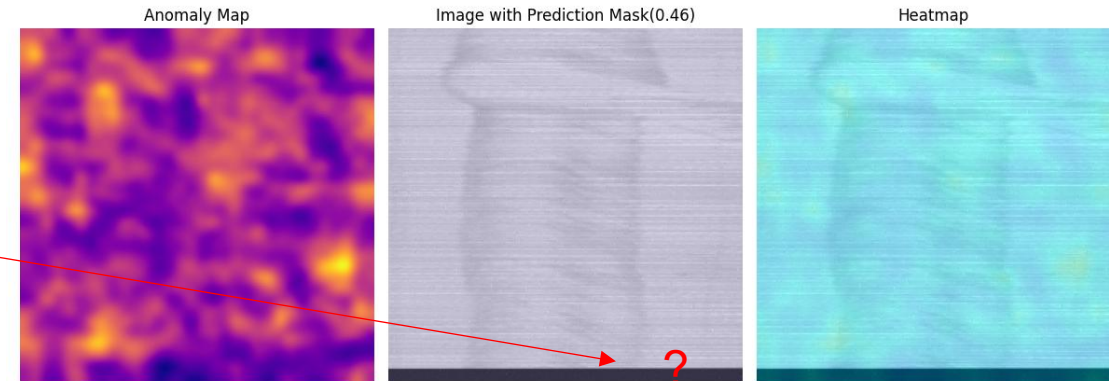
- More than 3000 components have large anomalies solely within the masked part of the image
 - These components are inserted into the excluded category
- 954 components are left inside the anomalous category (9%)

- In the same sample the operator found 24 faulty components (0.2 %)
- Out of those components our model marked 22 as anomaly (92 %)
- Going through a random sample of 100 images marked by our model as anomalous we estimate 24 real anomalies which were likely not seen by operator



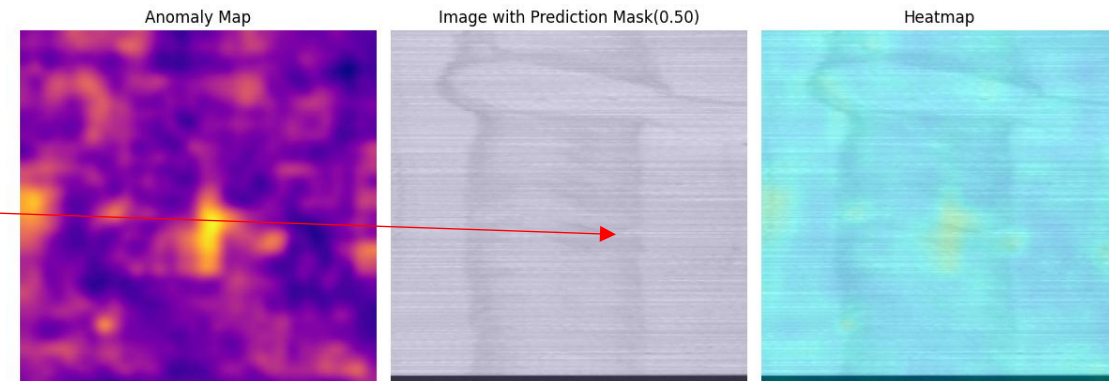
- Defects clearly visible by eye
- Case 1: defect not visible in ELO image, not yet clear why
- Case 2: anomaly visible, but anomaly score just below threshold

1.



00-48-29_err12_ORIG (Bauteil 22/30)

2.



19-20-33_err12_ORIG (Bauteil11/2)

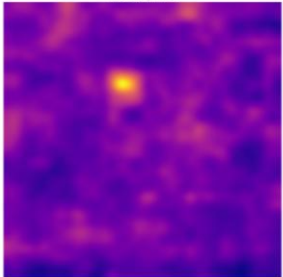
Likely anomalies, not seen by the operator

pro beam

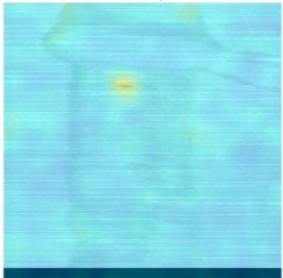
00-18-27_err12_ORIG.tif
(0.52)



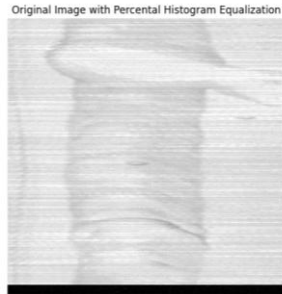
Anomaly Map



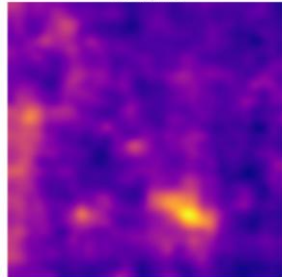
Heatmap



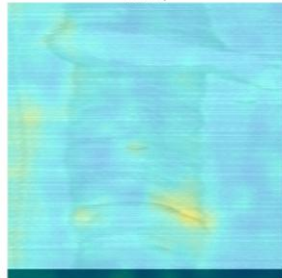
00-32-35_err12_ORIG.tif
(0.64)



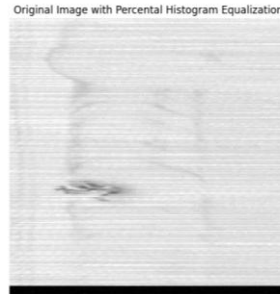
Anomaly Map



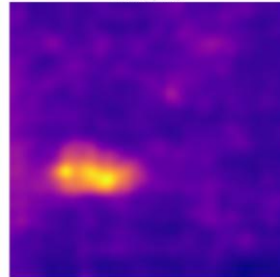
Heatmap



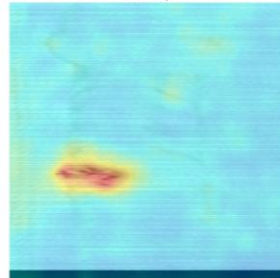
00-01-00_err12_ORIG.tif
(0.91)



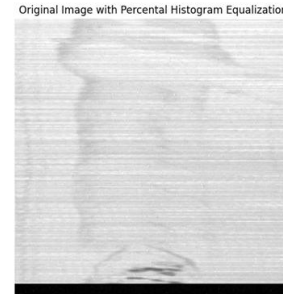
Anomaly Map



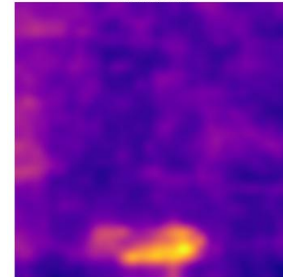
Heatmap



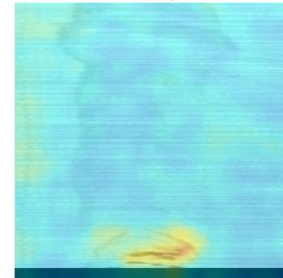
19-17-10_err12_ORIG.tif
(0.62)



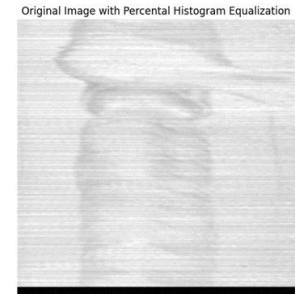
Anomaly Map



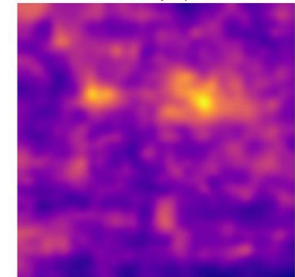
Heatmap



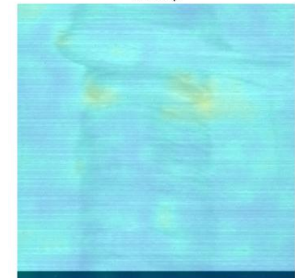
20-45-39_err12_ORIG.tif
(0.53)

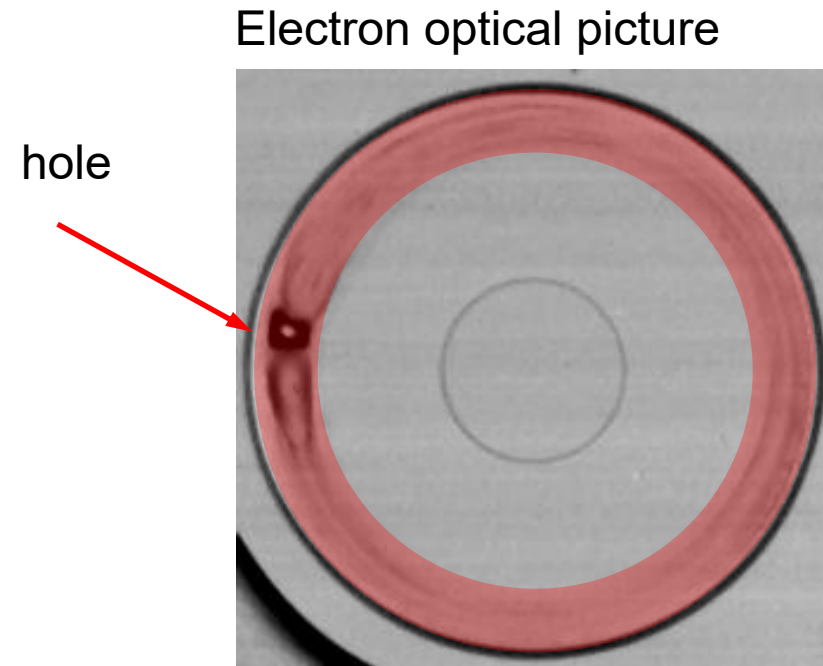
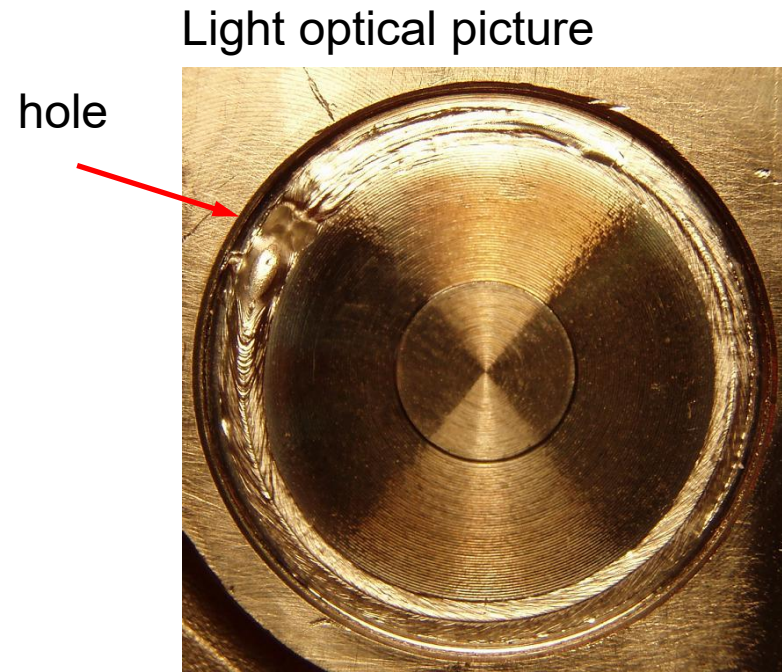


Anomaly Map



Heatmap





- ELO images are a very good addition to QA

- Our current model was trained with images generated by a single machine with a specific parameter set and a specific component with a certain material
- We want to find anomalies also in components which have a low volume, without the need to go through the whole process (collecting training data, fine tuning the model, ...)



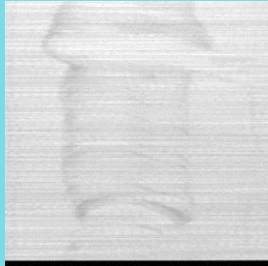
We need to extend and diversify our training data sample



Allow for anomaly detection even for individual components were we have a single long weld

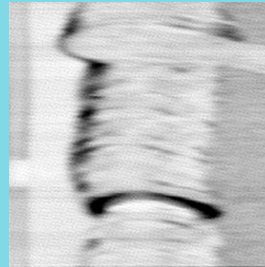
- Segmentation of SLW image into smaller parts which could be used as model input

Klap. 3/37 an S5-8 (69 cm)
scanzeit 1.72 μ s 120kV

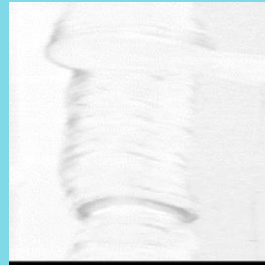


S5-8

Klap. 3/37 an K6-2 (18 cm)
scanzeit 1.72 μ s 120kV



Klap. 3/37 an K6-2 (18 cm)
scanzeit 1.76 μ s 120kV

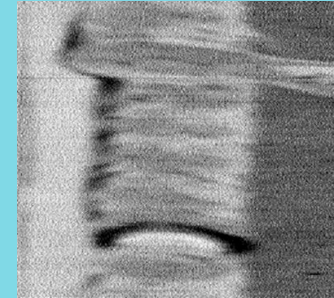


Klap. 3/37 an K6-2 (18 cm)
scanzeit 1.78 μ s 120kV

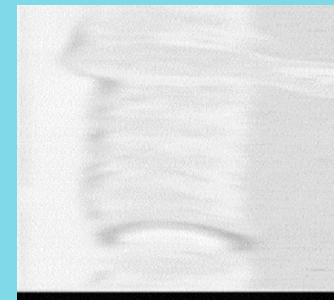


K6-2

Klap. 3/37 an K40 (69 cm)
scanzeit 1.72 μ s 60kV



Klap. 3/37 an K40 (69 cm)
scanzeit 1.78 μ s 60kV



K40



Palette #62:

<u>Bauteil #1</u> OK niO	<u>Bauteil #2</u> OK niO	<u>Bauteil #3</u> OK niO	<u>Bauteil #4</u> OK niO	<u>Bauteil #5</u> OK niO	<u>Bauteil #6</u> OK niO	<u>Bauteil #7</u> OK niO
<u>Bauteil #14</u> OK niO	<u>Bauteil #13</u> OK niO	<u>Bauteil #12</u> OK niO	<u>Bauteil #11</u> OK niO	<u>Bauteil #10</u> OK niO	<u>Bauteil #9</u> OK niO	<u>Bauteil #8</u> OK niO
<u>Bauteil #15</u> OK niO	<u>Bauteil #16</u> OK niO	<u>Bauteil #17</u> OK niO	<u>Bauteil #18</u> OK niO	<u>Bauteil #19</u> OK niO	<u>Bauteil #20</u> OK niO	<u>Bauteil #21</u> OK niO
<u>Bauteil #28</u> OK niO	<u>Bauteil #27</u> OK niO	<u>Bauteil #26</u> OK niO	<u>Bauteil #25</u> OK niO	<u>Bauteil #24</u> OK niO	<u>Bauteil #23</u> OK niO	<u>Bauteil #22</u> OK niO
<u>Bauteil #29</u> OK niO	<u>Bauteil #30</u> OK niO	<u>Bauteil #31</u> OK niO	<u>Bauteil #32</u> OK niO	<u>Bauteil #33</u> OK niO	<u>Bauteil #34</u> OK niO	<u>Bauteil #35</u> OK niO
<u>Bauteil #42</u> OK niO	<u>Bauteil #41</u> OK niO	<u>Bauteil #40</u> OK niO	<u>Bauteil #39</u> OK niO	<u>Bauteil #38</u> OK niO	<u>Bauteil #37</u> OK niO	<u>Bauteil #36</u> OK niO

- AI anomaly detection has been applied successfully in series production of Klappenteller
 - Anomaly score is calculated live and can give direct feedback to operator
 - Current analysis performed offline, to optimize model and parameters
- For a batch of 10000 components our model flagged 10% as anomalous
 - Visual inspection by operator required only for 1000 instead of 10000 components
 - False-negative rate of 0.02% shall be further optimized
- Generalization for different machines, components and materials is currently under study