Trial of defect finding using machine learning

The 11th IHEP-KEK SCRF Collaboration Meeting

20th November 2023

KEK iCASA SRF group

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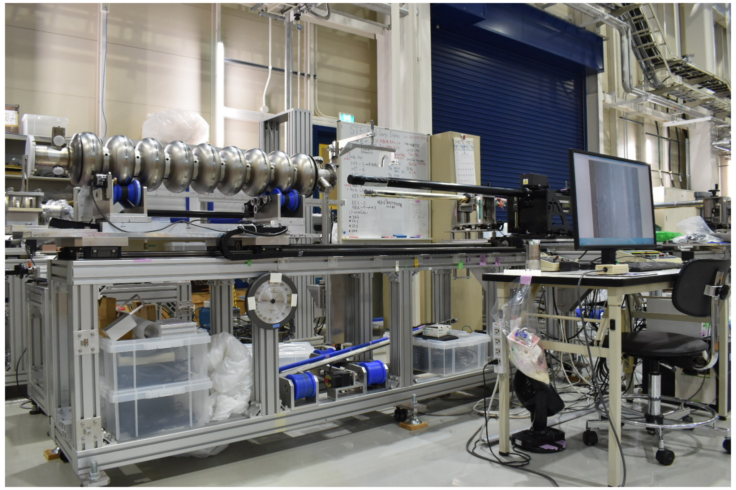
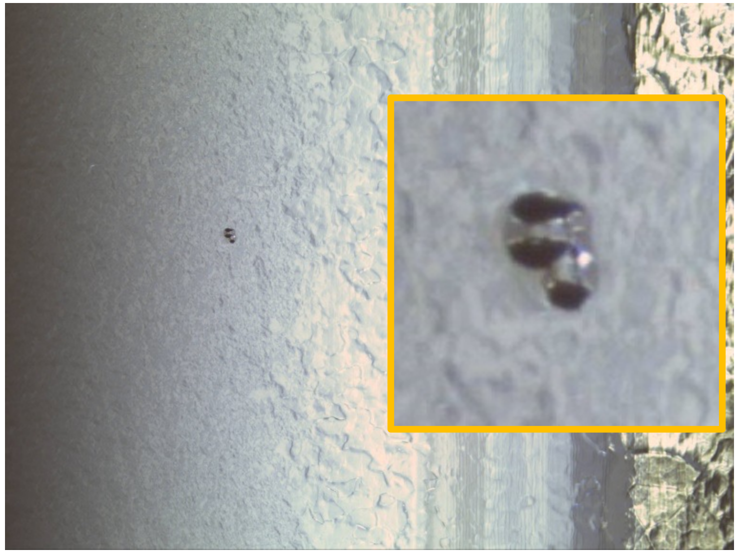
Introduction

“Defect” and optical inspection

- “Defect”
  - Reason of **limiting the acceleration gradient**
  - Impurities: Large surface resistance
  - Bump and dip: Local enhancement
- Optical inspection machine
  - Developed in 2008
  - Resolution: 3418 x 2616
  - Field of view: ~8 x 6 mm^2
  - About 3,000 pictures per one 9-cell cavity



Optical inspection machine in KEK.

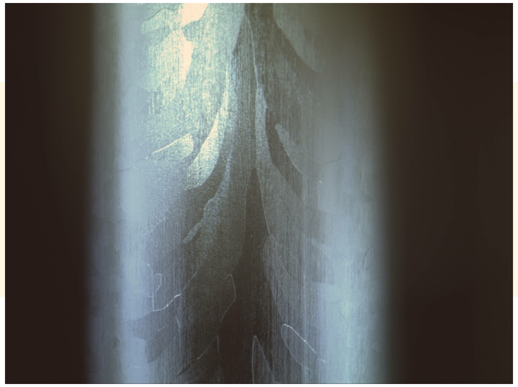


MT-5 after 1st VT, cell #1, 108°
A defect found near the quench location at 37 MV/m.

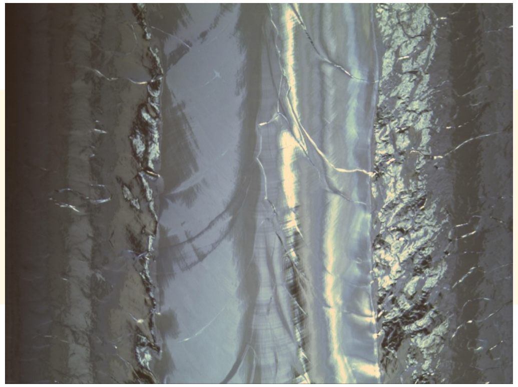
Cavity processing cycle

- Fabrication
- Pre-EP, EP-1
- HPR
- Annealing
- Pre-tuning
- EP-1
- HPR
- Baking
- Vertical Test

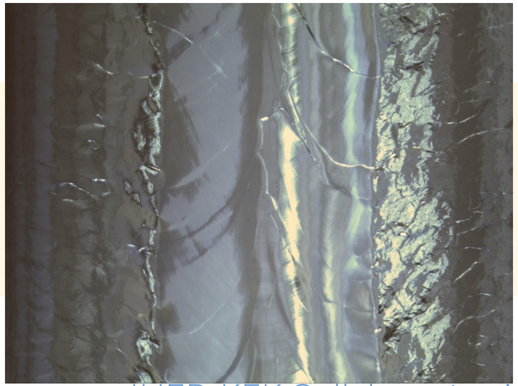
As received



After EP1



After VT



Legacy detection method

① Jefferson Lab
- D. Iriks and G. Eremeev, "Automatic Surface Defect Detection and Sizing for Superconducting Radio Frequency Cavity Using Haar Cascades," Proceedings of SRF2015, pp. 788-790 (2015).

② DESY
- M. Wenscat, "First Attempts in Automated Defect Recognition in Superconducting Radio-Frequency Cavities," JINST 14 (2019) 06, P06021.

③ Kyoto University
- Y. Kuriyama et al., "Improvement of Inner Surface Inspection System for Superconducting Cavities Applying Image Processing Technique," Proceedings of the 16th Annual Meeting of Particle Accelerator Society of Japan, pp. 32-35 (2019).

Machine learning but not deep learning

①

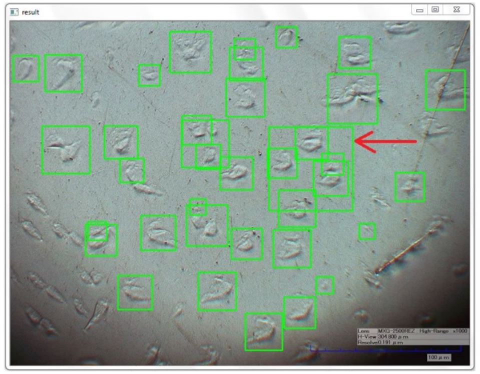


Figure 1: This is the output image for one of the positive test pictures from the Easy folder. One of the false positives is indicated by the arrow. It counted as a false positive for two reasons: more than 50% of contained defect area was contained in other, true positives, and it contained defects separated by more than 10 μm.

②

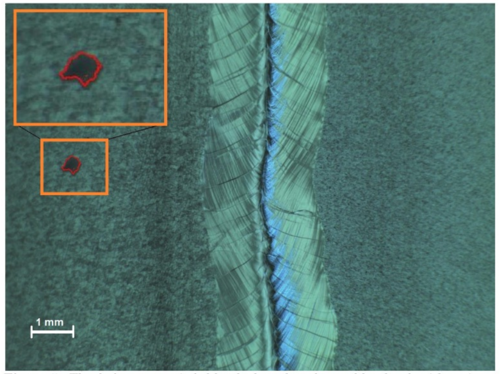


Figure 5. The dark spot - encircled by the boundary detected by the algorithm - is an aluminum contamination on an untreated surface introduced in the sheet after quality control and during rolling. This defect - after surface chemistry - reduced the quench field.

③

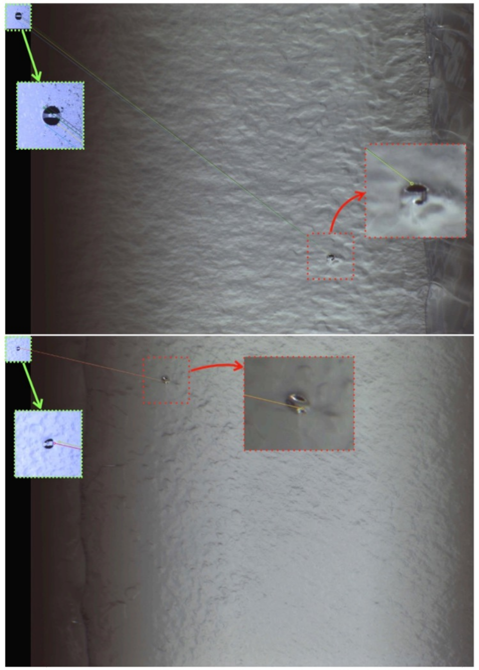
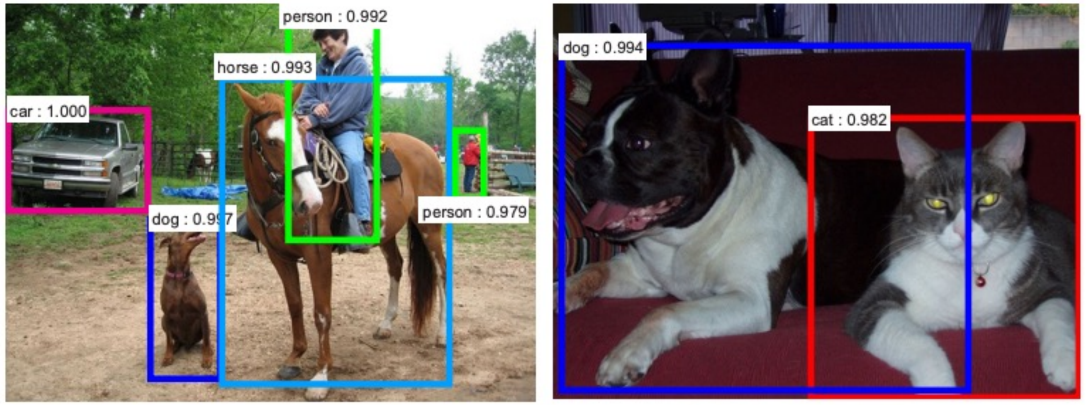


Figure 6: Examples of defect found by automatic detection using SURF.

Object detection with DL



Shaoqing Ren et al., "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks," Advances in Neural Information Processing Systems 28 (NIPS 2015).

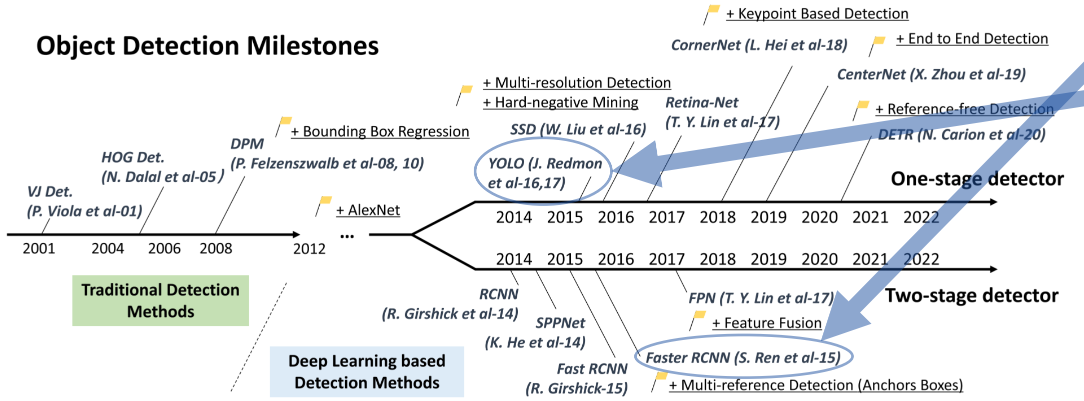


Fig. 2. ***Road map of object detection. Milestone detectors in this figure: VJ Det. [10], [11], HOG Det. [12], DPM [13], [14], [15], RCNN [16], SPPNet [17], Fast RCNN [18], Faster RCNN [19], YOLO [20], [21], [22], SSD [23], FPN [24], Retina-Net [25], CornerNet [26], CenterNet [27], and DETR [28].***

Z. Zou *et al.*, "Object Detection in 20 years: A Survey," arXiv, 2019; doi:10.48550/arXiv.1905.05055

- Position detection and Classification
  - Traditional object detection has history of more than 20 years.
  - Neural network (NN) technology caused a revolution in 2010s.
- Famous algorithm
  - Faster RCNN
    - The world's first end-to-end NN object detection.
    - Many implementation examples are available on the Internet.
  - YOLO
    - Very fast (more than 30 fps)
    - Updates are ongoing (v8 is released in 2023).

Development

Target

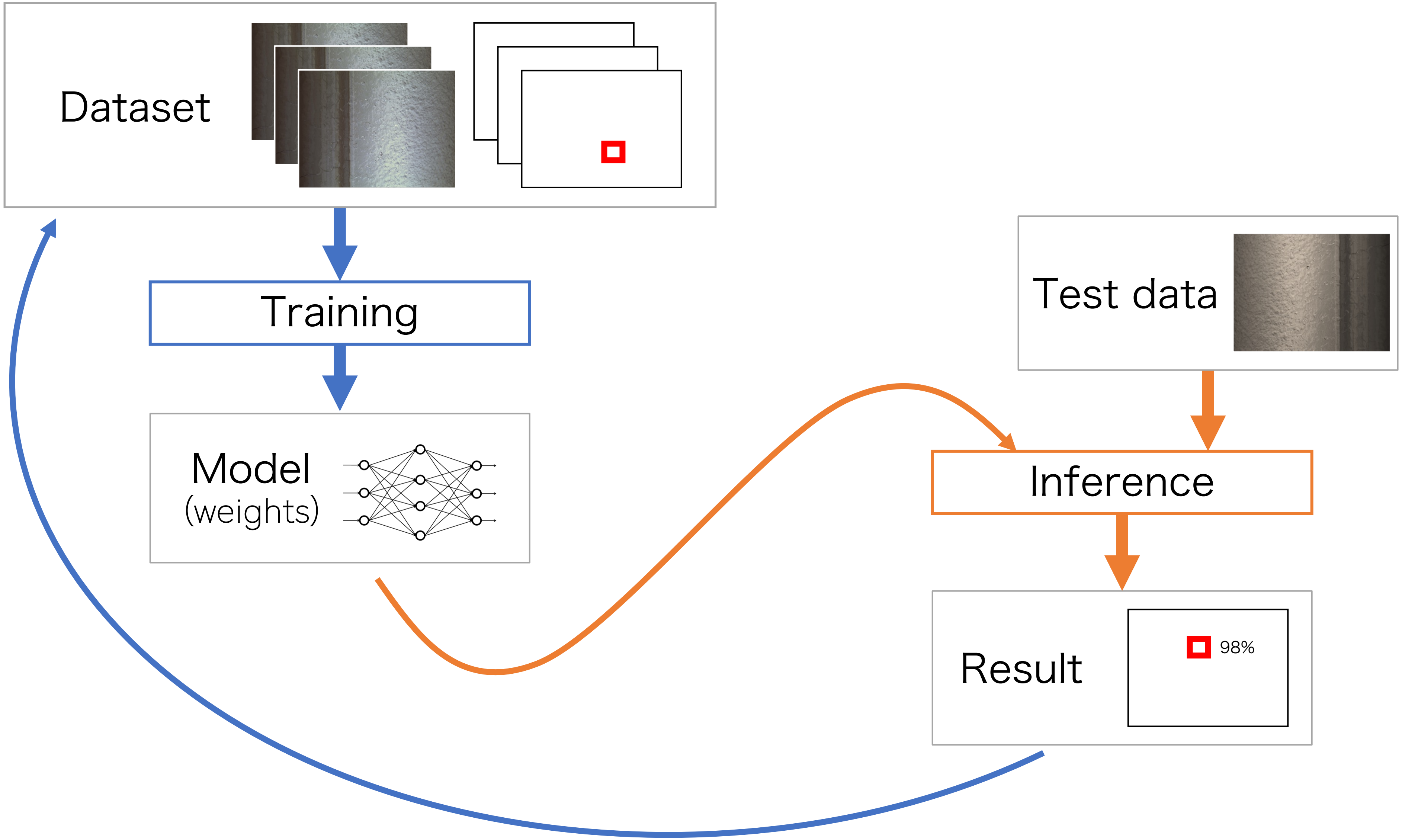
Step1. Screening for manual inspection

Reduce number of pictures (e.g. 3,000 to 100).
Leave final judgement of suspicious defects to humans.

Step2. Unmanned inspection

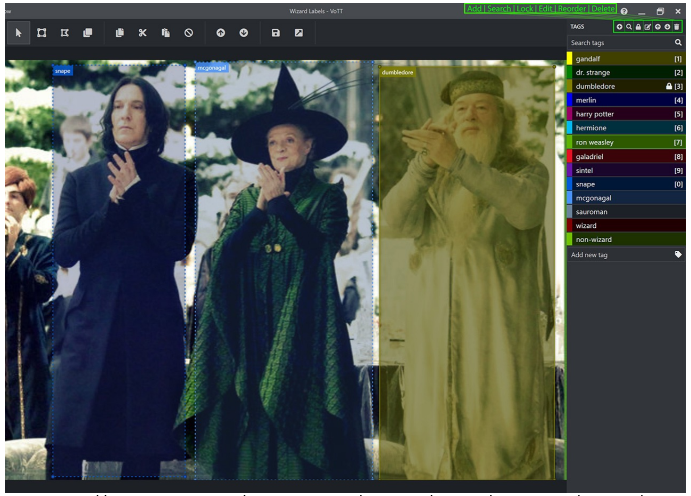
What humans have to do is only waiting the results come out.
High reliability required not to miss defects.

Flow


Dataset
Training
Model
(weights)
Test data
Inference
Result
98%

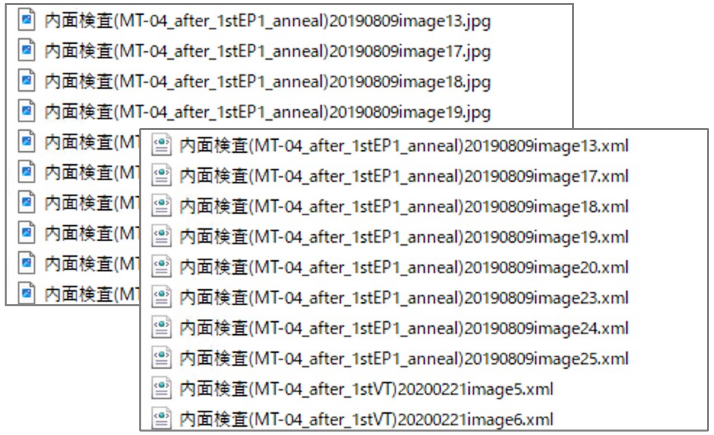
Dataset preparation

- Annotation tools
  - VoTT
    - Developed by Microsoft
    - Free software
    - Both Pascal VOC and YOLO format
  - Homebuilt GUI
    - Only one class “defect”
    - Written in python (PySimpleGUI)
- Datasets
  - 3,984 pictures (from 2010 to 2021)
  - Checked by an expert (more than 10 years of experience)
  - Took 3 weeks



https://github.com/microsoft/VoTT/blob/master/docs/images/reorder-tag.jpg

Homebuilt GUI



Dataset (pairs of .jpg and .xml)

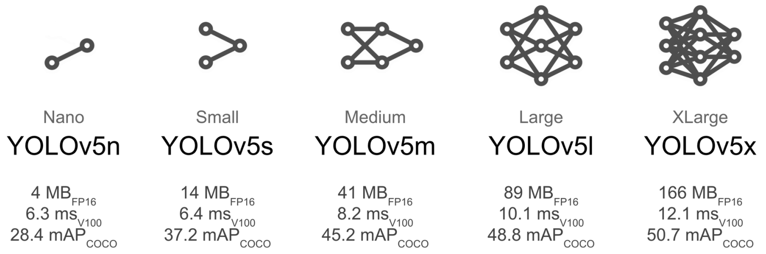
Algorithms

- Faster RCNN
  - License: MIT
  - Label: [x_min, y_min, x_max, y_max] (Pascal VOC)
  - Models can be imported from **PyTorch** Torchvision.
  - Independent on the size of input image.
  - We used "ResNet50-FPN"
- YOLO
  - License: GPL 3.0
  - Label: [x_center, y_center, width, height]
  - Models can be imported from **PyTorch** Hub.
  - Input images are reshaped to square.
    - We used 1280x1280 (default 640x640)
  - We used "YOLOv5x"

Table 3. Comparison of YOLOv5 and Faster R-CNN performance.

Metrics	YOLOv5			Faster R-CNN [43]				
	Y_l	Y_m	Y_S	ResNet50 (FPN)	VGG16	MVGG16	Mobile-Net V2	Inception V3
Precision (P)	86.43%	86.96%	76.73%	91.9%	69.8%	81.4%	63.1%	72.3%
Training Loss	0.015	0.017	0.020	0.065	0.226	0.136	0.209	0.194
Mean Average Precision (mAP@0.5–0.95)	63.43%	61.54%	58.9%	64.12%	35.3%	45.4%	30.5%	32.3%
Inference speed: Image resolution (1774 × 2365)	0.014 s	0.012 s	0.009 s	0.098 s	0.114 s	0.047 s	0.036 s	0.052 s
Inference speed: Image resolution (204 × 170)	0.018 s	0.013 s	0.009 s	0.065 s	0.119 s	0.052 s	0.032 s	0.056 s
Training time/epoch	26 s	16 s	12 s	124 s	173 s	105 s	80 s	95 s
Total training time	31,200 s	19,200 s	14,400 s	12,400 s	17,300 s	10,500 s	8000 s	9500 s
Model Size (MB)	95.3	43.3	14.8	165.7	175.5	134.5	329.8	417.2

K. R. Ahmed, "Smart Pothole Detection Using Deep Learning Based on Dilated Convolution," Sensors 2021, 21, 8406. doi: 10.3390/s21248406

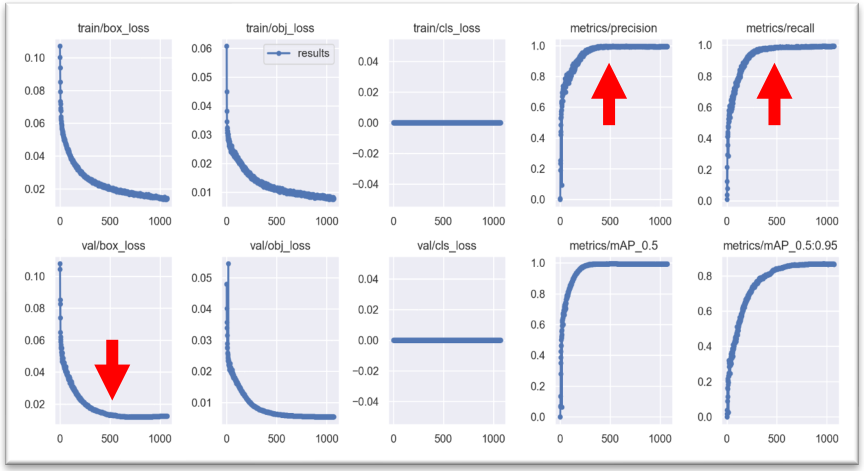


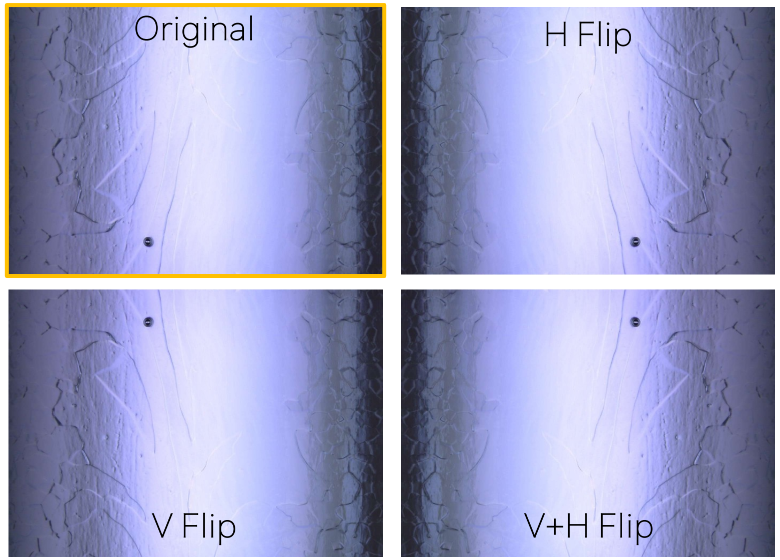
https://github.com/ultralytics/yolov5/wiki/Train-Custom-Data

Training

- Machine environment
  - CPU: Intel Core i9-10900K
  - GPU: Nvidia Quadro RTX 4000
- Iterations (for both Faster RCNN and YOLO)
  - In our experience, 100-500 is good.
  - Took several days
    - Log output for debugging could have been a bottleneck.
- Data augmentation
  - Technique to reduce overfitting
  - We used a python library “Albumentations”
    - VerticalFlip
    - HorizontalFlip
    - Blur
    - RandomBrightnessContrast
    - ShiftScaleRotate

An example of YOLO v5x training result





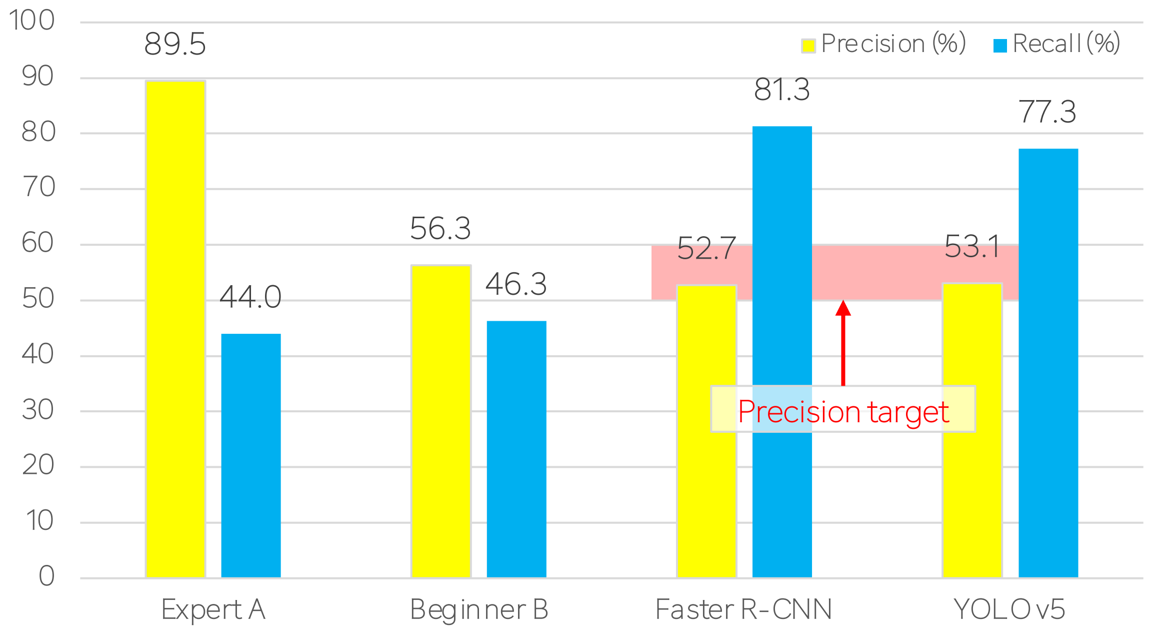
Evaluation

Benchmark 1

Comparison with manual inspection

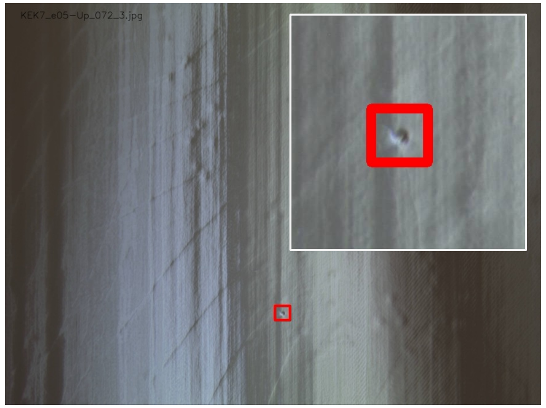
- Auto detection software
  - Threshold was set to achieve **50-60% of precision**. (for screening purpose)
  - Inference: a few seconds
- Manual inspection
  - Expert A: A different person from the dataset creator
  - Beginner B: Received only a brief explanation
- Test data
  - 100 pictures
  - A part of past inspection data in KEK
  - Excluded from the dataset
  - “Correct answers” are defined by the dataset creator.

- Result
  - Expert A had highest precision.
  - Target value of precision was similar level of Beginner B.
  - Both architectures had much **higher recall** than manual inspection.
  - No large difference between architectures.



Benchmark 2

- New cavity KEK-7
  - Fabrication finished in March 2022.
  - Completely excluded from the dataset.
  - Newest cavity in KEK
    → Expected most advanced welding technique
- Test data: inspection after EP-1
  - Total 2,694 pictures
  - **One defect** (**three pictures** including the defect)
  - Features specific to this cavity:
    - Noticeable grain boundaries
    - Bubble marks of EP acid



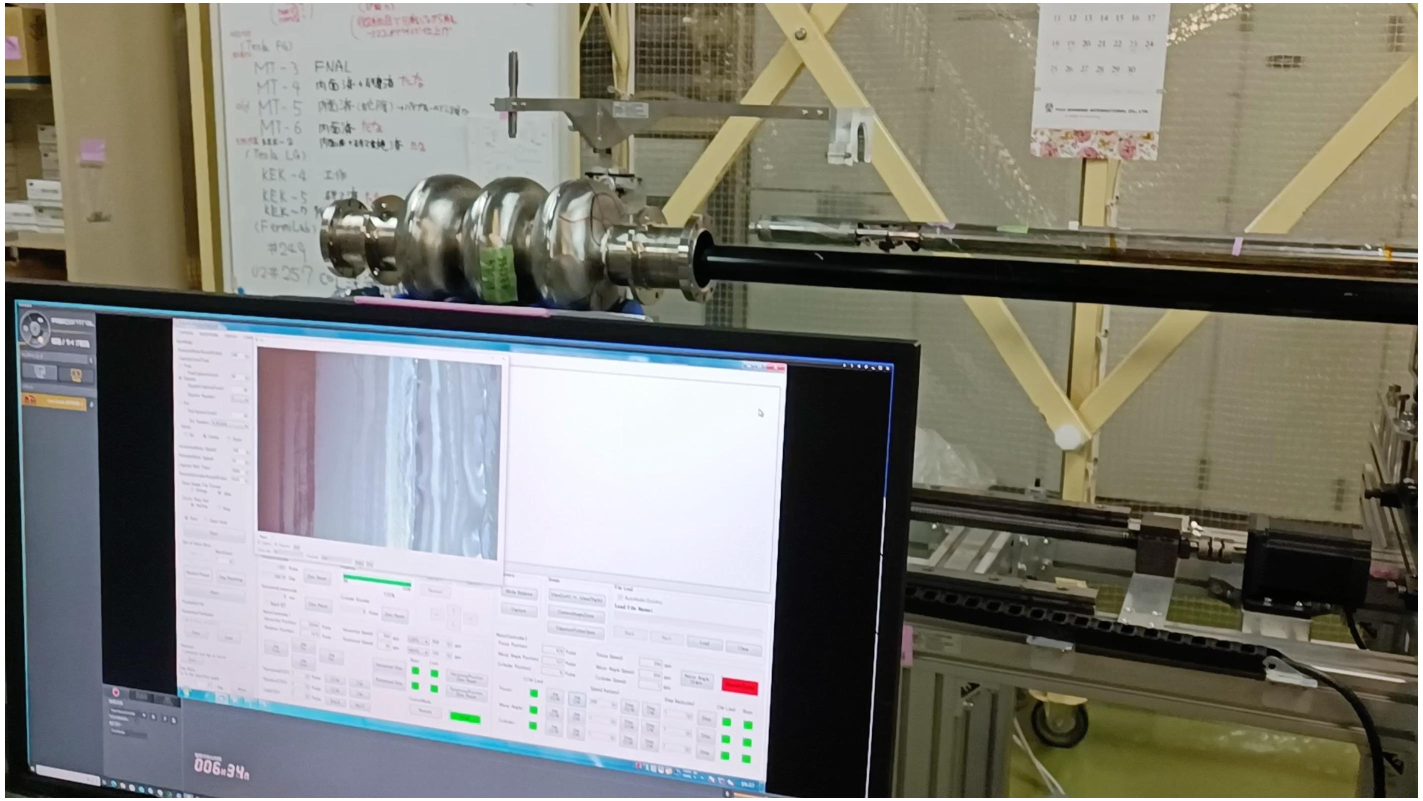
- Software setup
  - Same model/parameter as Benchmark 1.
  - Inference: ~90 seconds
- Result
  - Number of pictures detected to contain defects:
    - Faster R-CNN: 246
    - YOLO: 618
  - Both archtechtures **successfully detected all the defects** in 3 pictures.
  - Faster R-CNN had higher precision (the threshold seemed too low for YOLO).
  - Other detected objects were mainly small scratches on irises.

Satisfied the necessary condition for screening!

Future updates

Real-time detection

- As a function of Camera
  - Update of the inspection camera control system is planned by Kyoto University.
- Demonstration
  - Detect the control window via display capture
    - Camera control PC is Windows 7 and does not have GPU.
  - Achieved ~10 fps with Faster RCNN
    - GPU: NVIDIA Geforce GTX 1660 Super
    - Framerate of the camera is lower than 10 fps.
    - YOLO could be faster (not tried)



Other updates

- Larger dataset
  - Current dataset was taken from past "defect report" files.
  - More than 700,000 pictures (170 GB) are not used.
  - To ensure the quality of the dataset, the final check should be done by human eyes.
- Server-client system
  - Current software is a standalone application.
  - Need to transfer pictures from the inspection machine.
  - WEB application makes easier to access GUI for users, and safer from the viewpoint of security.

Summary

Summary

- The performance of SRF cavity is often limited by "defects" and optical inspection machine is used to find them from the inner surface. It is a powerful tool but takes much time to manually find out the performance-limiting defect from a large amount of pictures.
- We developed a software which automatically detects defects with machine learning based archtectures: **Faster RCNN** and **YOLO**.
- From two benchmarks, it became clear that the software has **higher recall** than manual inspection by a beginner and achieved **enough performance for screening**.
- Some upgrades is ongoing.

- There are a lot of helpful information (tutorials and articles) about machine learning techniques on the Internet.

Backup

Optical inspection

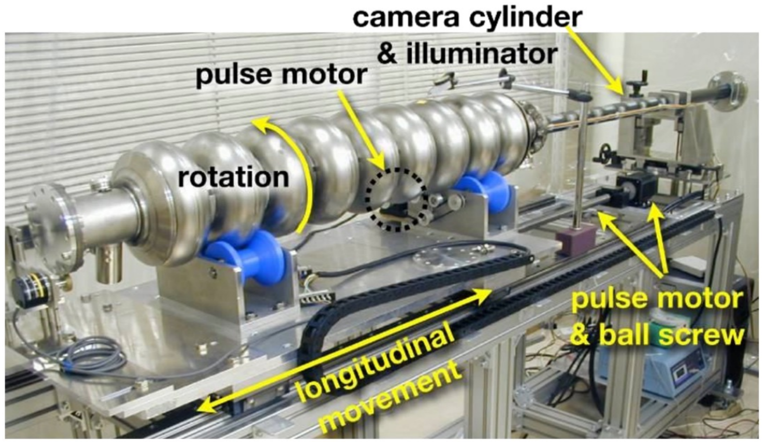


FIG. 3. (Color) Overview of our inspection system.

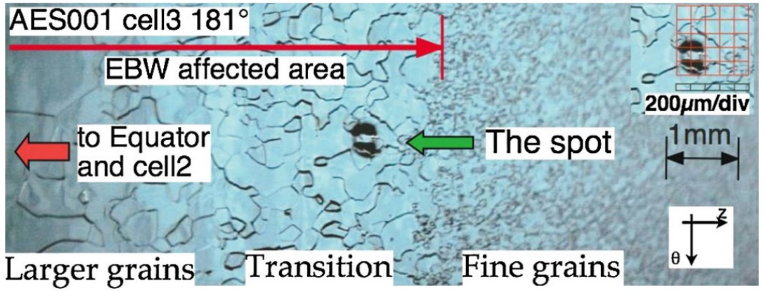


FIG. 8. (Color) Cat's-eye spot found at the equator region of cell 3, 181°. The diameter is about 400 μm.

Y. Iwashita et al., "Development of high resolution camera for observations of superconducting cavities," Phisical Review Special Topics - Accelerators and Beams 11, 093501 (2008); http://dx.doi.org/10.1103/PhysRevSTAB.11.093501

Surface inspection machine

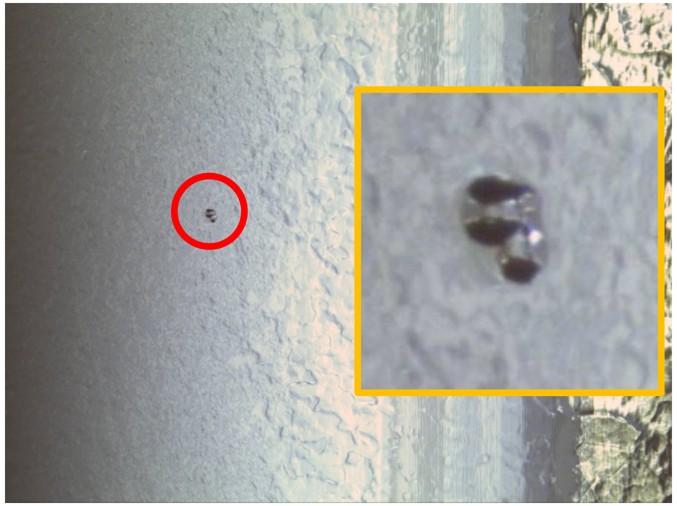
- Developed in 2008
- Specification of camera:
  - Resolution: 9.0 MP (3488×2616)
  - Viewing range: ~ 8 mm × 6 mm
- 9-cell cavity inspection:
  - **2,600 pictures**
  - 1.5 days to take pictures (semi-automatic)
  - **1 day to check**

All the pictures are checked by human

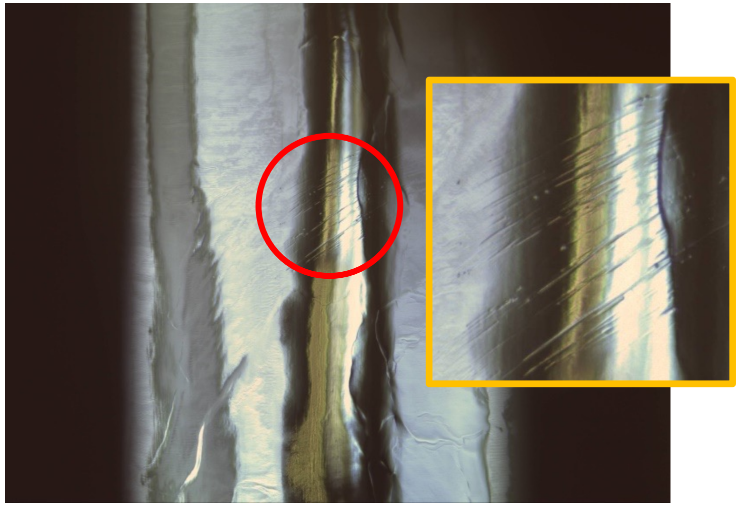
Definition of "defect"

What we want to find: objects which **limit the performance** of the cavity

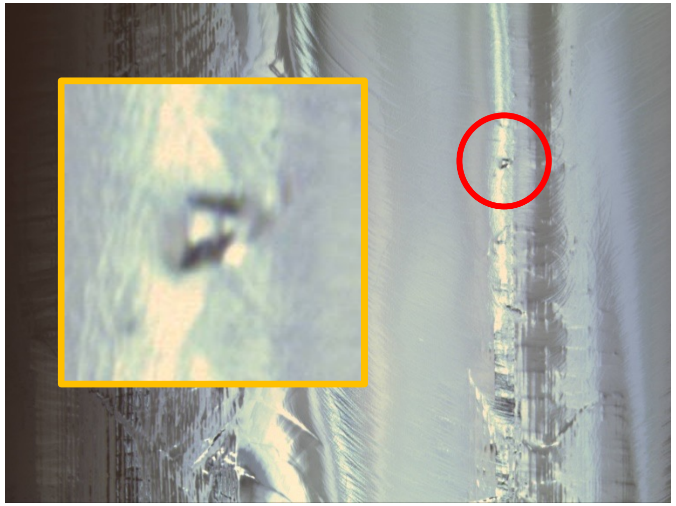
- Not only "welding defect" in industrial meaning.



MT-5 after 1st VT, cell #1, 108°
A defect found near the quench location at 37 MV/m.
Cavity performance was limited by this defect



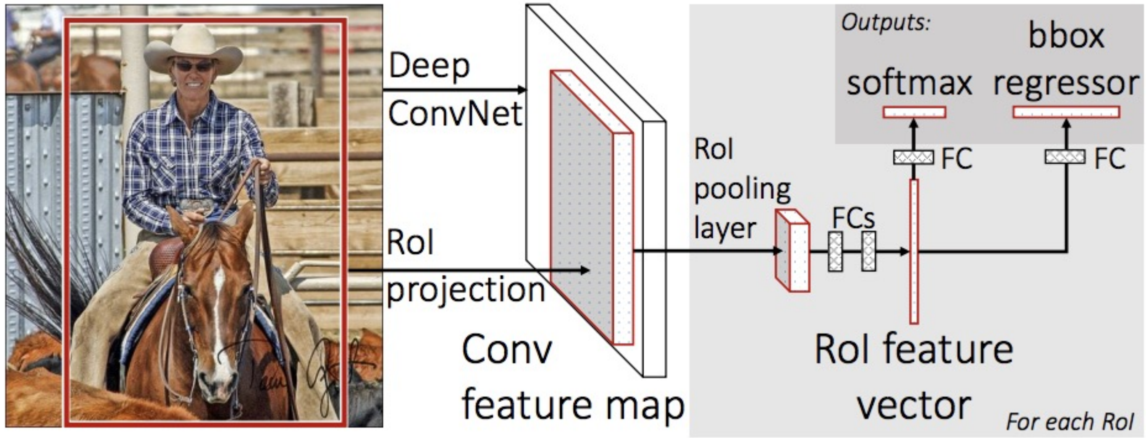
KEK-R17 after 1st VT, 1-2 iris, 216°
Scrathces at iris section which seemed to be damaged after welding.
Not welding defect but "should be removed"

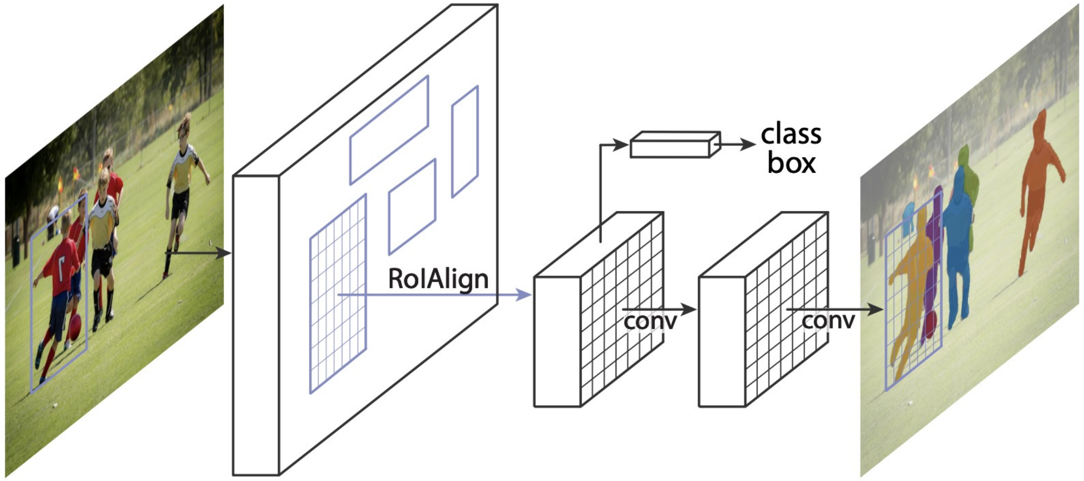


KEK-R16 after 1st VT, cell #2, 58°
A small bump looks like a defect, but not quenched over 43 MV/m.
Not limiting cavity performance

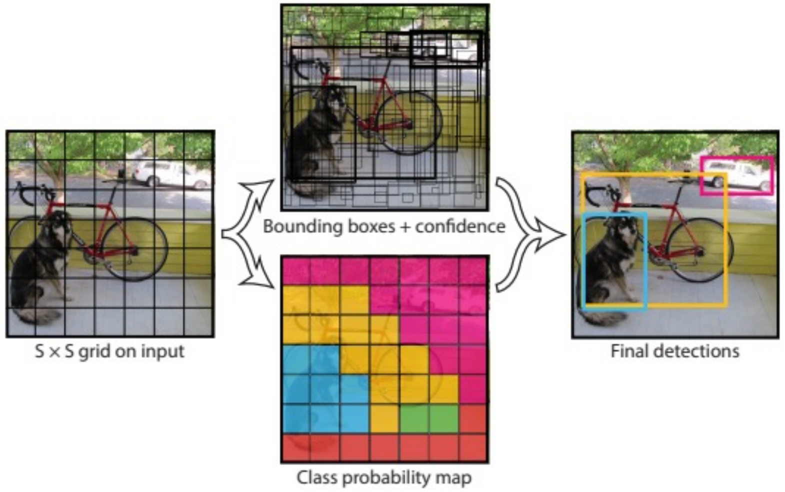
Relationship between shape of defect and cavity performance is not clear.

Faster R-CNN

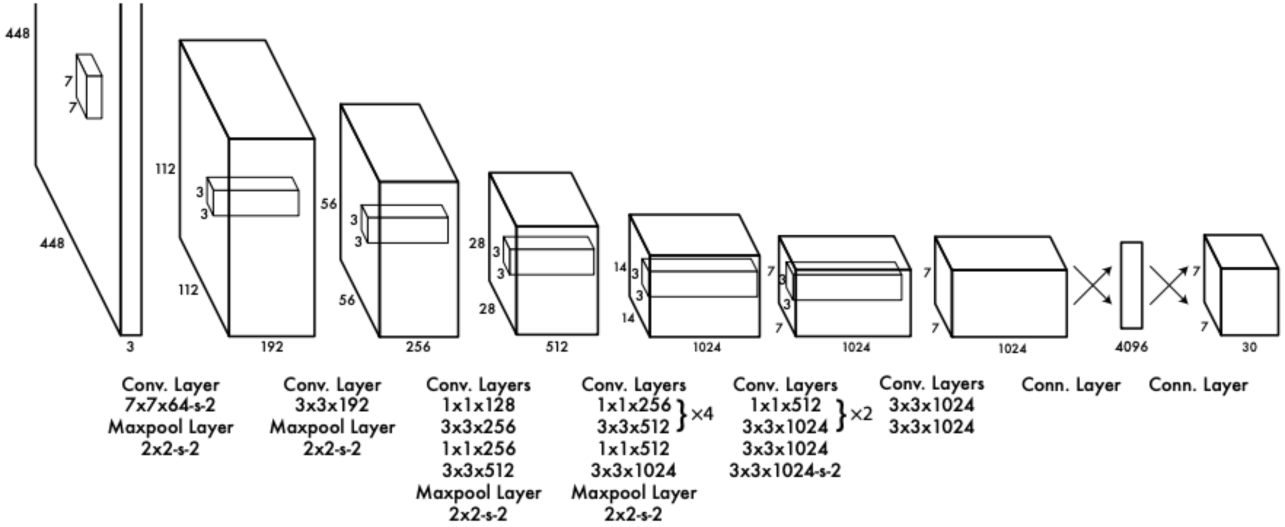

Deep
ConvNet
RoI
projection
Conv
feature map
RoI
pooling
layer
FCs
Outputs:
softmax
bbox
regressor
FC
FC
RoI feature
vector
For each RoI


RoIAlign
class
box
conv
conv

YOLO



Bounding boxes + confidence
S × S grid on input
Final detections
Class probability map



448
7
7
448
3
112
3
3
112
192
56
3
3
56
256
28
3
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512
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3
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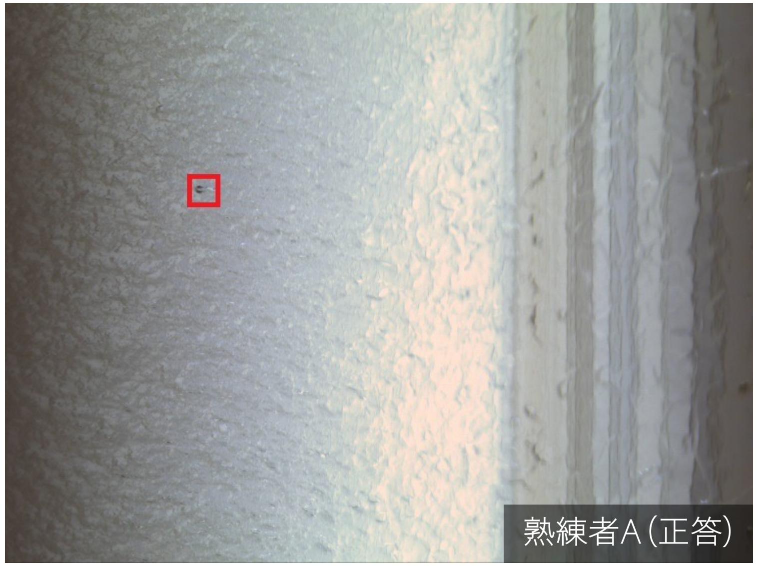
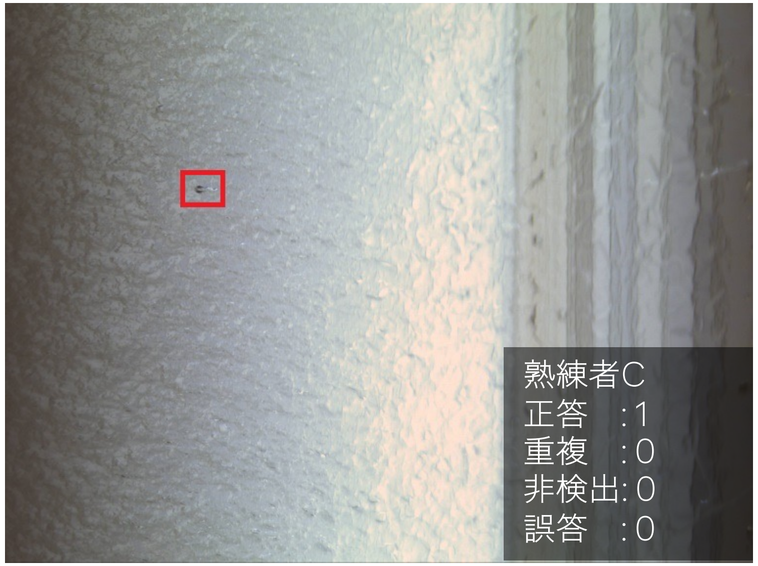
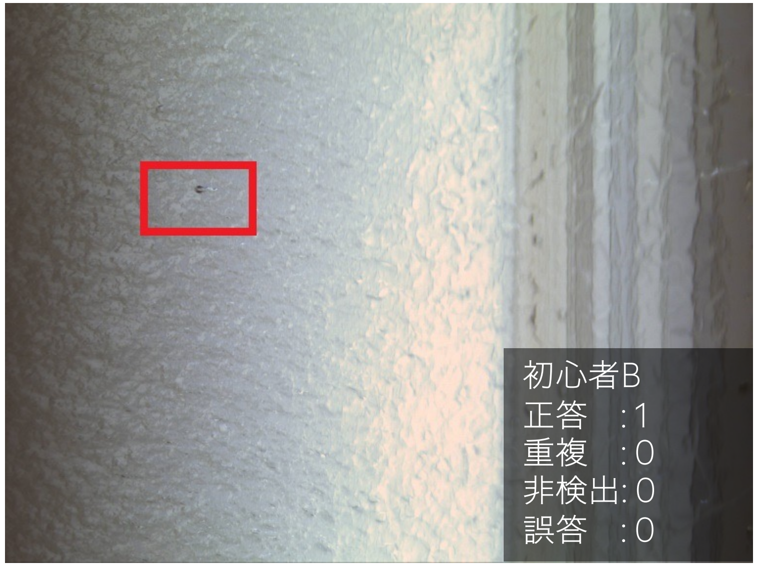
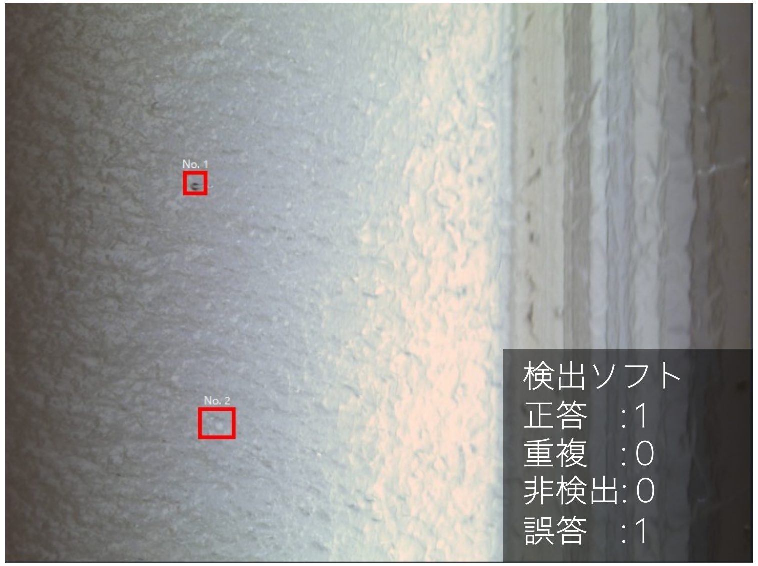
14
1024
7
3
3
7
1024
7
7
1024
4096
7
7
30
Conv. Layer
7x7x64-s-2
Maxpool Layer
2x2-s-2
Conv. Layer
3x3x192
Maxpool Layer
2x2-s-2
Conv. Layers
1x1x128
3x3x256
1x1x256
3x3x512
Maxpool Layer
2x2-s-2
Conv. Layers
1x1x256 }×4
3x3x512
1x1x512
3x3x1024
Maxpool Layer
2x2-s-2
Conv. Layers
1x1x512 }×2
3x3x1024
3x3x1024
3x3x1024-s-2
Conv. Layers
3x3x1024
3x3x1024
Conn. Layer
Conn. Layer

検査結果の例

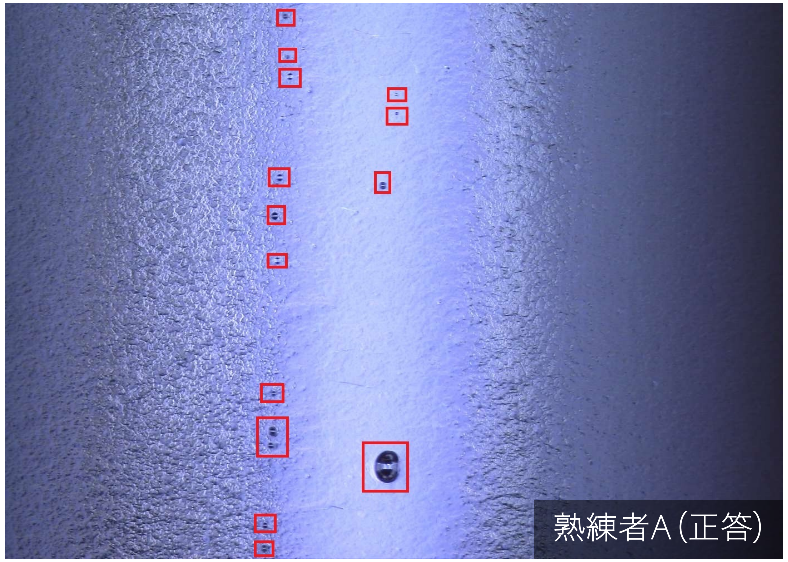

熟練者A(正答)

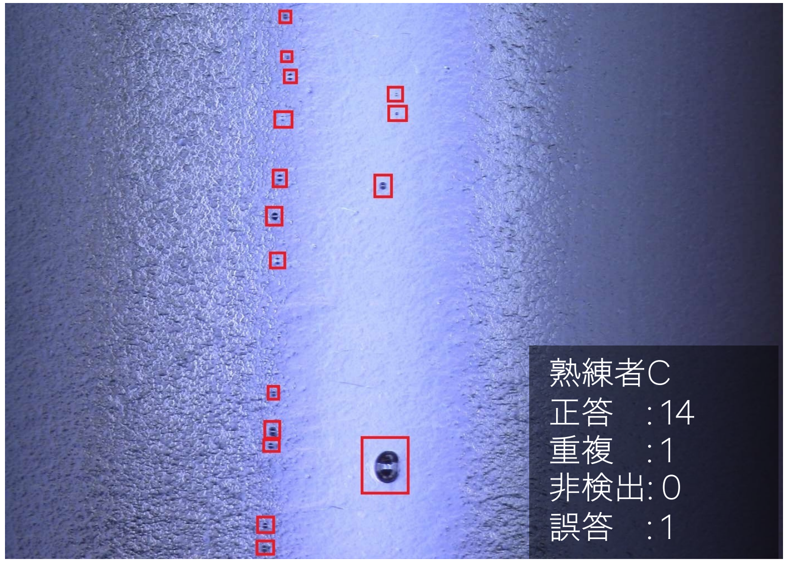

熟練者C
正答　:1
重複　:0
非検出:0
誤答　:0


初心者B
正答　:1
重複　:0
非検出:0
誤答　:0


No. 1
No. 2
検出ソフト
正答　:1
重複　:0
非検出:0
誤答　:1

検査結果の例


熟練者A(正答)


熟練者C
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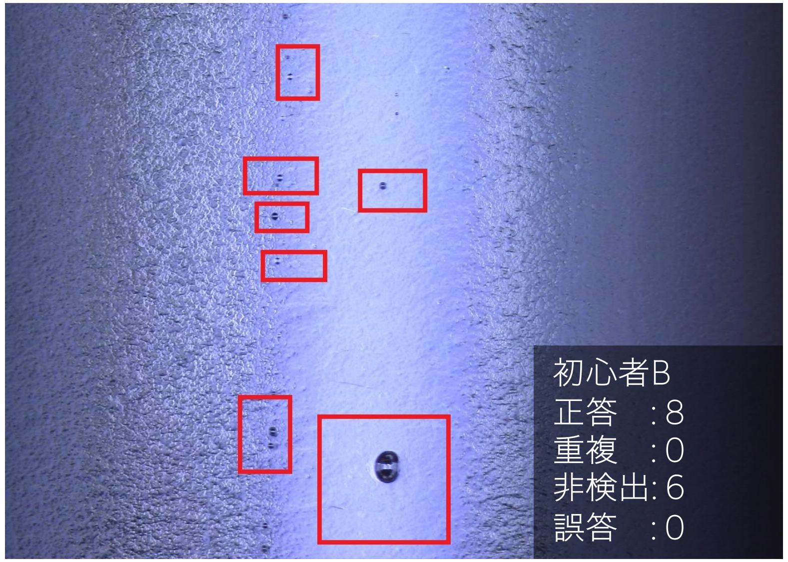
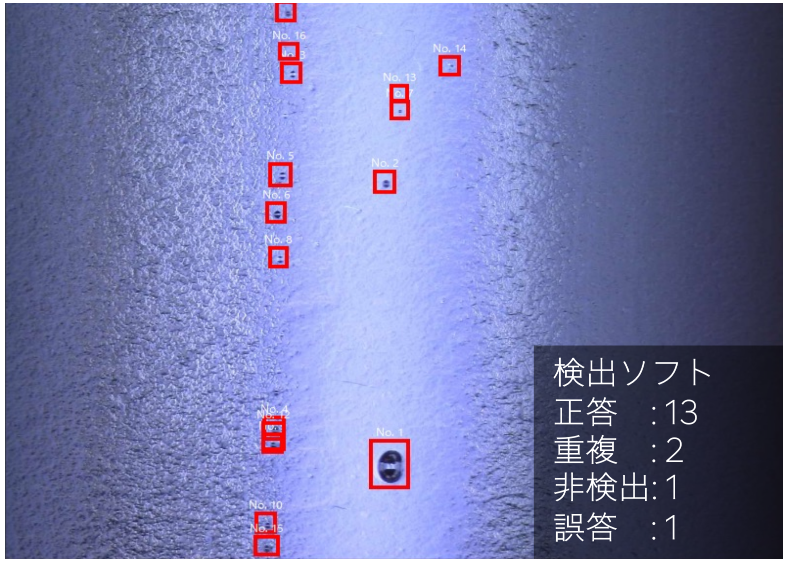
重複　:1
非検出:0
誤答　:1


初心者B
正答　:8
重複　:0
非検出:6
誤答　:0


検出ソフト
正答　:13
重複　:2
非検出:1
誤答　:1

検査結果の例

Innovation Center for Applied Superconducting Accelerators
応用超伝導加速器イノベーションセンター