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Al Day 2021

Object detection for the analysis of creep voids in high-temperature metallic structures

Akhtar Zeb, Mikko Tahkola, Rami Pohja, Janne Pakarinen

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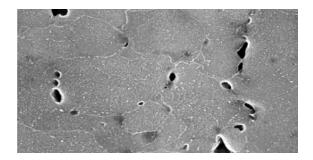
Problem:

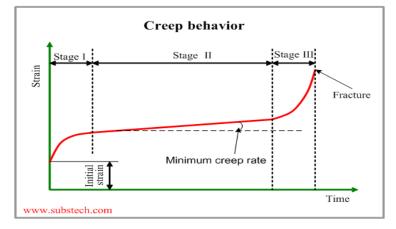
Creep voids in metallic structures



Problem of creep void in metallic structures

- High-temperature metallic structures under load experience creep at temperature about 0.3 times the material's melting temperature
- Creep means significant viscous time-dependent and liquidlike material flows in the direction of principal stress
- Prolonged creep condition leads to rupture and component failure
- At relatively early stages of creep, one important manifestation is the creep void at the grain boundaries of the material
- Reliable and accurate detection of creep void size and density helps in improving the life cycle management of high-temperature components





Creep void analysis – traditional vs machine learning approach

- Creep void inspection in service conditions is usually performed by replica inspection
- Replica inspection samples are taken from components and inspected via optical and/or scanning electron microscope (SEM)
- However, interpretation of the results is often difficult and timeconsuming
- ML can help in reducing human errors and speed up the process by analyzing large areas and multiple sample images







Our solution:

YOLO object detection algorithm

YOLO algorithm

- You Only Look Once
- Object detection algorithm popular for its speed, and outperformed, e.g., Sliding Window Object Detection, R CNN, Fast R CNN, Faster R CNN algorithms
- Built on PyTorch framework and tells about object class and object localization, i.e. bounding box
- Makes all the predictions in one forward pass
- Yolo v1, Yolo v2, Yolo v3, Yolo v4, Yolo v5
- YOLOv5 is a family of object detection architectures and models pretrained on the COCO dataset, and represents Ultralytics¹ open-source research into future vision AI methods
- We use the YOLOv5s, which is the smallest and fastest model
- We take advantage of pre-trained weights and default configuration of YOLOV5s

\$	*			
Small	Medium	Large	XLarge	
YOLOv5s	YOLOv5m	YOLOv5I	YOLOv5x	
14 MB _{FP16}	41 MB _{FP16}	90 MB _{FP16}	168 MB _{FP16}	
2.0 ms _{V100}	2.7 ms _{V100}	3.8 ms _{v100}	6.1 ms _{V100}	
37.2 mAP _{coco}	44.5 mAP _{coco}	48.2 mAP _{coco}	50.4 mAP _{COCO}	

Pretrained Checkpoints							
Model	size (pixels)	mAP ^{val} 0.5:0.95	mAP ^{test} 0.5:0.95	mAP ^{val} 0.5	Speed V100 (ms)	params (M)	FLOPs 640 (B)
YOLOv5s	640	36.7	36.7	55.4	2.0	7.3	17.0
YOLOv5m	640	44.5	44.5	63.1	2.7	21.4	51.3
YOLOv5l	640	48.2	48.2	66.9	3.8	47.0	115.4
YOLOv5x	640	50.4	50.4	68.8	6.1	87.7	218.8
YOLOv5s6	1280	43.3	43.3	61.9	4.3	12.7	17.4
YOLOv5m6	1280	50.5	50.5	68.7	8.4	35.9	52.4
YOLOv5l6	1280	53.4	53.4	71.1	12.3	77.2	117.7
YOLOv5x6	1280	54.4	54.4	72.0	22.4	141.8	222.9
YOLOv5x6 TTA	1280	55.0	55.0	72.0	70.8	-	-

¹https://ultralytics.com/

Source: https://github.com/ultralytics/yolov5



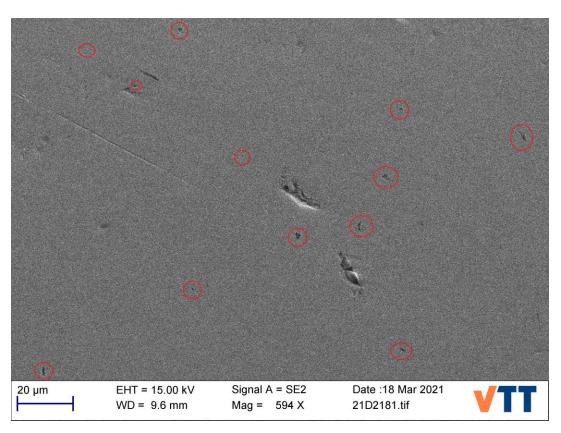
Data:

Scanning electron microscope images



Scanning electron microscope images

- 100 SEM images of oxygen-free phosphorous doped copper sample surfaces
- With creep voids of different shapes and sizes
- Distinguishing creep voids from other damages could be challenging task even for the material expert





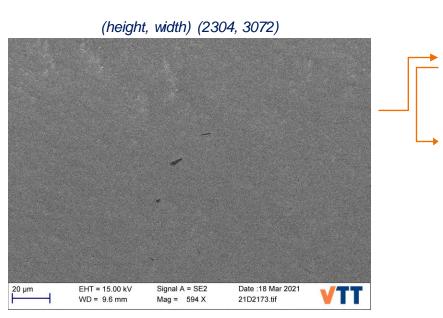
Data pre-processing and annotation

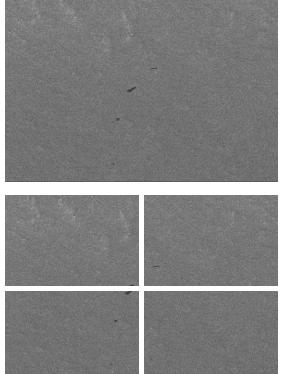
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Pre-processing images

- Formatting and cropping
- Resizing
- Splitting



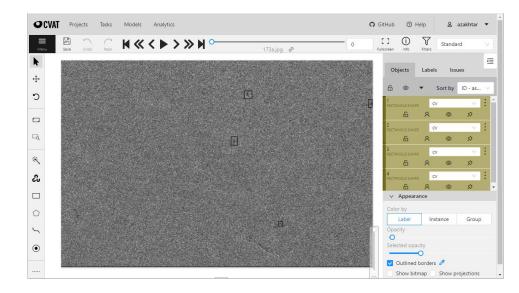


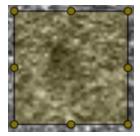




Labelling and annotation

- CVAT computer vision annotation tool
- Free, online, interactive video and image annotation tool for computer vision
- Supports several annotation formats (coco, yolo, etc.)
- Only one class "cv", in this study





Yolo format:

Bounding box coordinates are in normalized xywh format (from 0 -1) Each row is <u>class x center y center width height</u> format

/// 173c.txt - Notepad				
File Edit Fo	ormat View	Help		
0 0.083626	0.784424	0.083268	0.054590	



YOLO training, inference, and calculations

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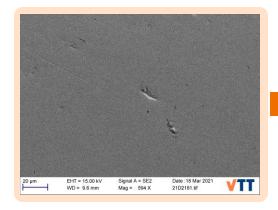
Training and results

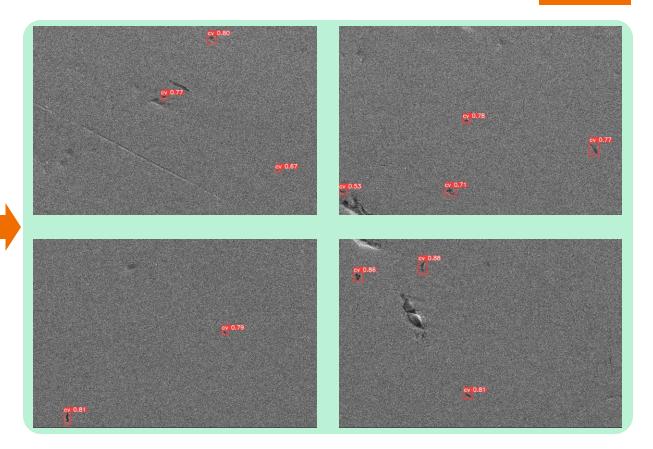
- Google Colab
- Images annotated using CVAT and exported in yolo format
- YOLOv5s model is trained using pretrained weights and default configuration and architecture

Images	Epochs	Training time	mAP_0.5
64	100	45 min	0.85
64	150	1 hour	0.83
200	100	2 hours	0.82



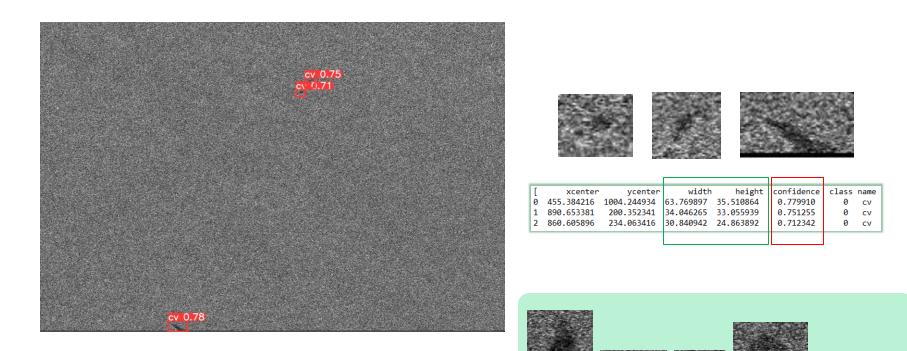
YOLOv5 inference – detections on full-size images







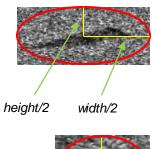
YOLOv5 inference – bounding boxes and creep void images



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Creep void calculations

- $cv_area = \pi \times width/2 \times height/2$
- cv_num = len(cv_area)
- cv_frac_area =
 sum(cv_area)/image(w*h)*100





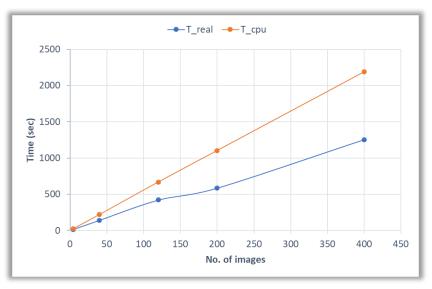
Fractional area (percentage) of (all) creep-voids in an image: [0.3635374031375304, 0.10300326269379431, 0.4792252592922566, 0.21302700214886802, 0.23649661238944594, 0.0, 0.0, 0.14832590684477895 Area of creep-void in an image: 788.529447 [0] 1 599.364558 2 1353.928740 3 559,977414 Δ 550.245897 5 1865,902885 Name: height, dtype: float64, 0 1620.101238 Name: height, dtype: float64, 0 1795.564032 1478.330111 2 669.510445 3 2322.489817 435,992353 4 5 835.674824 Name: height, dtype: float64, 0 933.012768 960,984515 1 344,420429 2 3 606.764116 4 505,443199 Name: height, dtype: float64, 0 3111.030319 385.109797 1 2 223.629962 Name: height, dtype: float64, Series([], Name: height, dtype: object), Series([], Name: height, dtype: object), 0 989,901862 1 857.765641 2 485.297288

Number of creep-voids in an image: [6, 1, 6, 5, 3, 0, 0, 3]

Name: height, dtype: float64]

Inference time

- Total time taken by the algorithm starting from the initial pre-processing of the images to the saving of final results (Intel® Core[™] i7-8665U Processor, 16 GB RAM)
- T_real is the system time in seconds from the starting point to the end of a process
- T_cpu is the sum of the system and user CPU time from the beginning to the end of a process





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Conclusions

Conclusions and future work

- YOLOv5 built on PyTorch framework
- Easy to train, e.g. using free Google Colab environment including GPUs
- Local installation is straightforward
- Cropped images of the creep voids are obtained, in addition to the detections on full-size images
- Detected all the creep voids correctly
- Bounding boxes coordinates enable calculation of desired parameters
- Labelling accuracy would result in better inferences
- Creep void images can be further investigated using other tools, e.g. ImageJ



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