Multi-device dataset of infrared images for the control of thermal loads with machine learning

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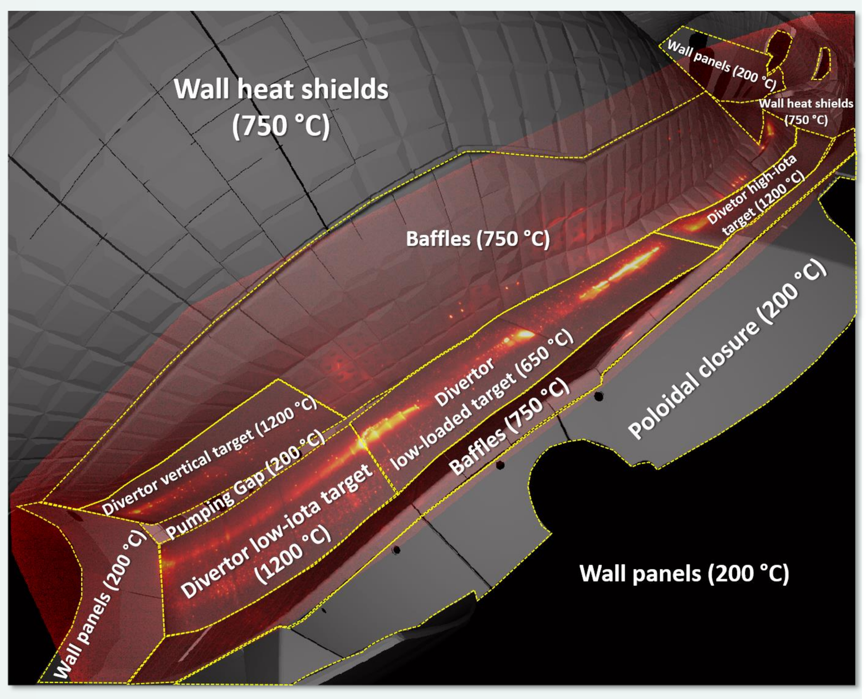
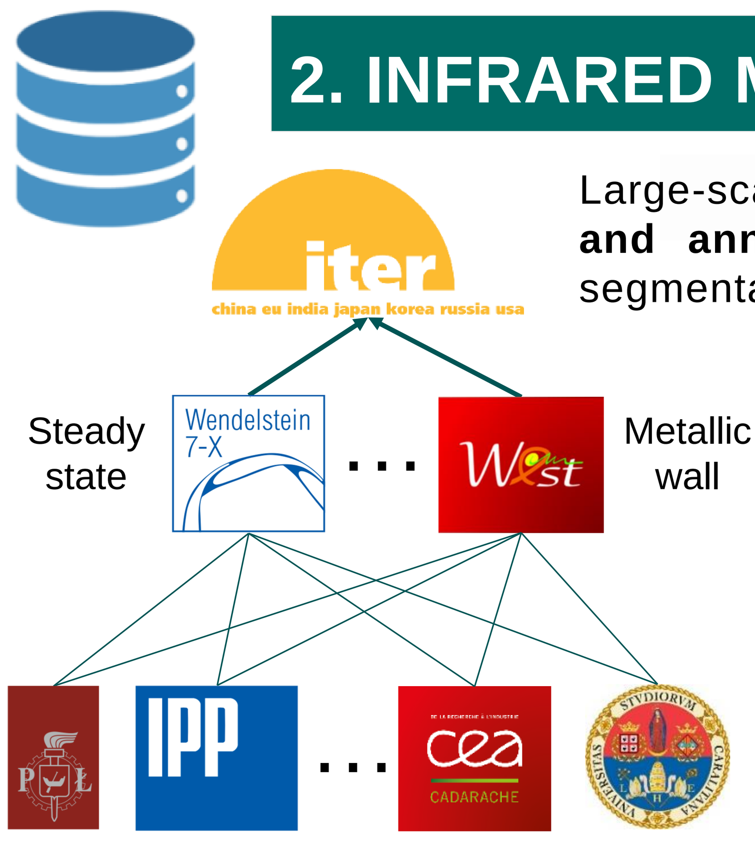
1. MOTIVATION

- **Control of the thermal loads** is required to guarantee a safe operation of high-performing fusion devices (W7-X or ITER)
- Thermal load control demands in-depth knowledge about thermal events to inform the feedback control. This is possible with **machine learning techniques**.
- ITER / DEMO necessitate thermal load **protection from day one**, leaving scarce time for gathering **sufficient data**.
- It is required to train models on current devices and **transfer large-scale models** with zero-shot learning to ITER.



2. INFRARED MULTI-DEVICE DATASET

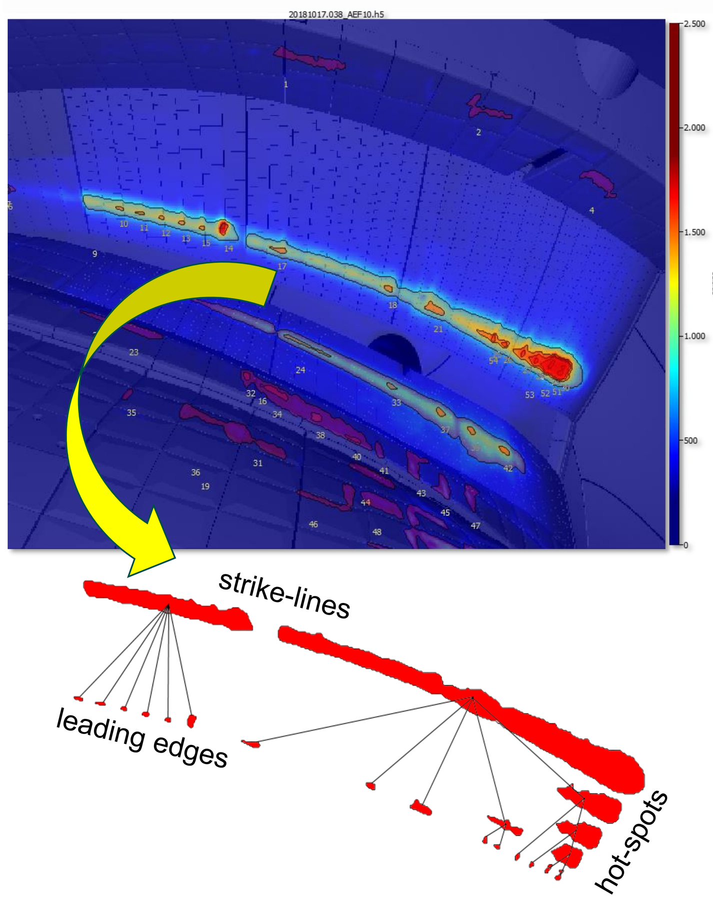


Large-scale deep-learning models require **large diverse and annotated datasets** (very cumbersome for video segmentation) → **We propose:**

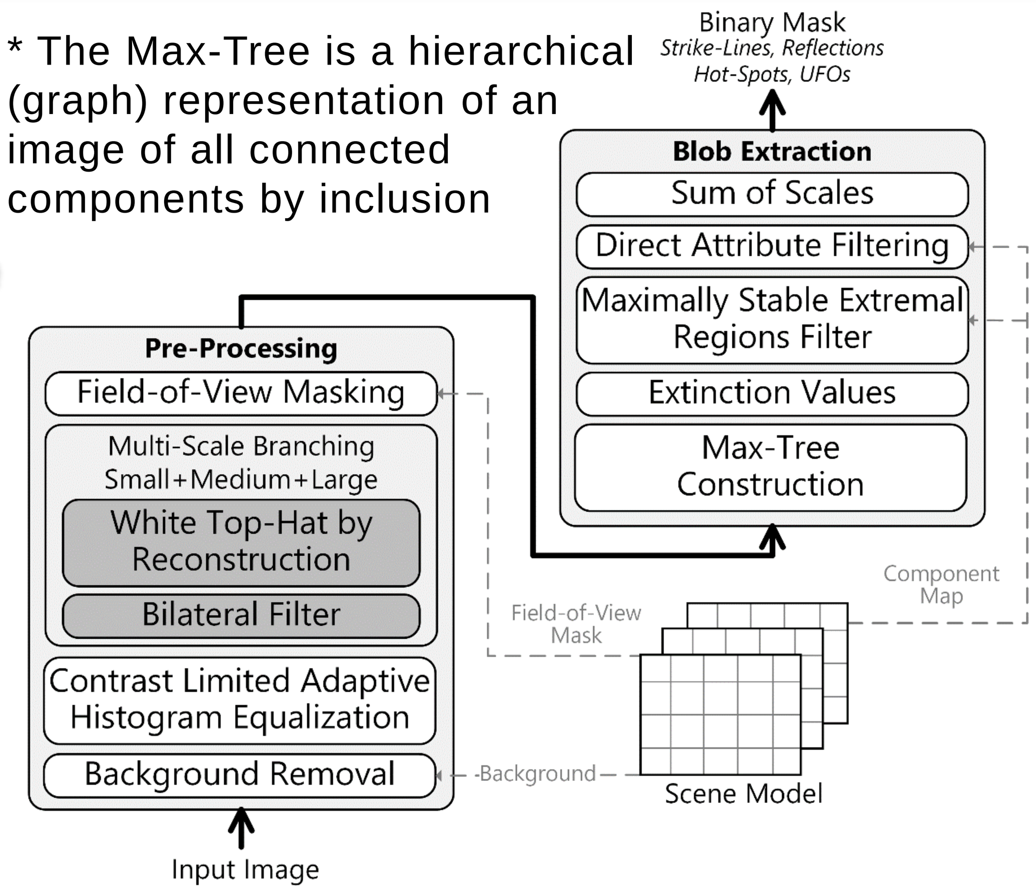
- A multi-device IR dataset (tokamaks and stellarators)
- Diverse first-wall materials (C and W)
- Initially, from W7-X and WEST (100s TB in HDF5 format)
- Metadata for physics, geometrical and material context information
- Semi-automated annotation in COCO format
- Compliant with FAIR principles

3. SEMI-AUTOMATIC DATASET ANNOTATION [1]

- The dataset is segmented with the Max-Tree algorithm*
- A reference frame is created by taking the maximum of each pixel along time
- The reference frame is manually annotated and labels propagated with tracking

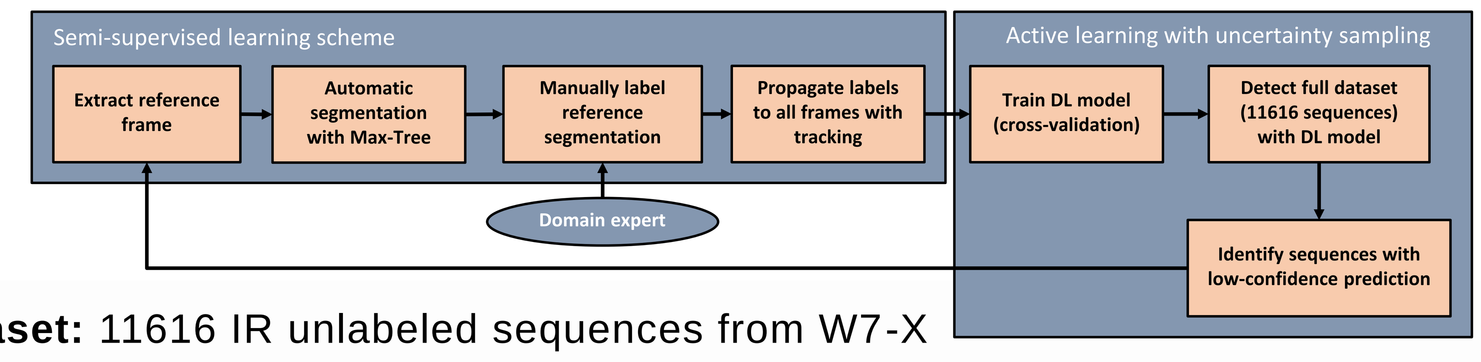


* The Max-Tree is a hierarchical (graph) representation of an image of all connected components by inclusion



4. SEMI-SUPERVISED THERMAL EVENT DETECTION

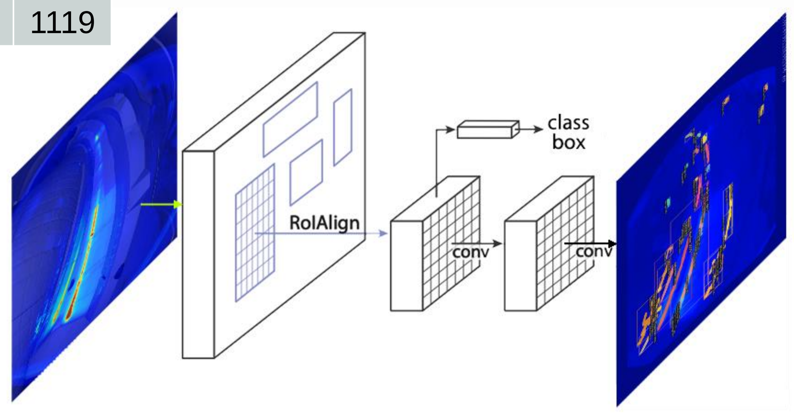
- The semi auto-annotated dataset is used to train a deep-learning model.
- The model is used to detect the thermal events of the full (unlabeled) dataset
- The sequences with low-confidence labels are re-labelled and the model retrained



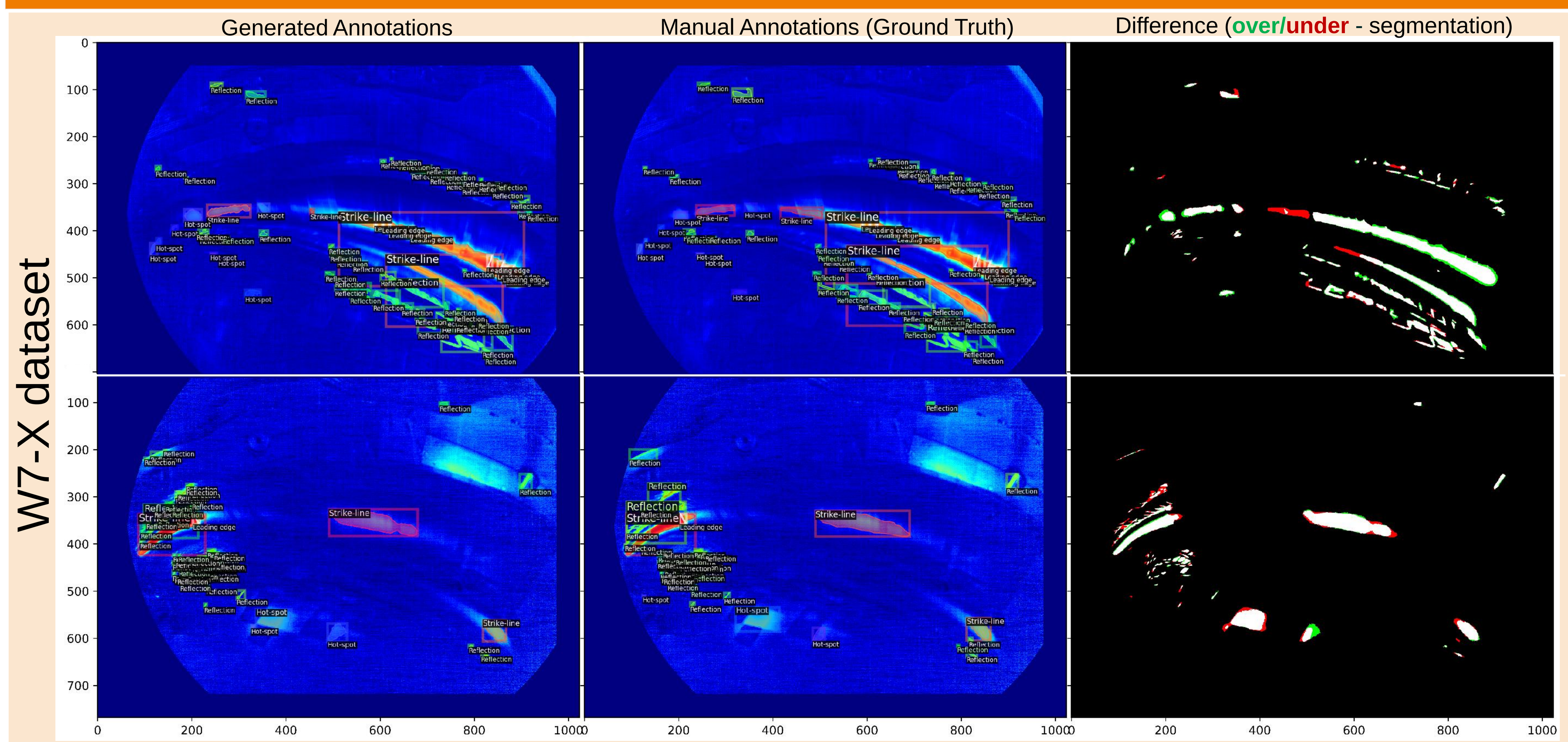
- **Full dataset:** 11616 IR unlabeled sequences from W7-X
- **Annotated dataset**: 130 sequences → 109 train / 21 test (subsampled 1/10)

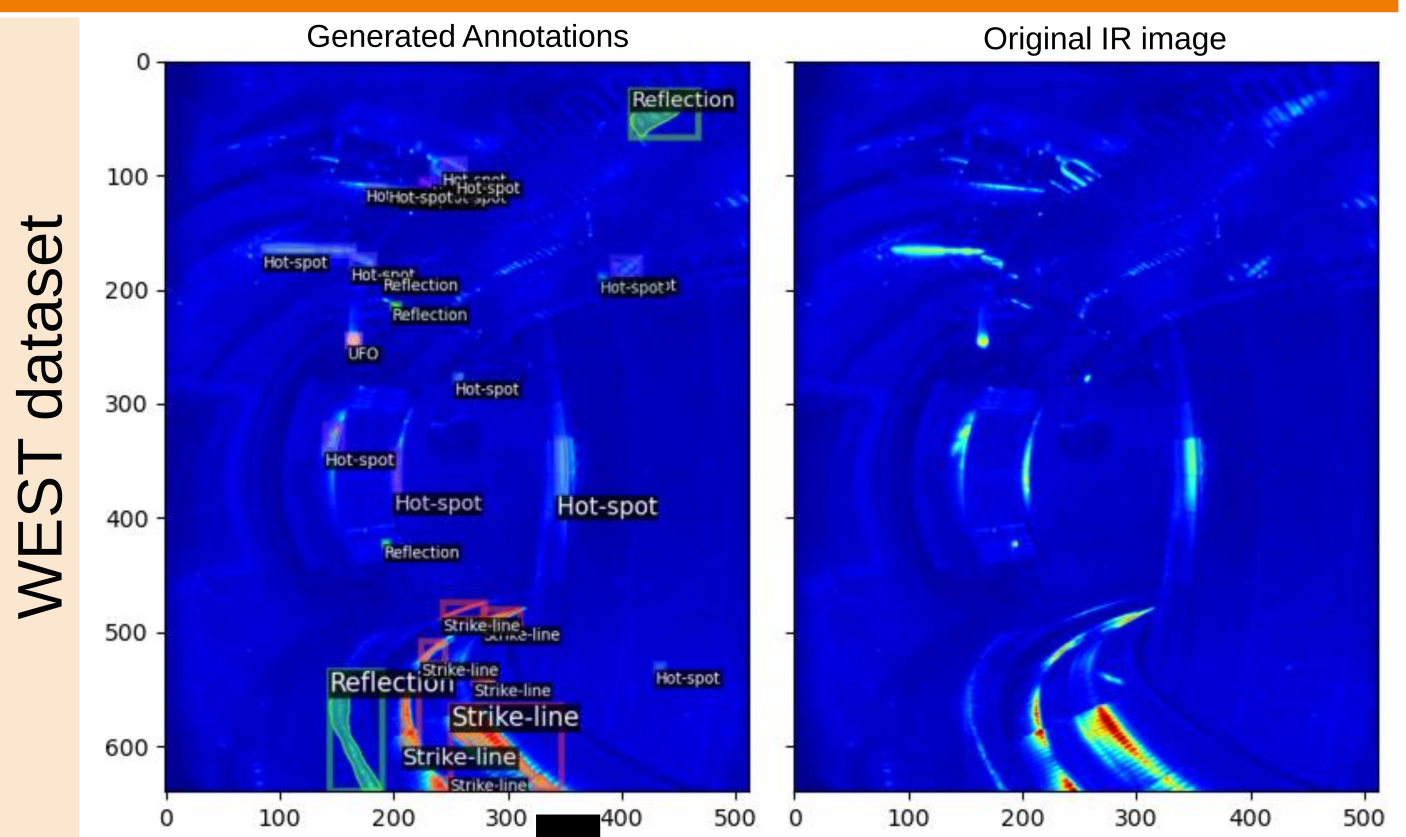
Class	Strike-line	Hot-spot	Leading edge	Reflection	UFO
Instances	619611	659262	291320	3180343	1119

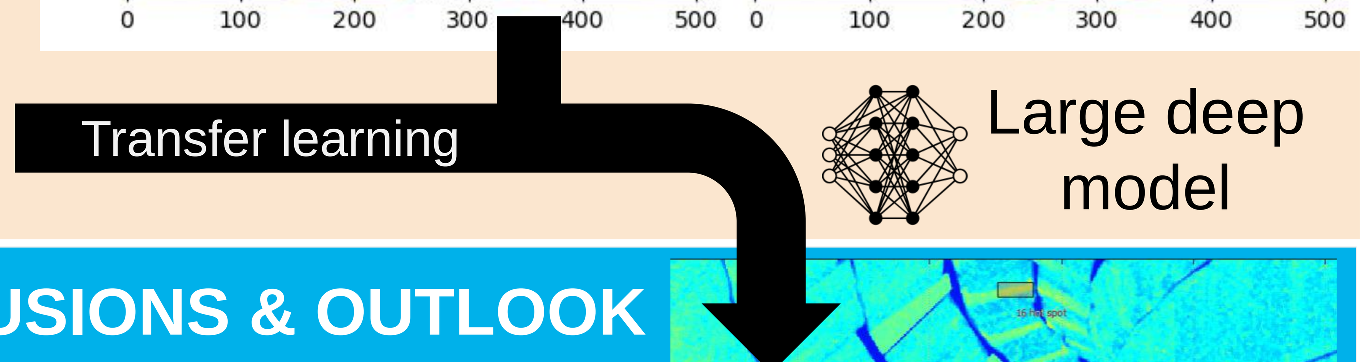
- **Models (size) being trained**:
  - Mask R-CNN (ResNet-50, 45.3M)
  - Cascade Mask R-CNN (71.8M)
  - YOLOv8 Large (45.9M)
  - MaskDINO (ResNet-50, 43.8M)



5. SEMI-AUTOMATIC ANNOTATION RESULTS [1]







Metrics:

Sørensen–Dice Coefficient (SDC)

$$SDC(a,b) = \frac{2\sum_i^N a_i b_i}{\sum_i^N a_i + \sum_i^N b_i}$$

Temperature over limit weighted SDC (tlwSDC)

$$tlwSDC(a,b,w) = \frac{2\sum_i^N a_i b_i w_i}{\sum_i^N a_i w_i + \sum_i^N b_i w_i}, \quad w_i = \frac{T_i - T_i^{Back}}{T_i^{Limit}}$$

Test dataset: 21 IR reference frames

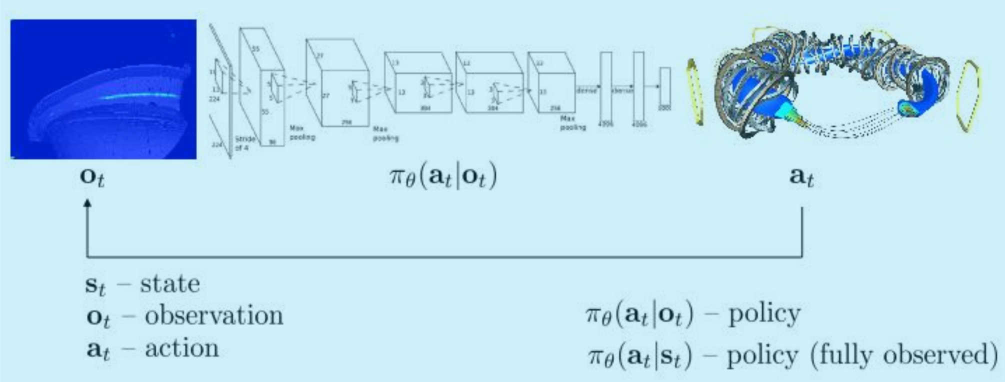
	Otsu's thresholding		Adaptive Gaussian		Proposed method	
Mask	$SDC \pm s_{sdc}$	$tlwSDC \pm s_{tlwSDC}$	$SDC \pm s_{sdc}$	$tlwSDC \pm s_{tlwSDC}$	$SDC \pm s_{sdc}$	$tlwSDC \pm s_{tlwSDC}$
Any	0.586±0.173	0.777±0.085	0.780±0.050	0.881±0.035	**0.825 ±0.030**	**0.904 ±0.018**
Strike-line	0.721±0.230	0.860±0.198	0.828±0.068	0.917±0.033	**0.868 ±0.048**	**0.935 ±0.024**
Reflection	0.108±0.126	0.194±0.189	0.679±0.072	0.761±0.073	**0.748 ±0.044**	**0.818 ±0.044**
Hot-spot	0.433±0.316	0.564±0.346	0.725±0.119	0.829±0.094	**0.787 ±0.097**	**0.877 ±0.069**

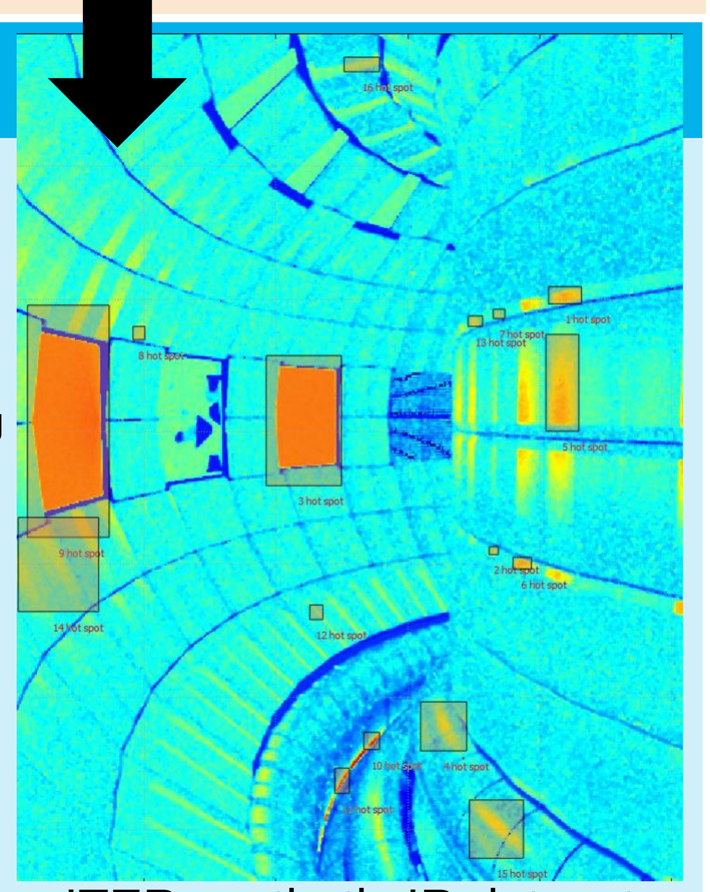
[1] B. Jabłonski, D. Makowski, A. Puig Sitjes, M. Jakubowski, "Enabling Instance Segmentation: A Semi-Automatic Method for Thermal Event Annotation", IEEE Transactions on Plasma Science (under review).

[2] Erwan Grelier et al., Deep learning and image processing for the automated analysis of thermal events on the first wall and divertor of fusion reactors, Plasma Phys. Control. Fusion 64 104010, 2022.

6. CONCLUSIONS & OUTLOOK

- IR large multi-device annotated dataset
- Semi-supervised learning for weak annotations
- Detection of thermal events for wall protection
- Transfer learning to ITER/DEMO
- Train intelligent agents with reinforcement learning for heat load control (ECRH, strike-line, detachment control) → fast simulators required





ITER synthetic IR dataset

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