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Ministero  
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Italiadomani

PIANO NAZIONALE  
DI RIPRESA E RESILIENZA



Centro Nazionale di Ricerca in HPC,  
Big Data and Quantum Computing

# *Radio U-Net: the convolutional neural network for diffuse radio sources detection*

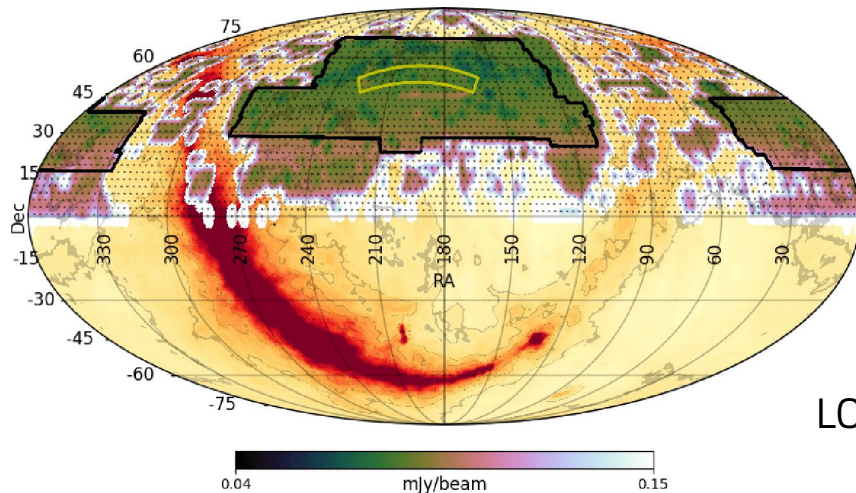
*Chiara Stuardi  
(IRA Bologna)*

*Claudio Gheller, Franco Vazza, Andrea Botteon*

**Spoke 3 General Meeting, Elba 5-9 / 05, 2024**

# Scientific Rationale

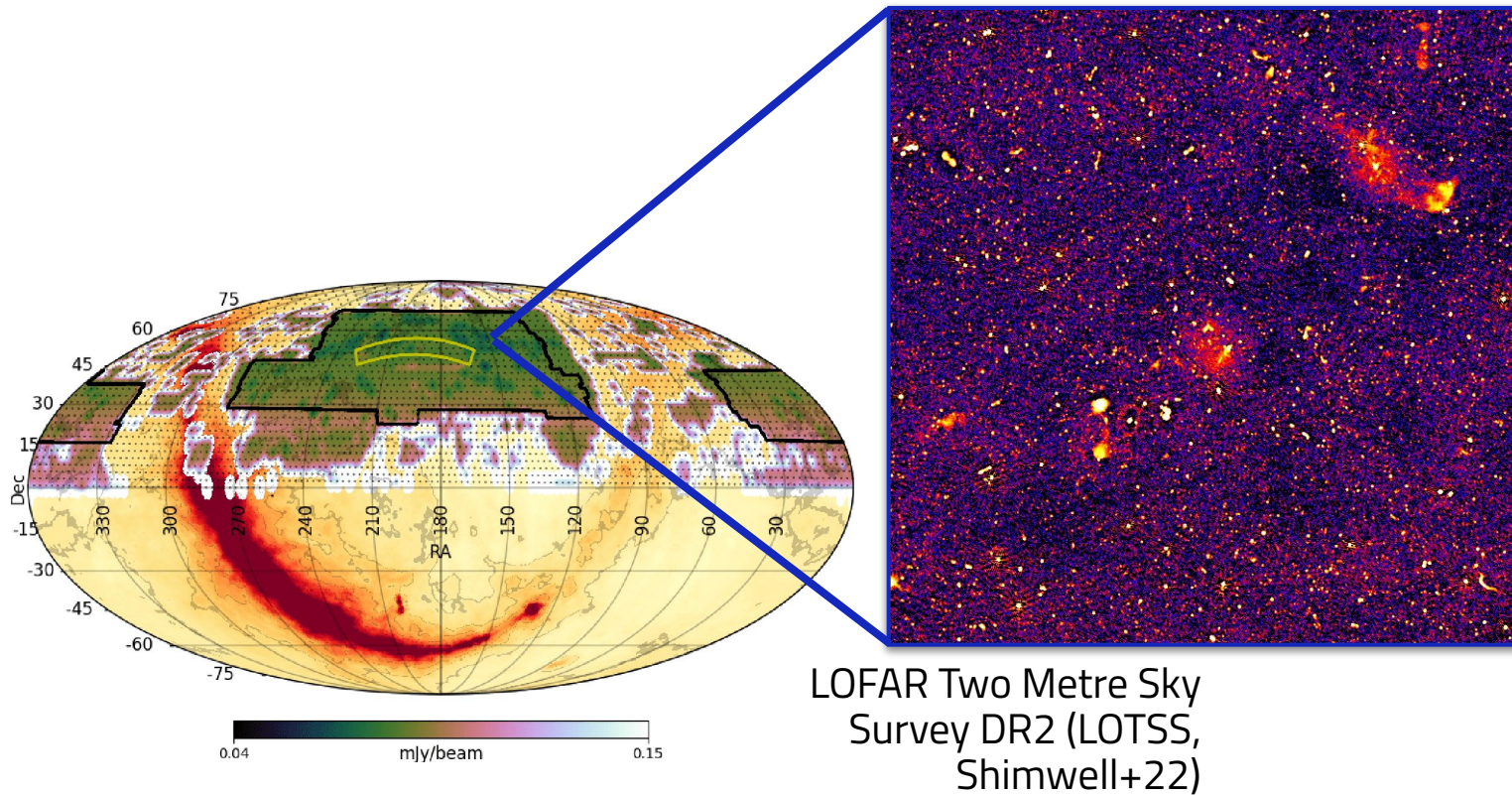
**Current radio surveys are challenging our detection and cataloging strategies  
-> new strategies to minimize human intervention in the data processing**



LOFAR Two Metre Sky  
Survey DR2 (LOTSS,  
Shimwell+22)

# Scientific Rationale

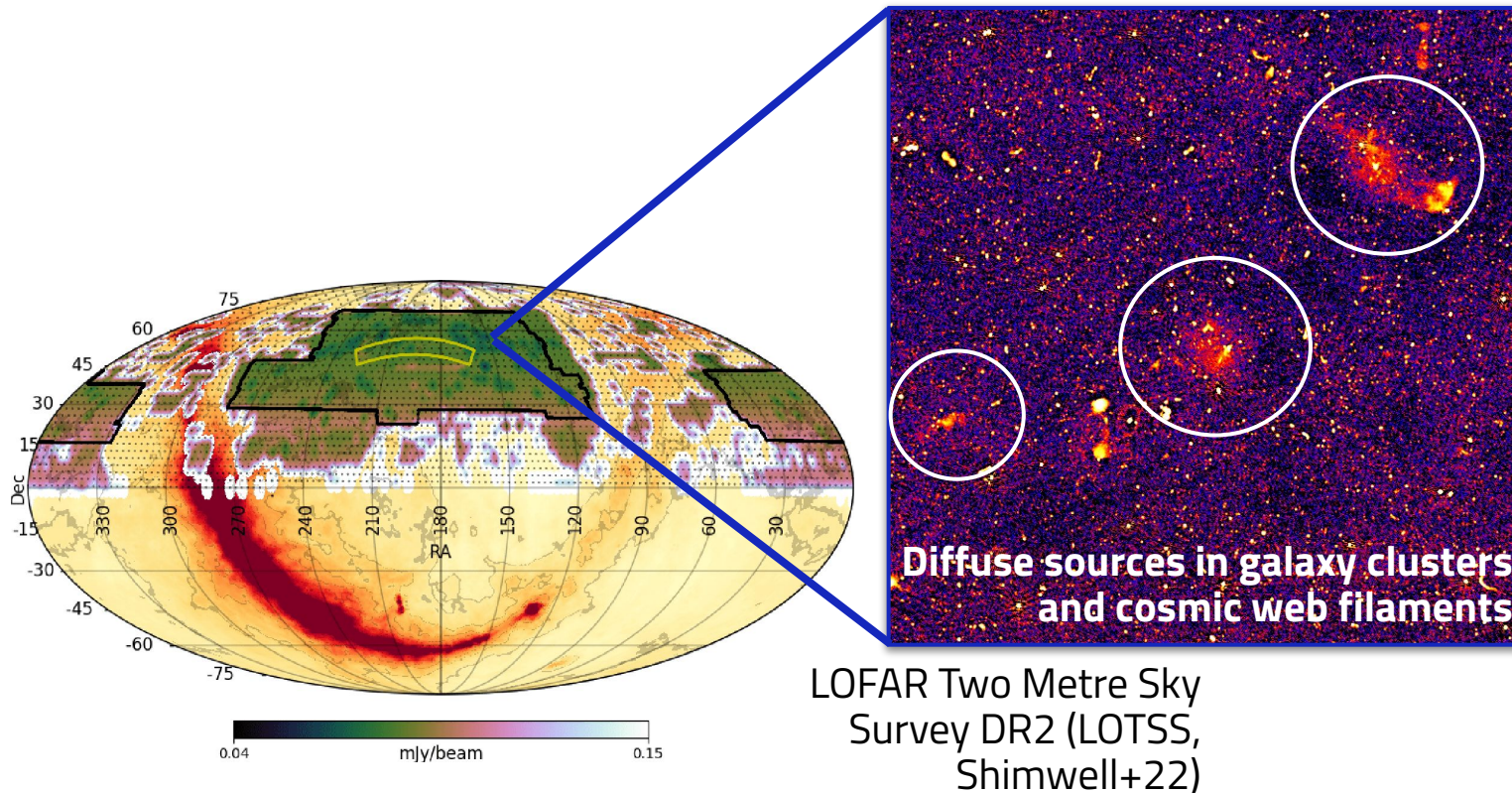
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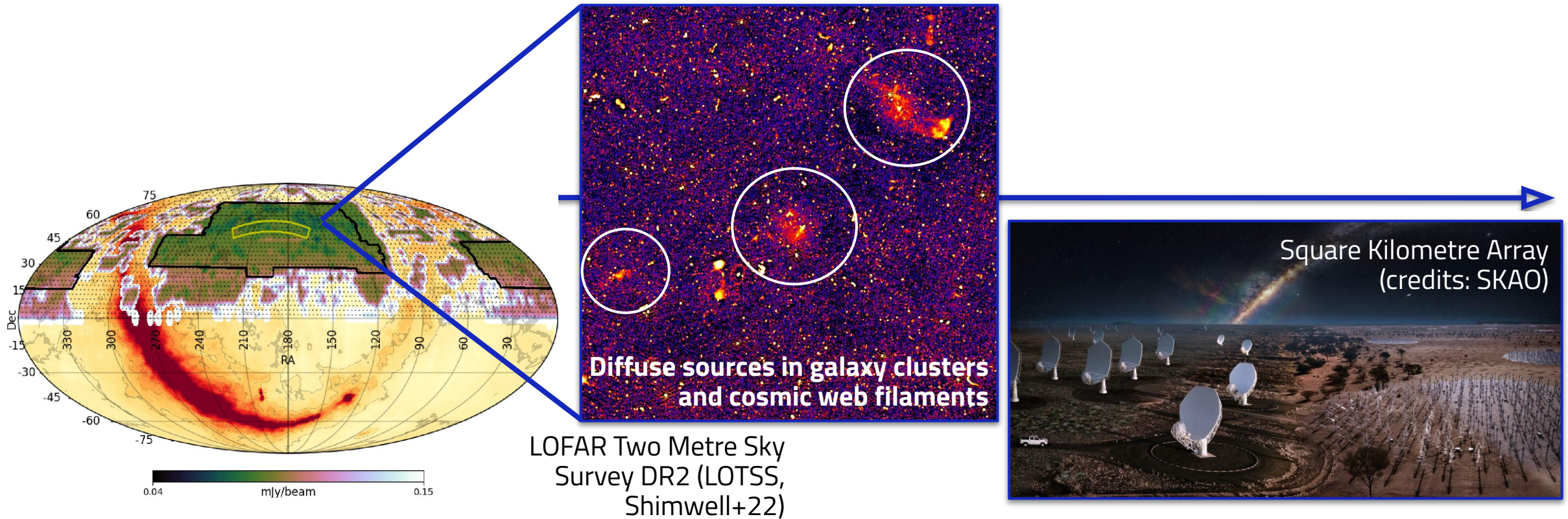
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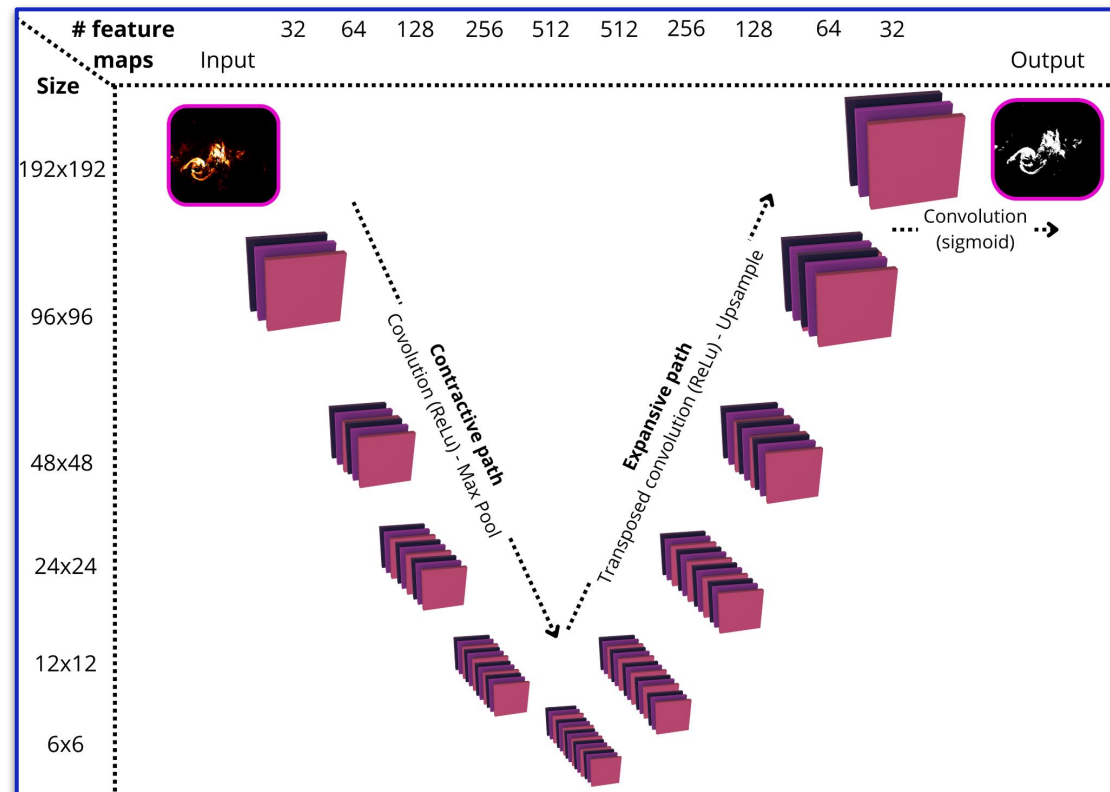
# Scientific Rationale

Current radio surveys are challenging our detection and cataloging strategies  
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# Technical Objectives, Methodologies and Solutions

Development of a Convolutional Neural Network (CNN) to perform the automated segmentation of diffuse radio emission in radio astronomical surveys: Radio U-Net, based on the U-Net architecture.



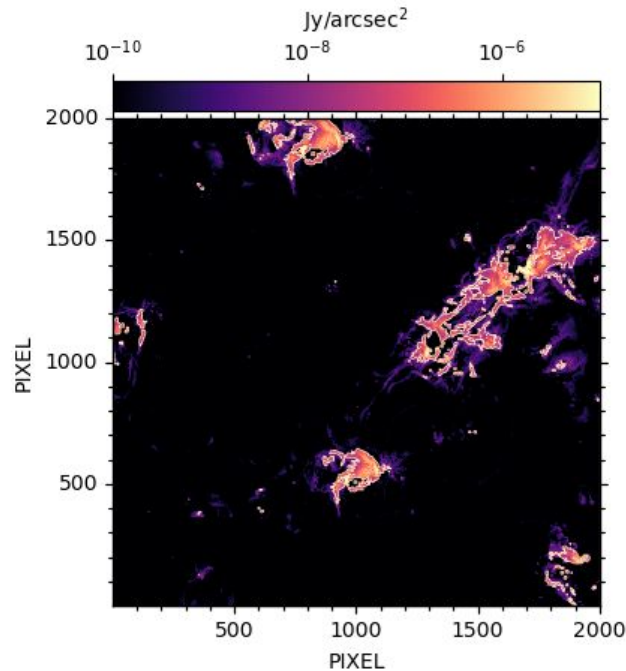
Python code with  
Keras Tensorflow

Scalable from CPU to GPU  
Run on CINECA HPC systems  
(Leonardo)

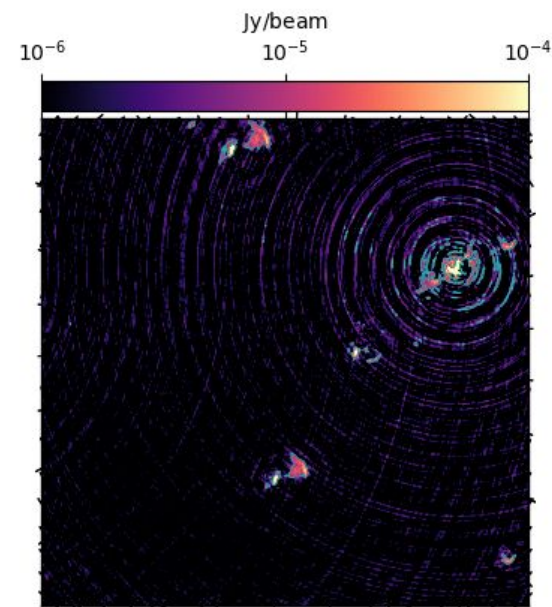
# Technical Objectives, Methodologies and Solutions

**Problem: small number of reference images for the training**

**Solution: train the network on synthetic observations built on cosmological simulations  
(Gheller&Vazza 2022)**



**Sky image - Reference mask**

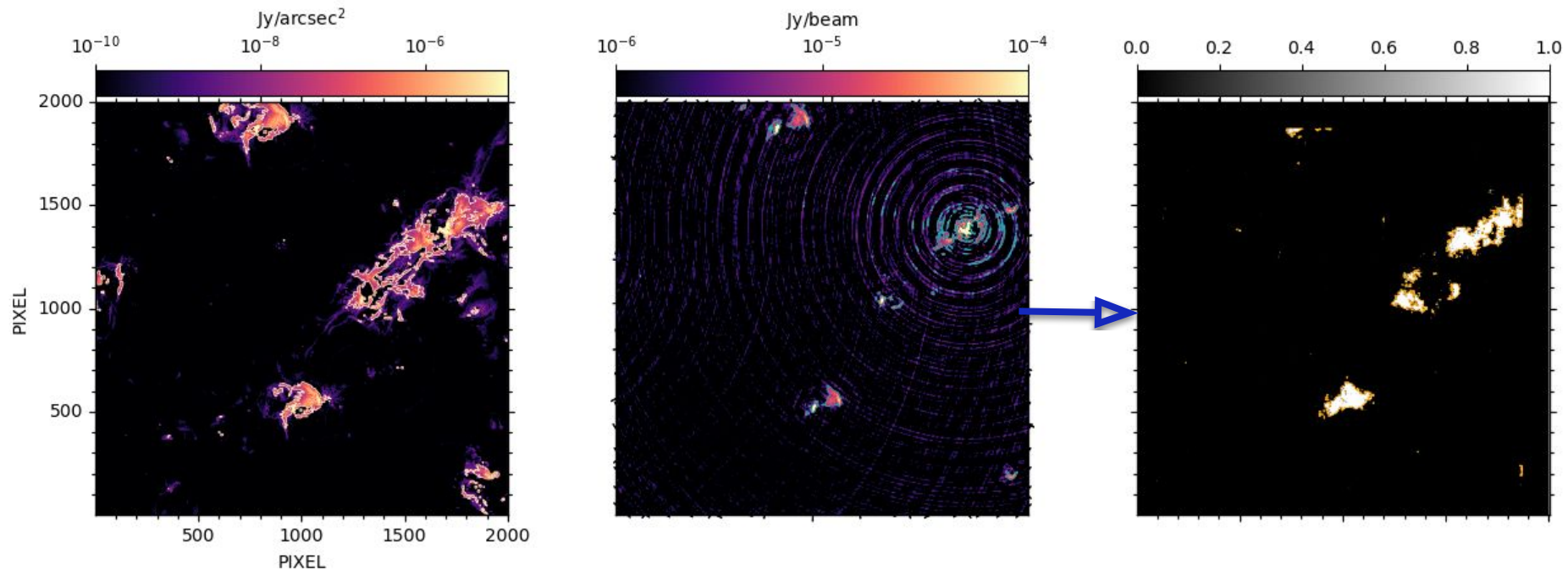


**Clean image - Input**

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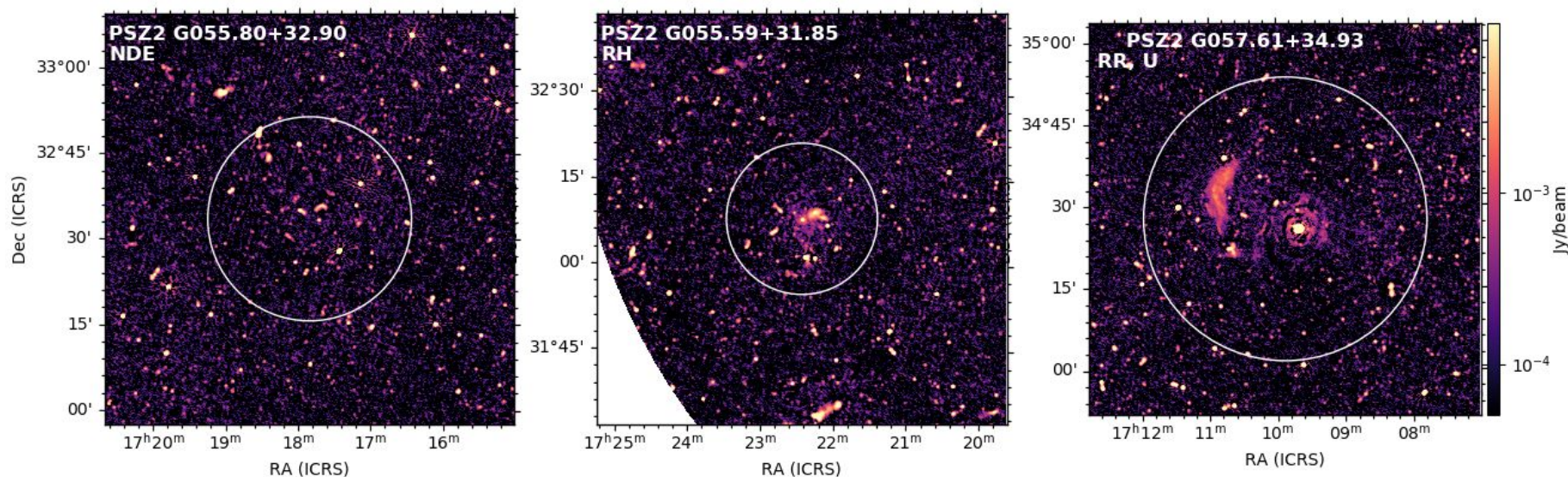
**Clean image - Input**

**Output probability**



# Technical Objectives, Methodologies and Solutions

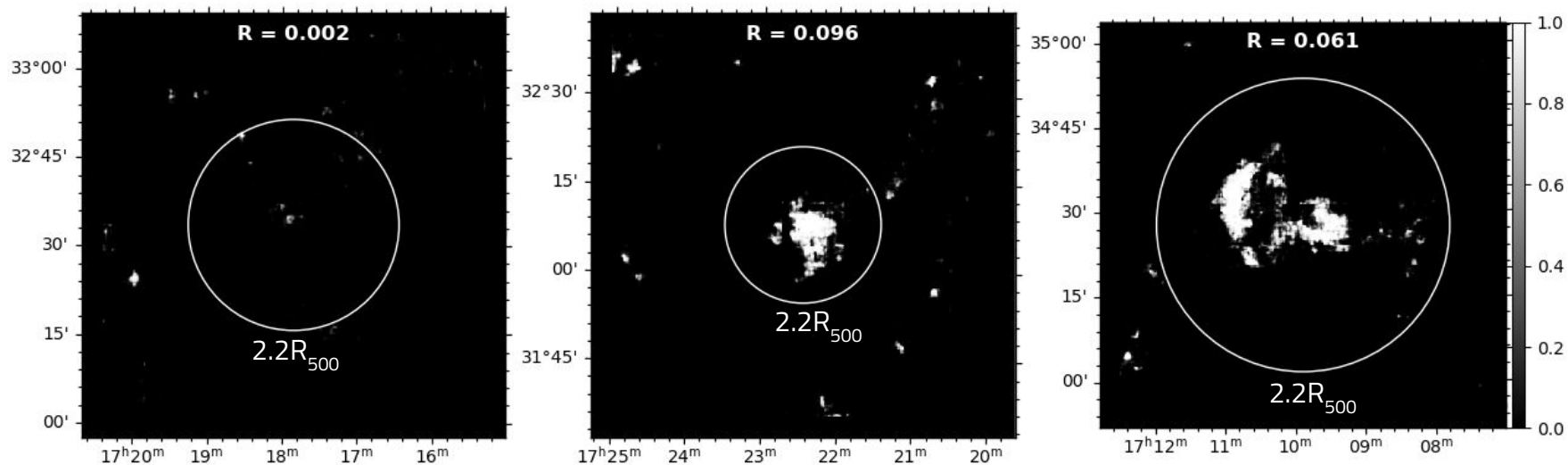
Application: apply Radio U-Net on LOFAR Two Metre Sky Survey Data  
-> PSZ2-LotSS2 sample of 309 galaxy clusters (Botteon+ 2023)



Images directly downloaded from the survey archive,  
without any tailored processing

# Technical Objectives, Methodologies and Solutions

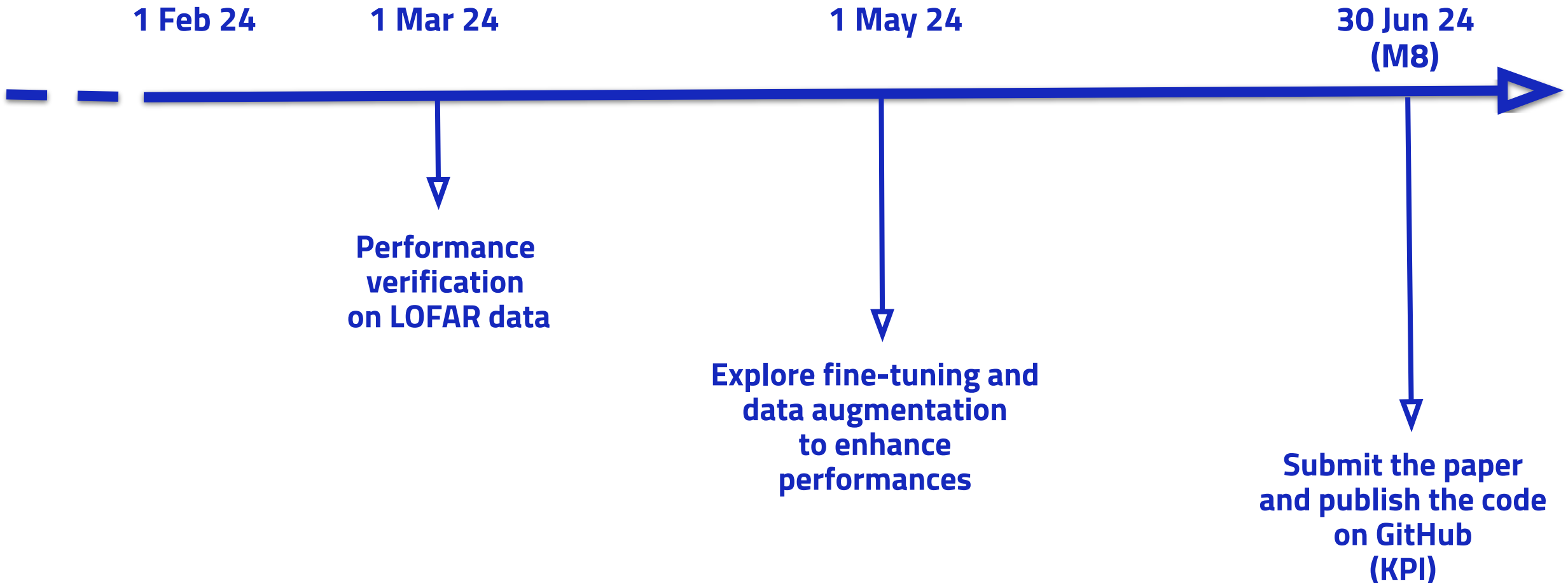
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Detection ratio

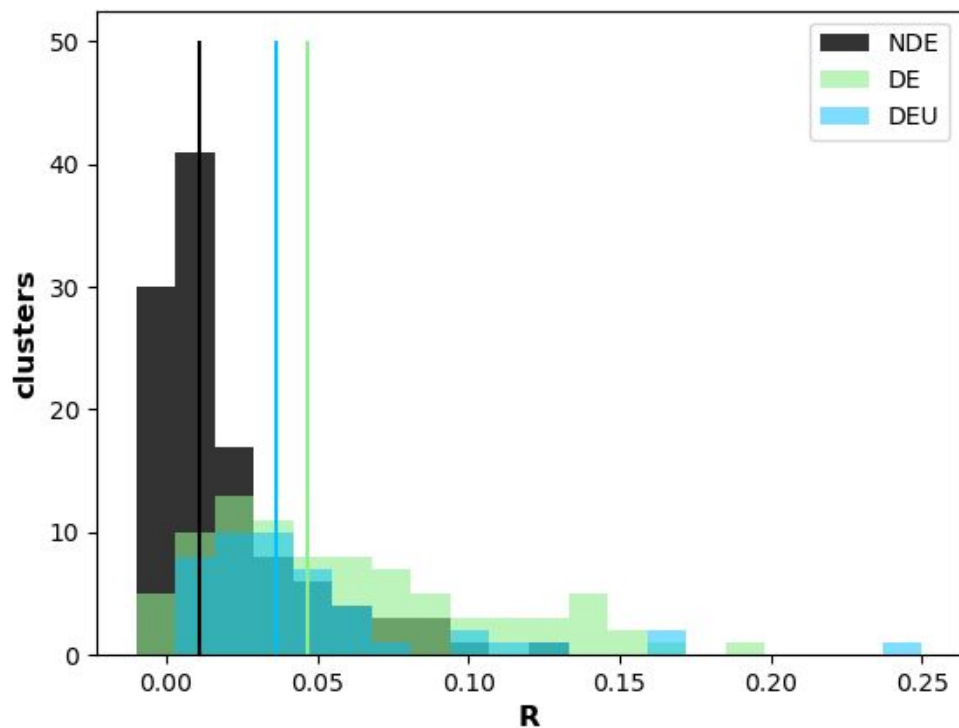
$$R = (\text{sum probability/number of pixels})_{2.2R_{500}}$$

# Timescale, Milestones and KPIs



# Accomplished Work, Results

## Performance verification on LOFAR data

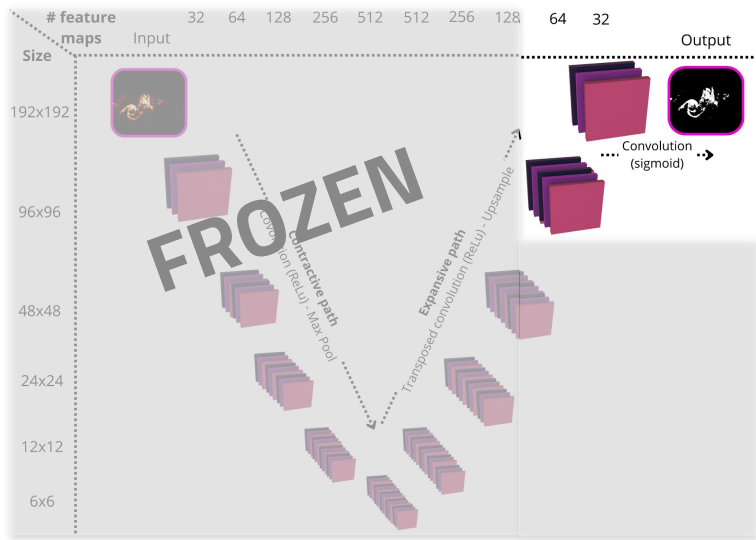


	non-detected	detected	uncertain	
	NDE	DE	DEU	tot
Initial test set	114	85	47	246
True <sub>R=0.015</sub>	71 (62%)	70 (82%)	39 (83%)	180 (73%)

**Result: detection accuracy 73%** (how many are correctly classified?)  
**precision 72%** (how many detections are true?)  
**false negative 17%** (how many sources are missed?)

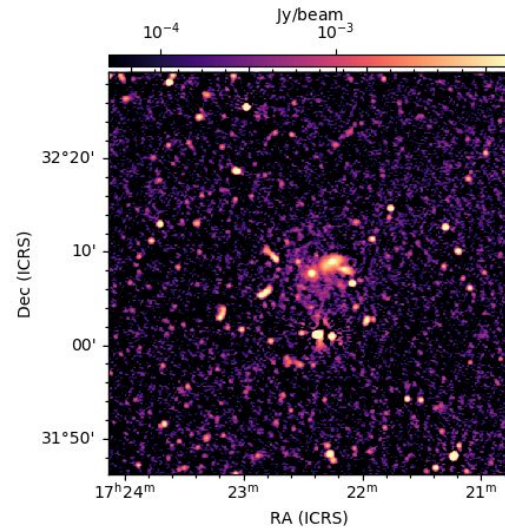
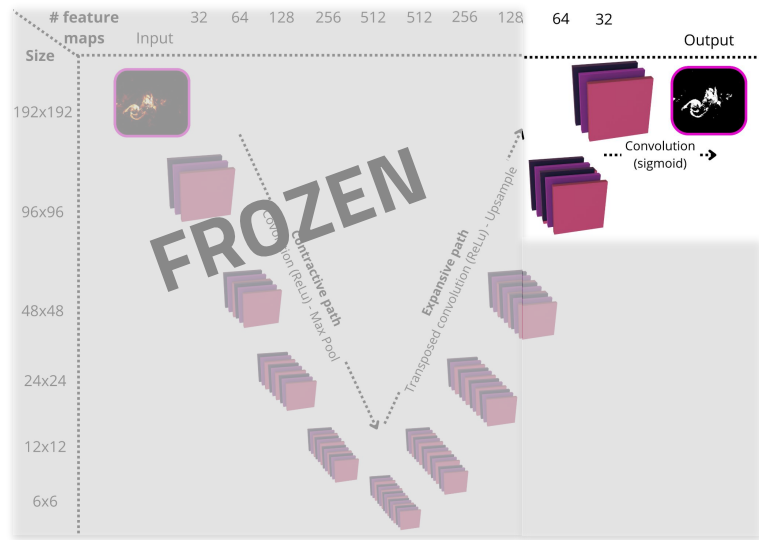
# Accomplished Work, Results

## Explore fine-tuning using LOFAR data

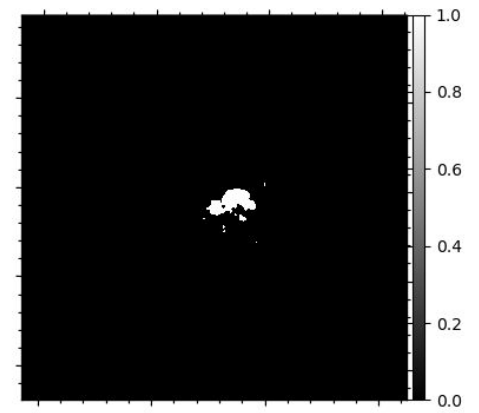
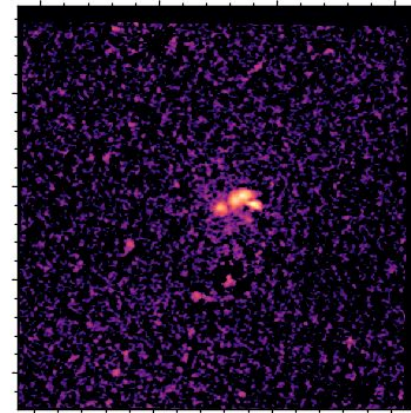


# Accomplished Work, Results

## Explore fine-tuning using LOFAR data



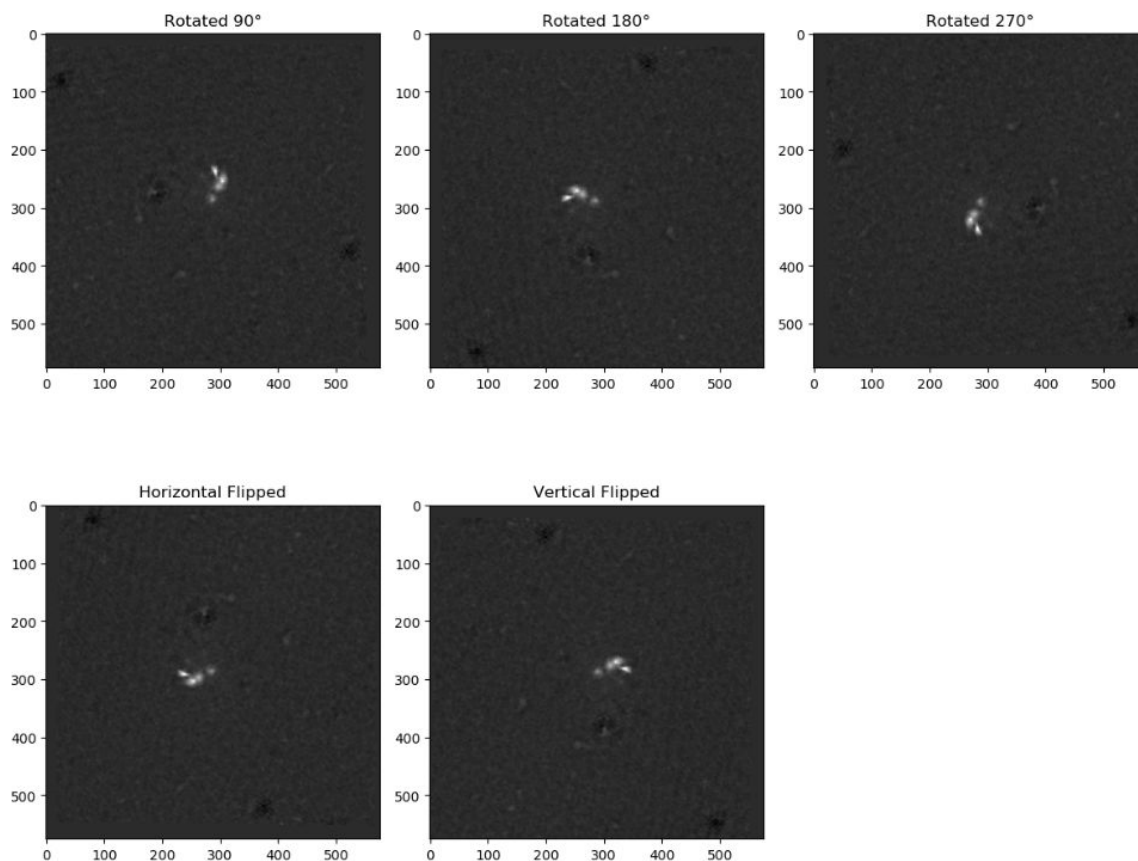
Input image (DE)



Reference mask

# Accomplished Work, Results

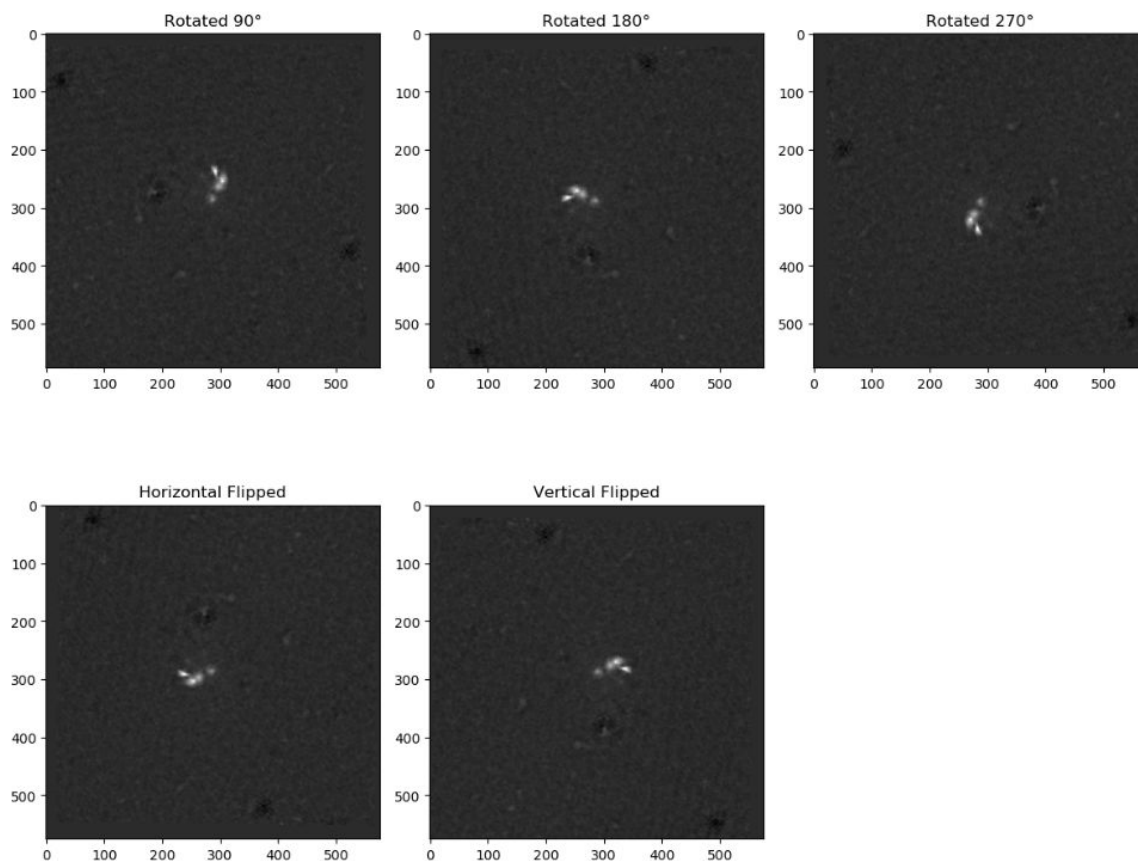
Explore fine-tuning using LOFAR data and data augmentation.



Test of several hyperparameters

# Accomplished Work, Results

Explore fine-tuning using LOFAR data and data augmentation.



Test of several hyperparameters

	NDE	DEU	tot
Test set	54	47	108
$\text{True}_{\text{original}}R=0.026$	40 (74%)	34 (72%)	71%
$\text{True}_{\text{ft}}R=0.00084$	31 (57%)	42 (89%)	71%
$\text{True}_{\text{ft-da}}R=0.00081$	33 (61%)	41 (87%)	72%

**Result: fine-tuning reduces false negative rate but does not increase the overall accuracy**



## Next Steps and Expected Results

30 Jun 24  
(M8)

M9

M10



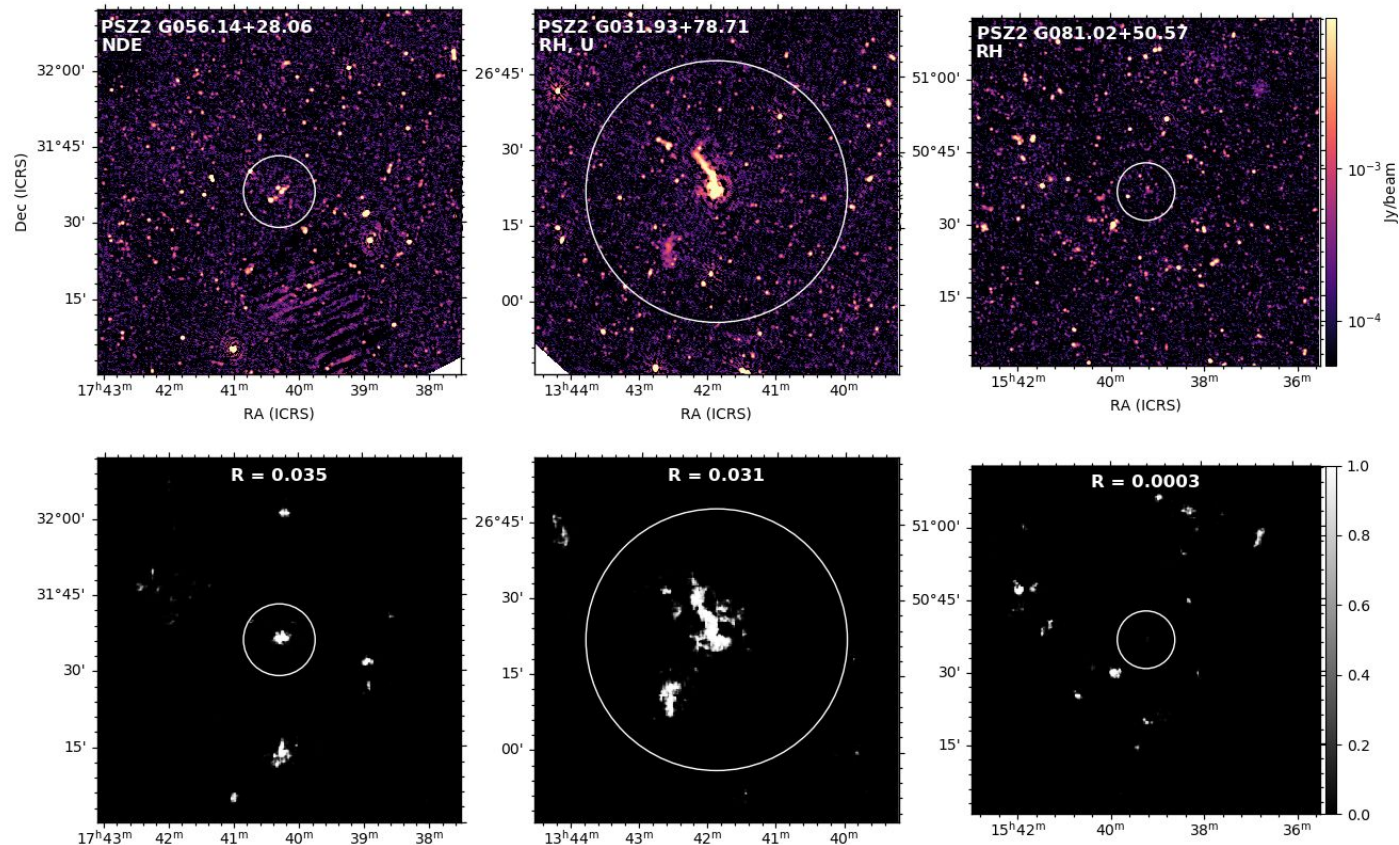
**Finalize and submit the paper**  
**Make the code publicly available**

### Further developments

- **Include radio galaxies in synthetic observations for the training**
- **Apply to other radio surveys**
- **Add a classification layer to the network**

# Accomplished Work, Results

## Performance verification on LOFAR data



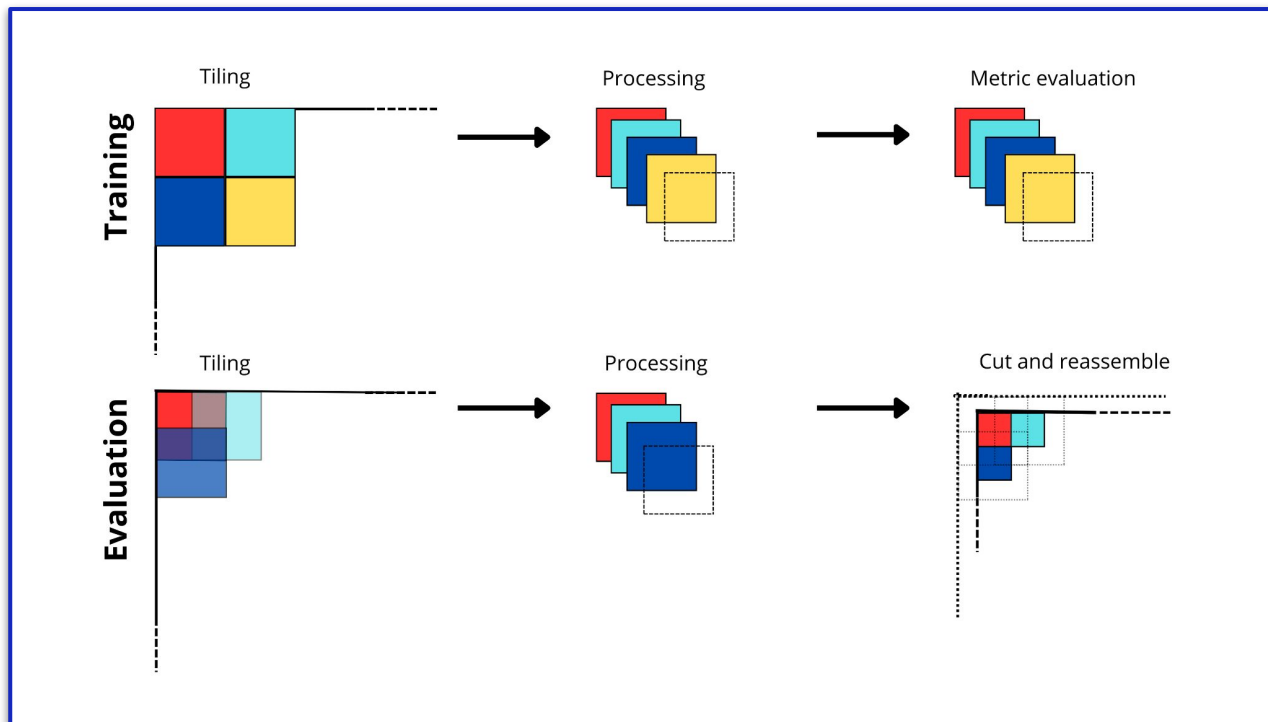
False positive mainly caused by extended and/or grouped radio galaxies which are not present in simulations

# Technical Objectives, Methodologies and Solutions

**Problem: small number of labelled images for the training**

**Solution: train the network on synthetic observations built on cosmological simulations**

**+ tiling strategy: increase the number of individual images and exploit parallel processing**



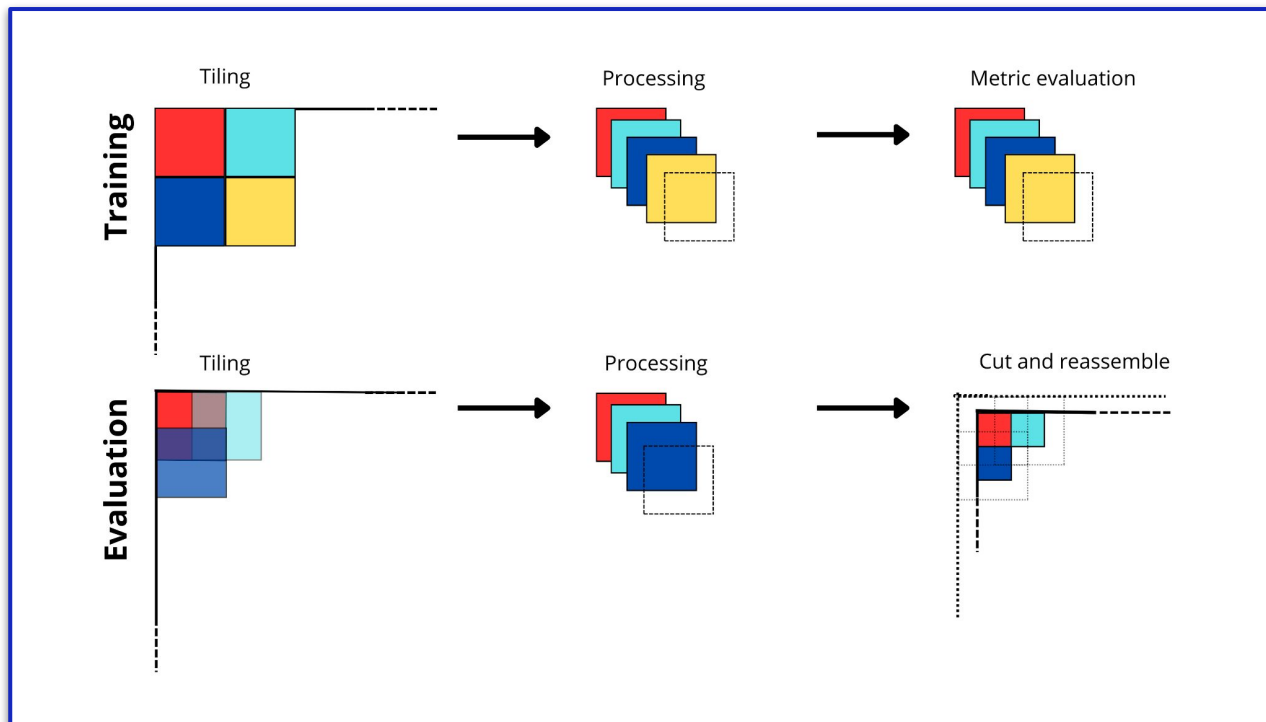
**1000 images 2000x2000**  
**100'000 tiles 192x192**

# Technical Objectives, Methodologies and Solutions

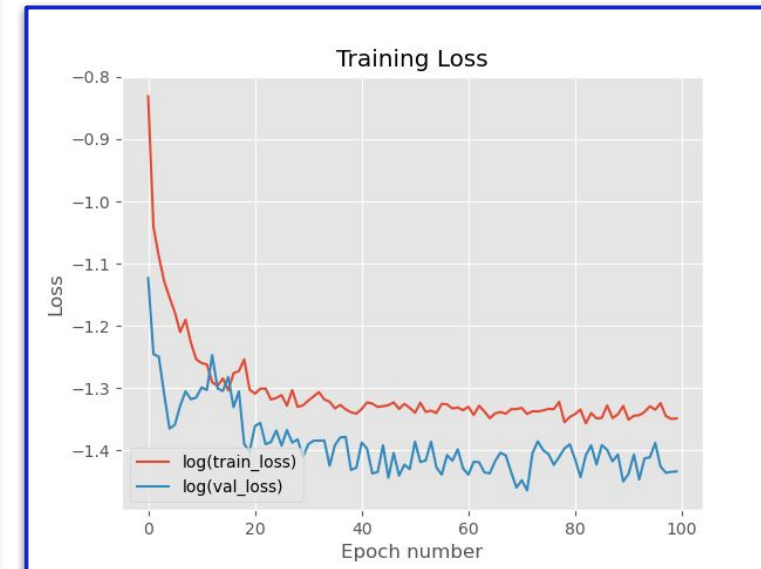
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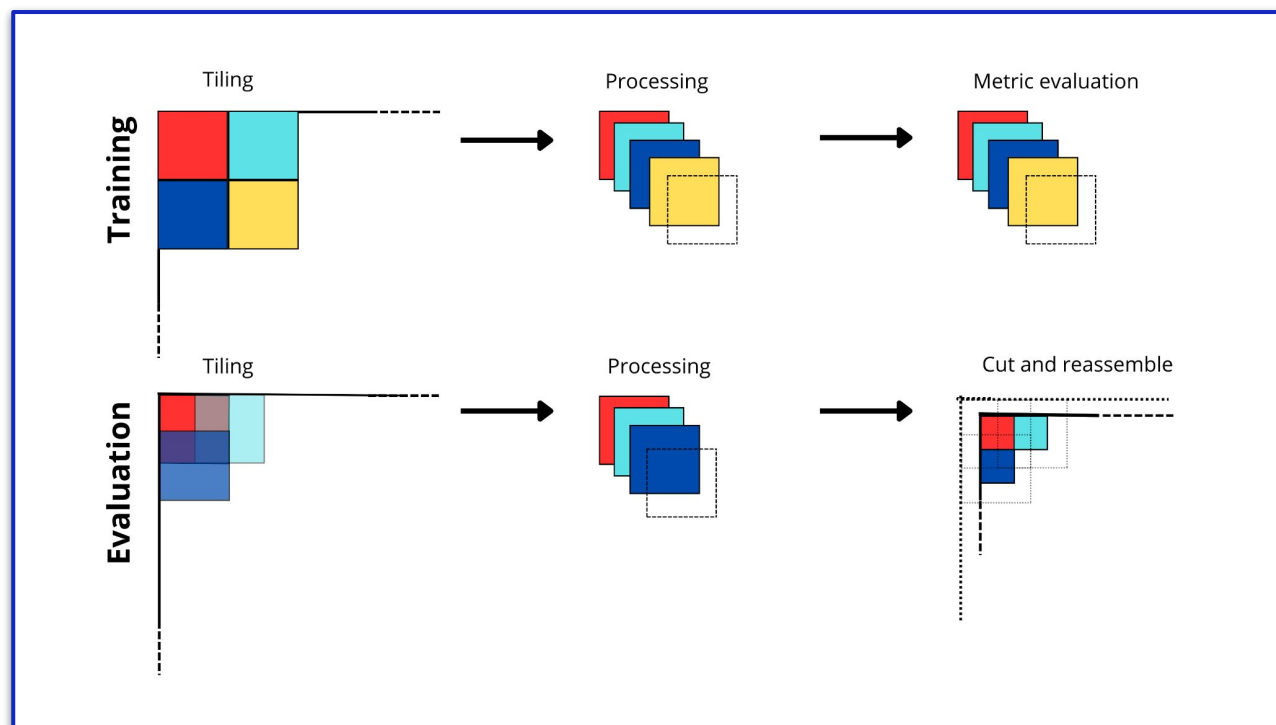


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**Solving boundary effects by cropping overlapped tiles when re-assembling the output mask**