Neural Networks for SAR Oil Spill Detection

Applied Data Science Project

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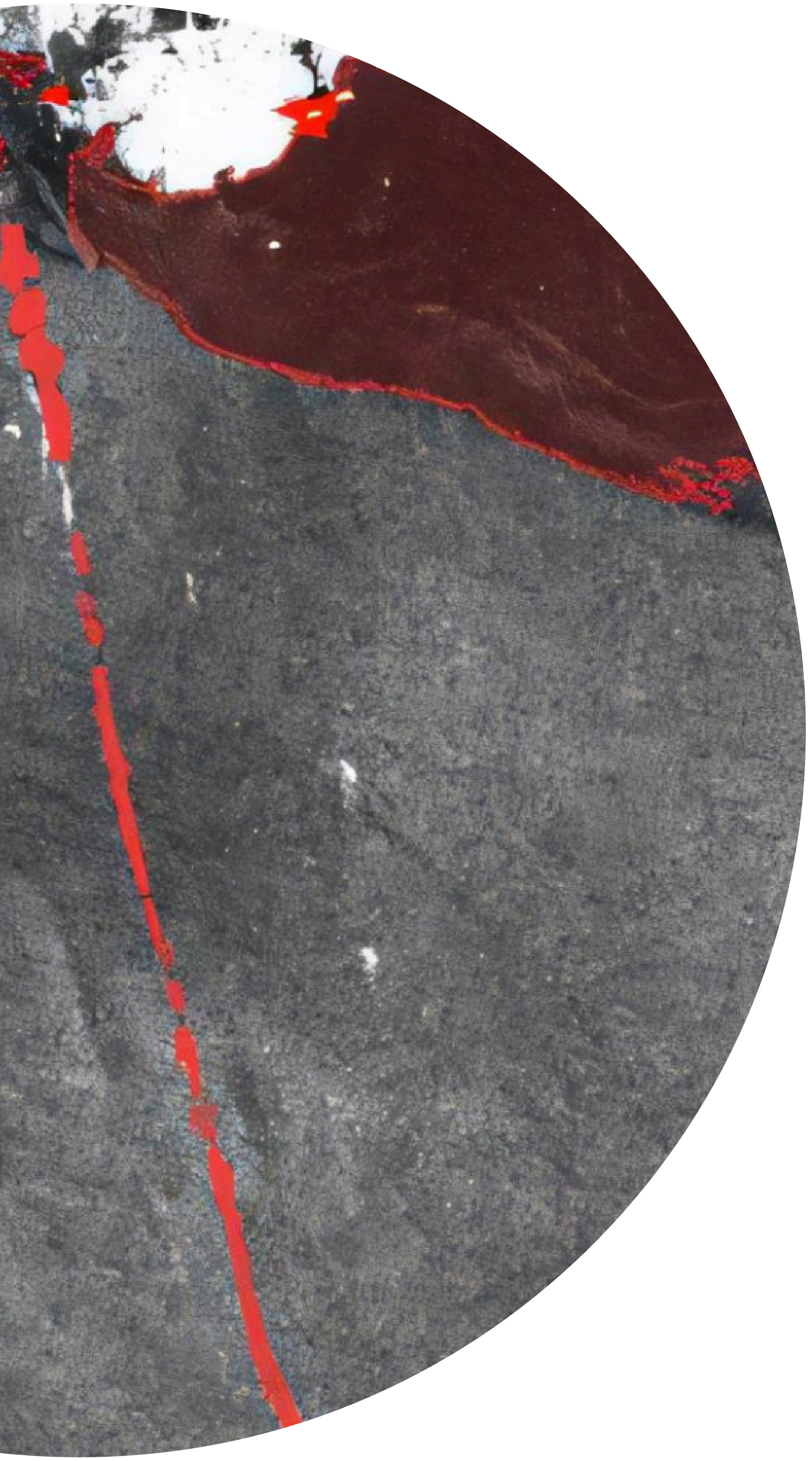
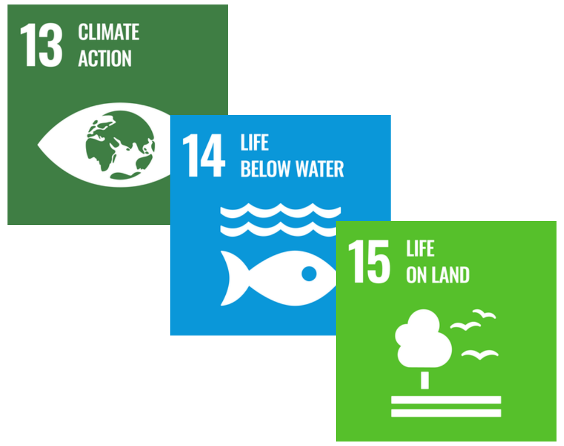
VALUE PROPOSITION



Oil spills pose a significant threat to marine ecosystems

Main goal of the project: developing models to enable continuous **monitoring** and precise **detection** of oil spills



Environmental Impact

Faster response times can significantly reduce the environmental damage caused by oil spills

Response Efficiency

Early detection and response help contain the spill, reducing the resources needed to manage its spread

Scalability

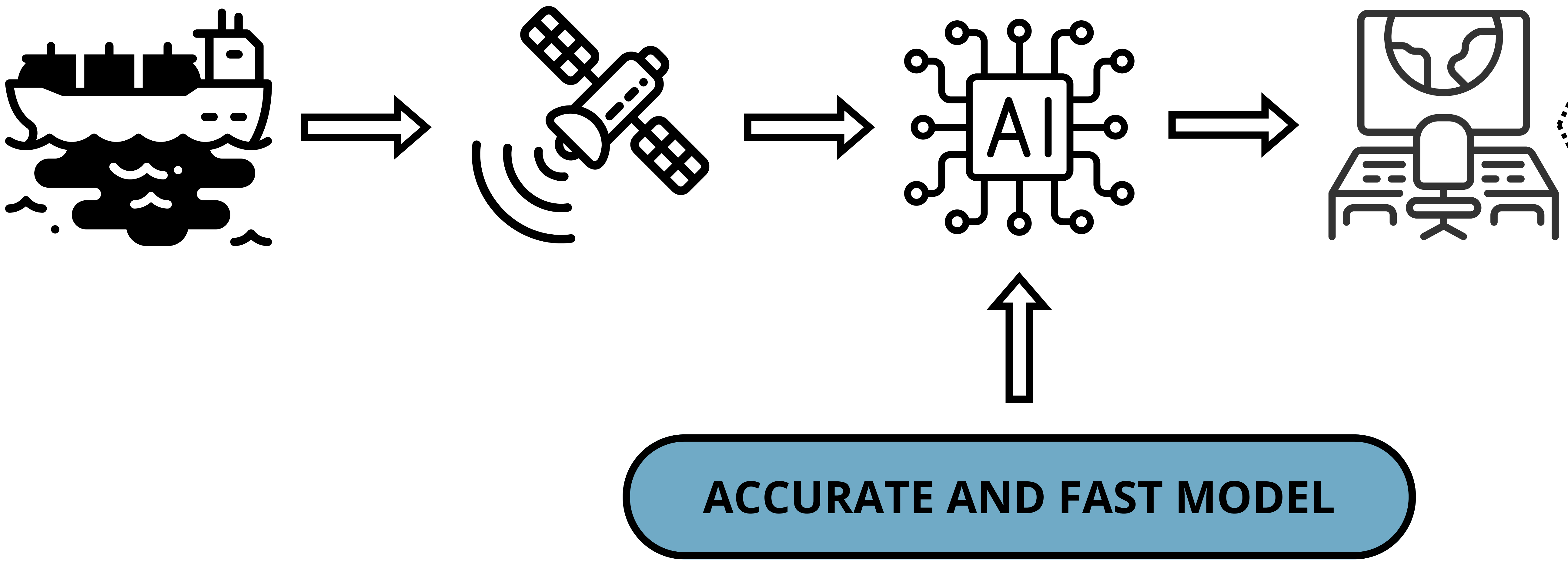
The developed system can be applied to any marine environment with SAR imaging availability, offering potential for global deployment


RESEARCH
QUESTIONS

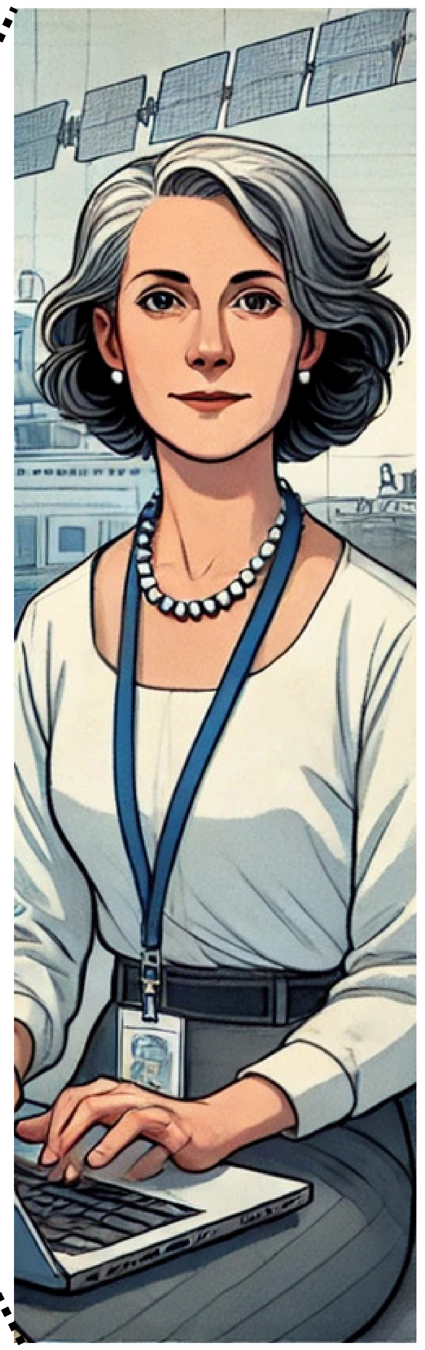
OBJECTIVE

Current monitoring systems, such as CleanSeaNet deployed by the European Union, lack AI-based solutions for detecting and pinpointing oil spills.

Our objective is to investigate the potential usage of Segmentation models to improve both the effectiveness and the responsiveness of the monitoring systems.



Maria
Environmental Supervisor



ACCURACY

Which ML model provides the best performance for oil spill segmentation in SAR images (IoU)?

- How does IoU performance vary across different classes?
- Are certain models better at distinguishing ships, oil spills, or look-alikes?

TRAINING TECHNIQUES

What kind of techniques on the dataset influence the detection of oil spills?

- Which techniques lead to more effective oil spill detection?
- Which strategy help the model achieve faster convergence?

COMPUTATIONAL EFFICIENCY

Balancing accuracy and efficiency:

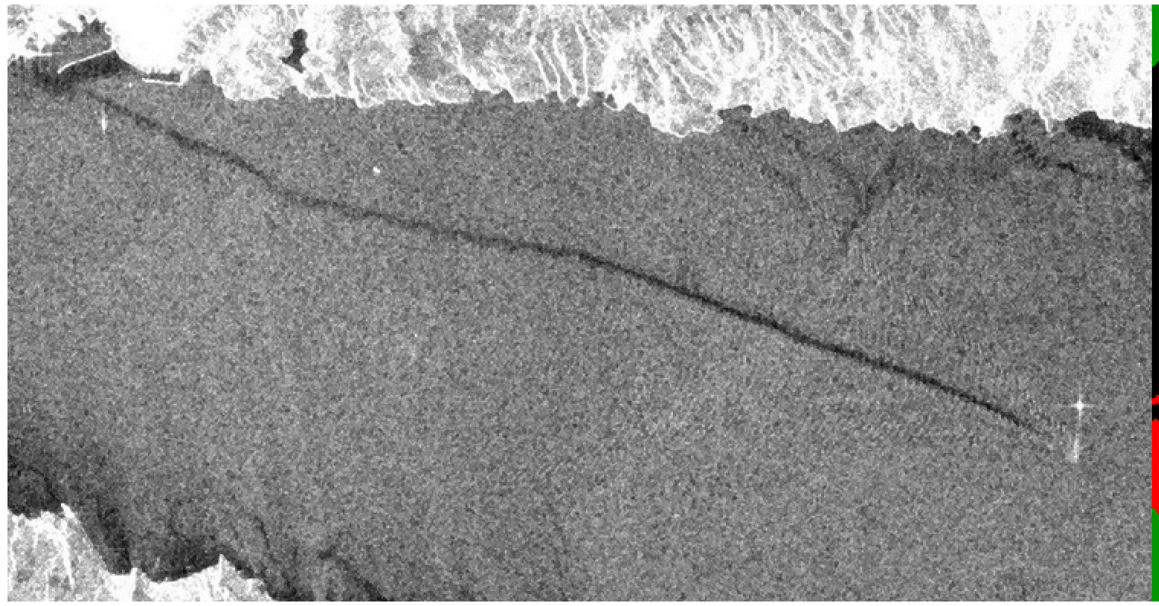
- What are the trade-offs?
- Can lightweight models achieve competitive accuracy?

DATASET EXPLORATION

Images are taken by the ESA Satellite Sentinel-1

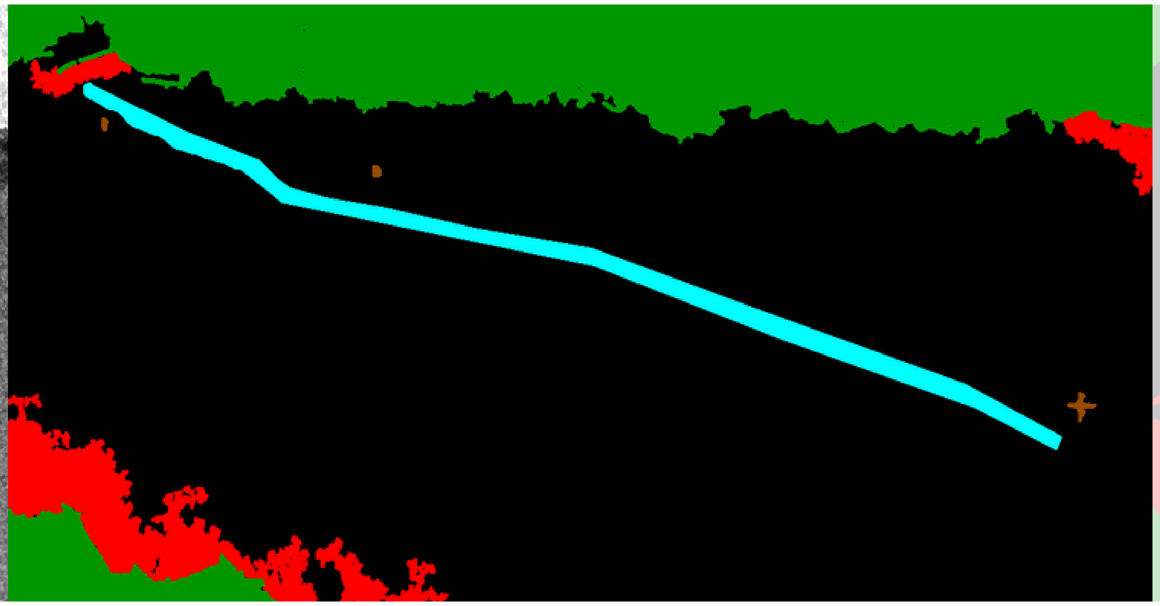
All images have dimensions *1250 x 650*

Patches of dimension *320 x 320* are fed to models



Original SAR image

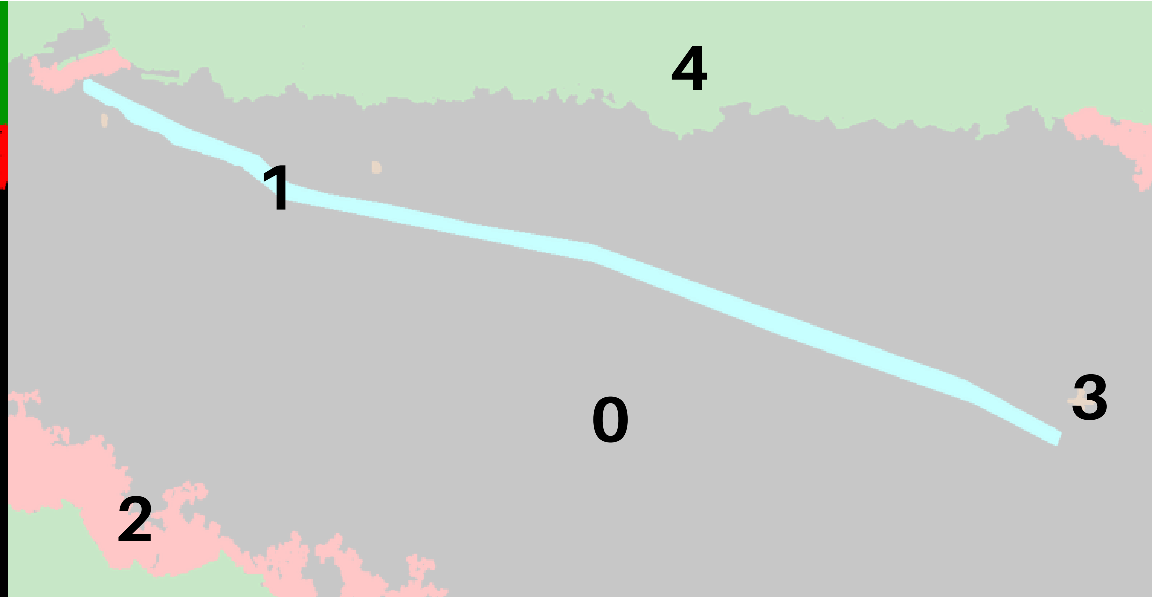
3 greyscale identical channels



Ground truth mask

3 rgb channels

- Sea Surface
- Oil Spill
- Look-alike
- Ship
- Land



Explicit labels mask

1 label channel

0	Sea Surface
1	Oil Spill
2	Look-alike
3	Ship
4	Land

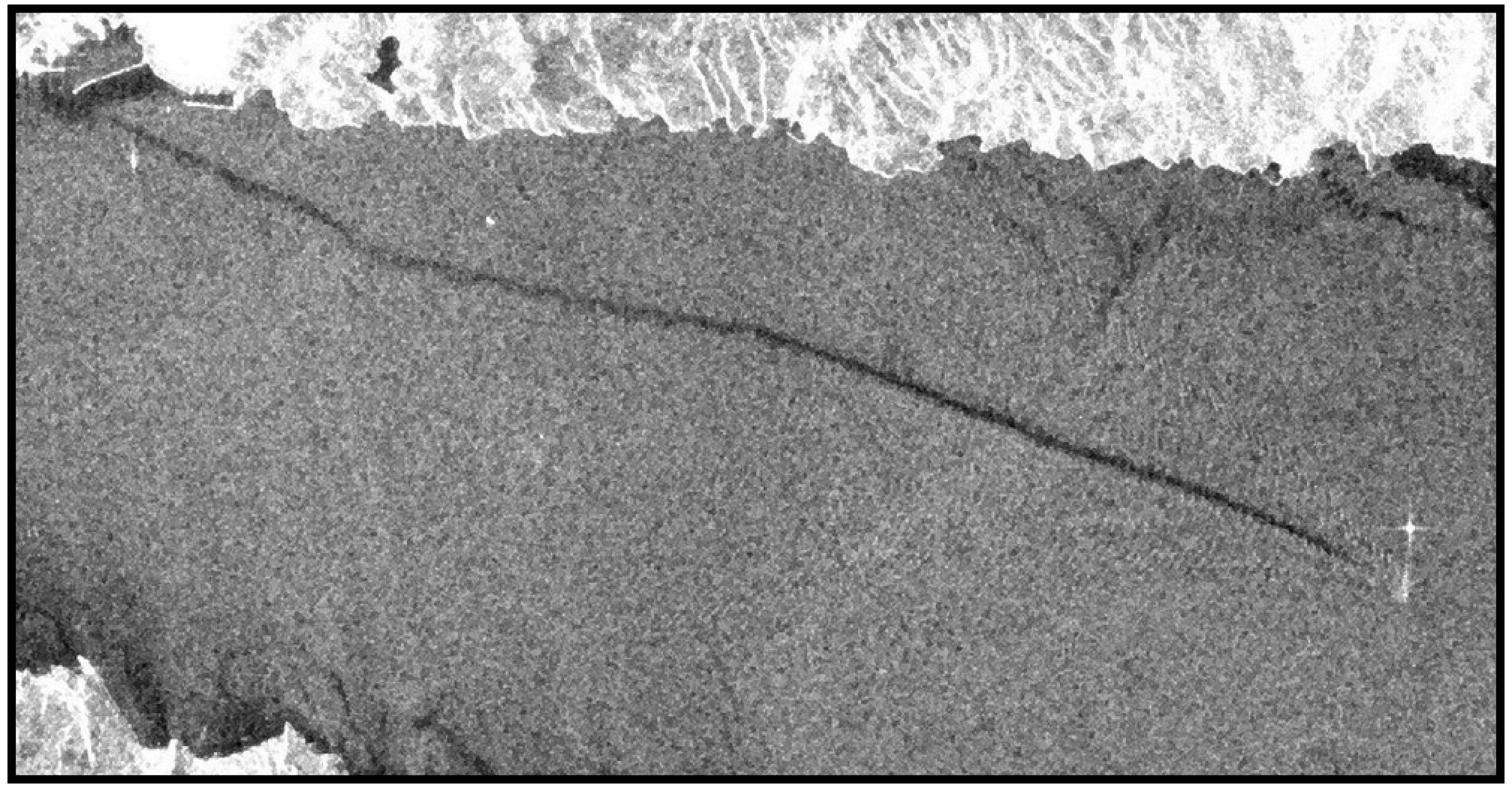
DATA PREPROCESSING

BASELINE AUGMENTATIONS

Starting from the original image, the applied transformations are:

- **Random resize**
  with a scale from *0.5x* to *1.5x*
- ***320x320* Crop**
- **Horizontal Flip**
  with a probability of *50%*
- **Vertical Flip**
  with a probability of *50%*

Original Image

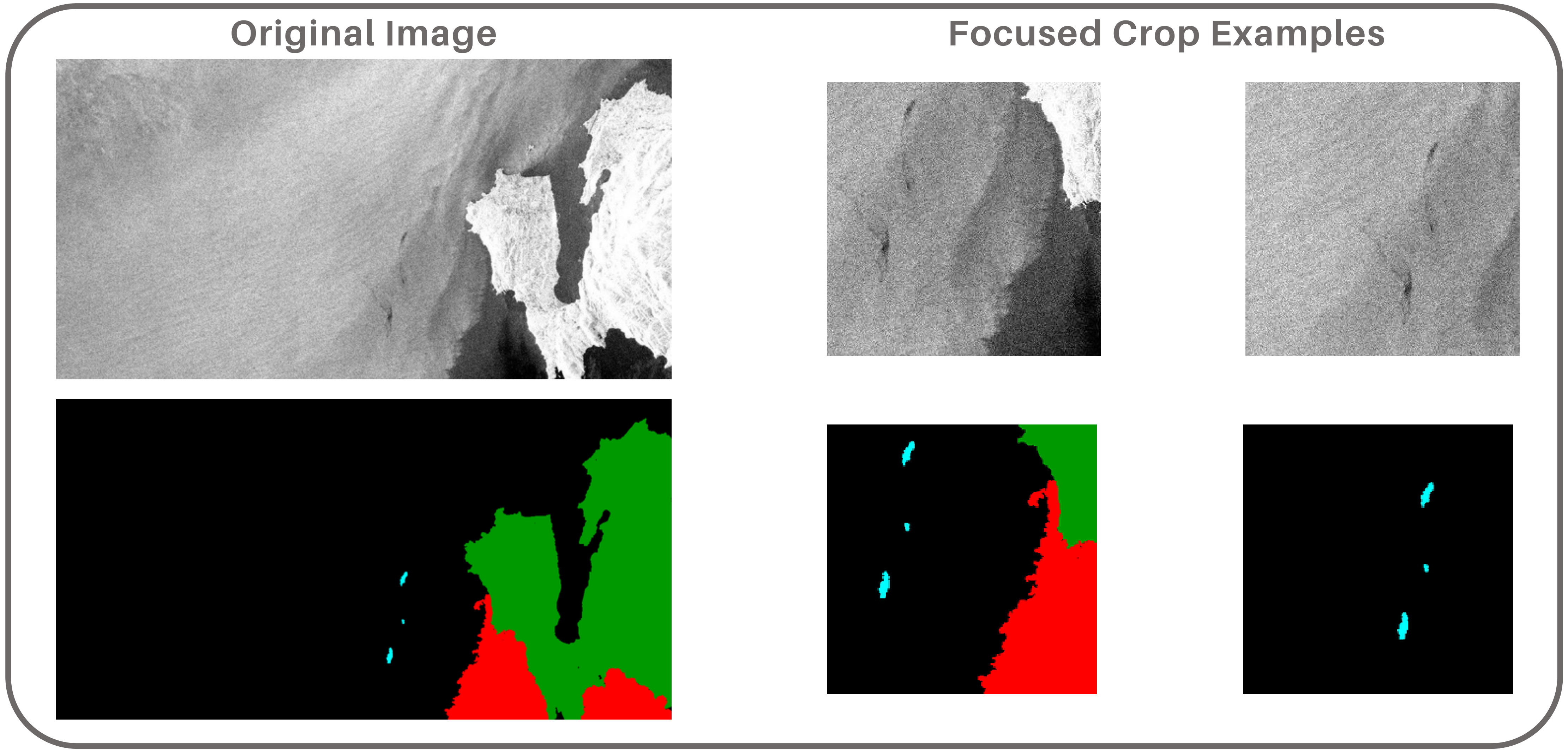


Augmented Image

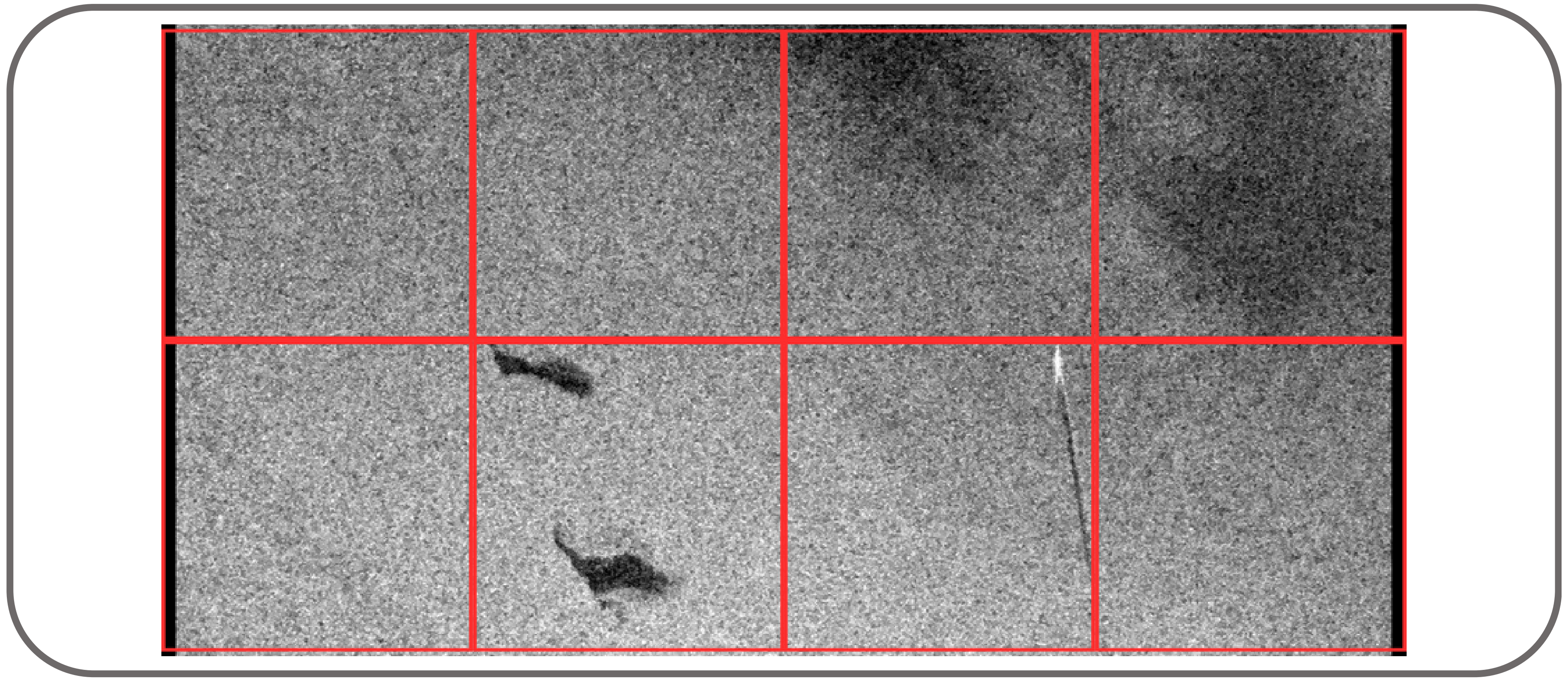
Augmented Mask

PROPOSED TRAINING TECHNIQUES

Focused Crop on Oil Spill

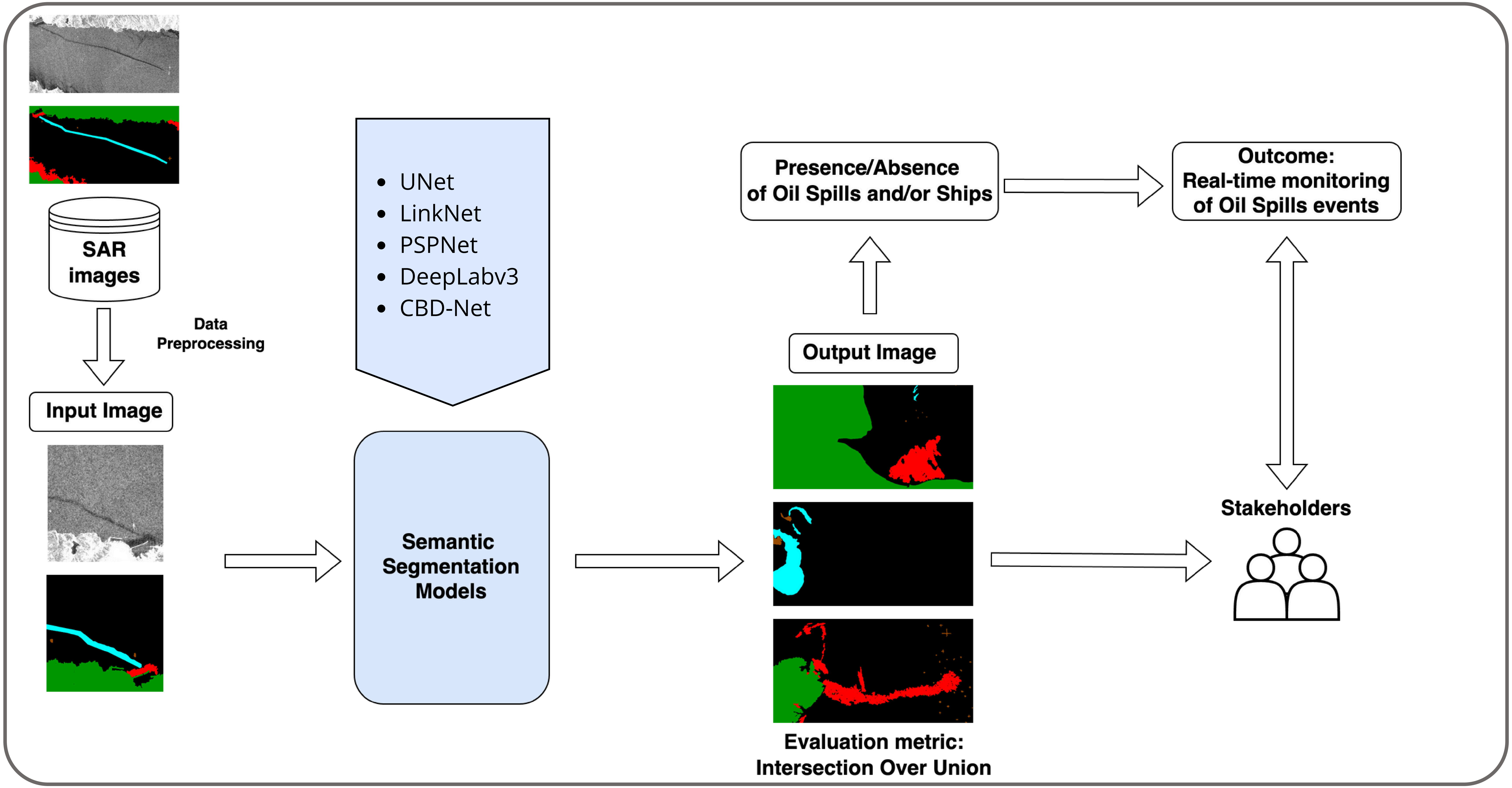


Sliding window Crop



IMPLEMENTATION & TRAINING

GENERAL OVERVIEW



TRAINING METHOD

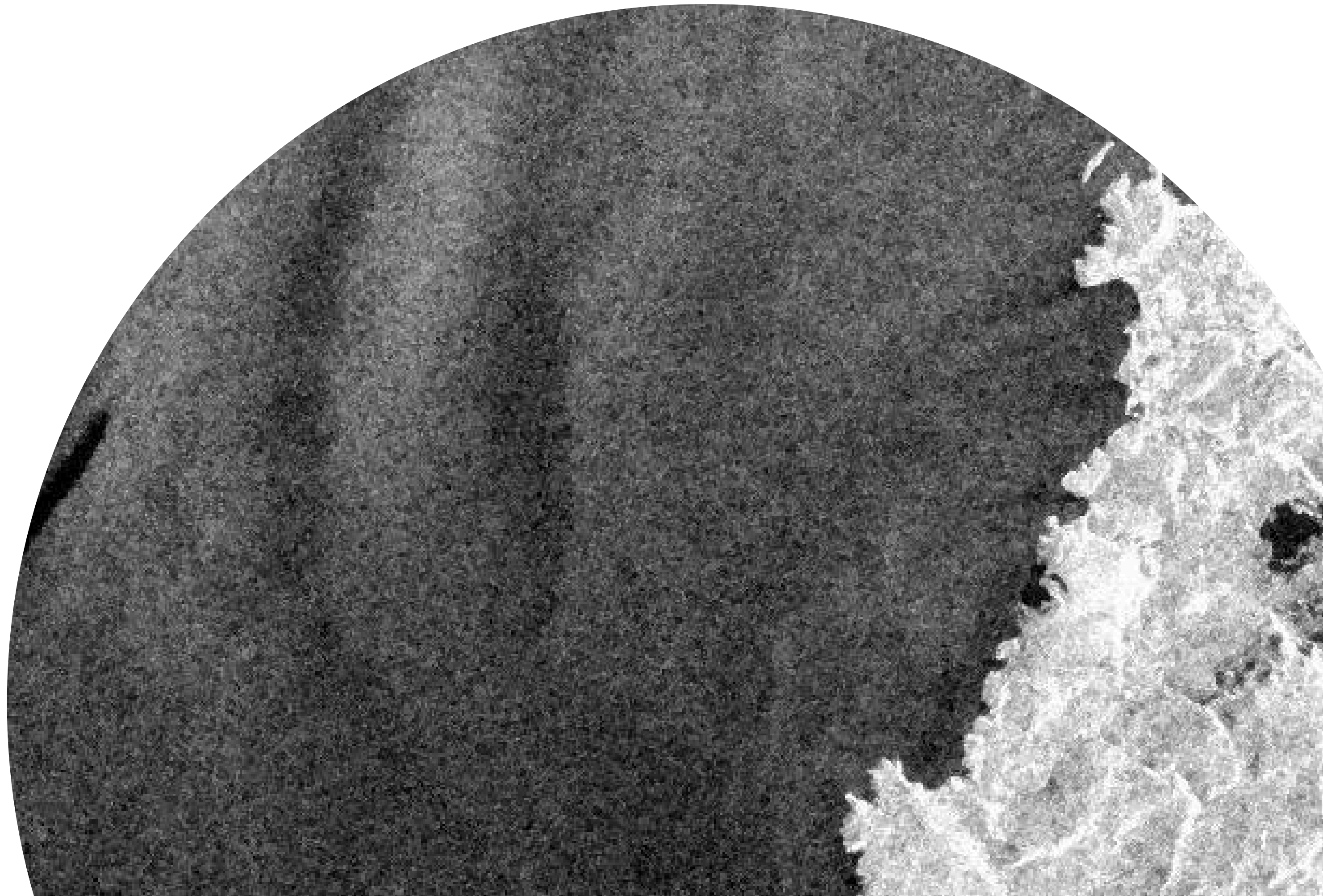
- **Model Details:**

Model	Learning rate	Parameters	Size (MB)
U-Net	0.0001	51.5M	541.67
LinkNet	0.00005	50.2M	539.74
PSPNet	0.0001	43.3M	168.76
DeepLabv3	0.0001	4.7M	49.88
CBD-Net	0.0001	38.8M	409.99

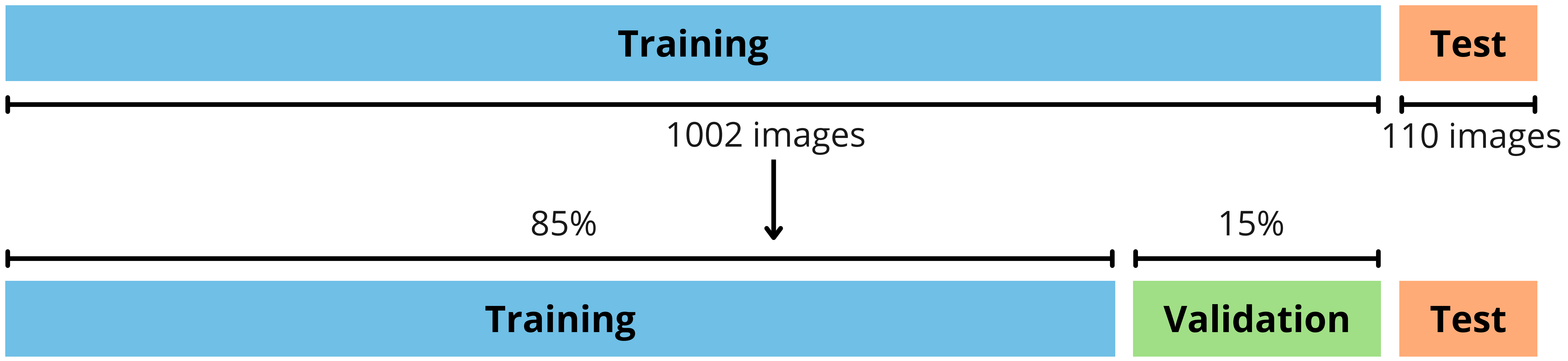
- **Training framework:**

We chose PyTorch Lightning for its modular workflow, which simplifies data handling, training, and testing, ensuring efficient and organized development.

PyTorch Lightning



DATASET HANDLING



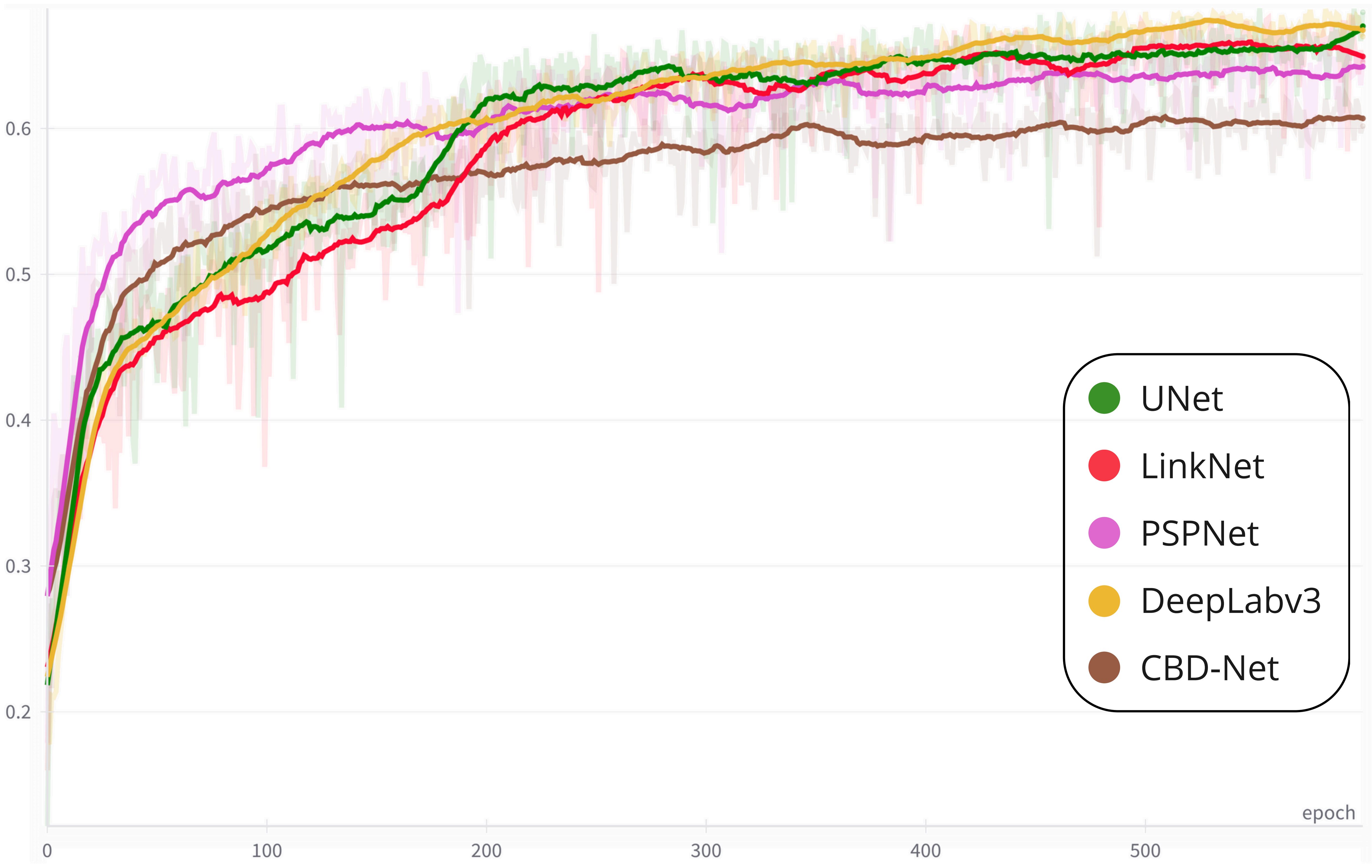
Dataset imbalance

We deal with an imbalanced dataset. To account for it, we applied this weighting scheme to the loss function of the trained models:

Class	Pixels	Loss Weight
Sea Surface	797.7M	1
Oil Spill	9.1M	2
Look-alike	50.4M	1
Ships	0.3M	4
Land	45.7M	1

EXPERIMENT & RESULTS

TRAINING COMPARISON

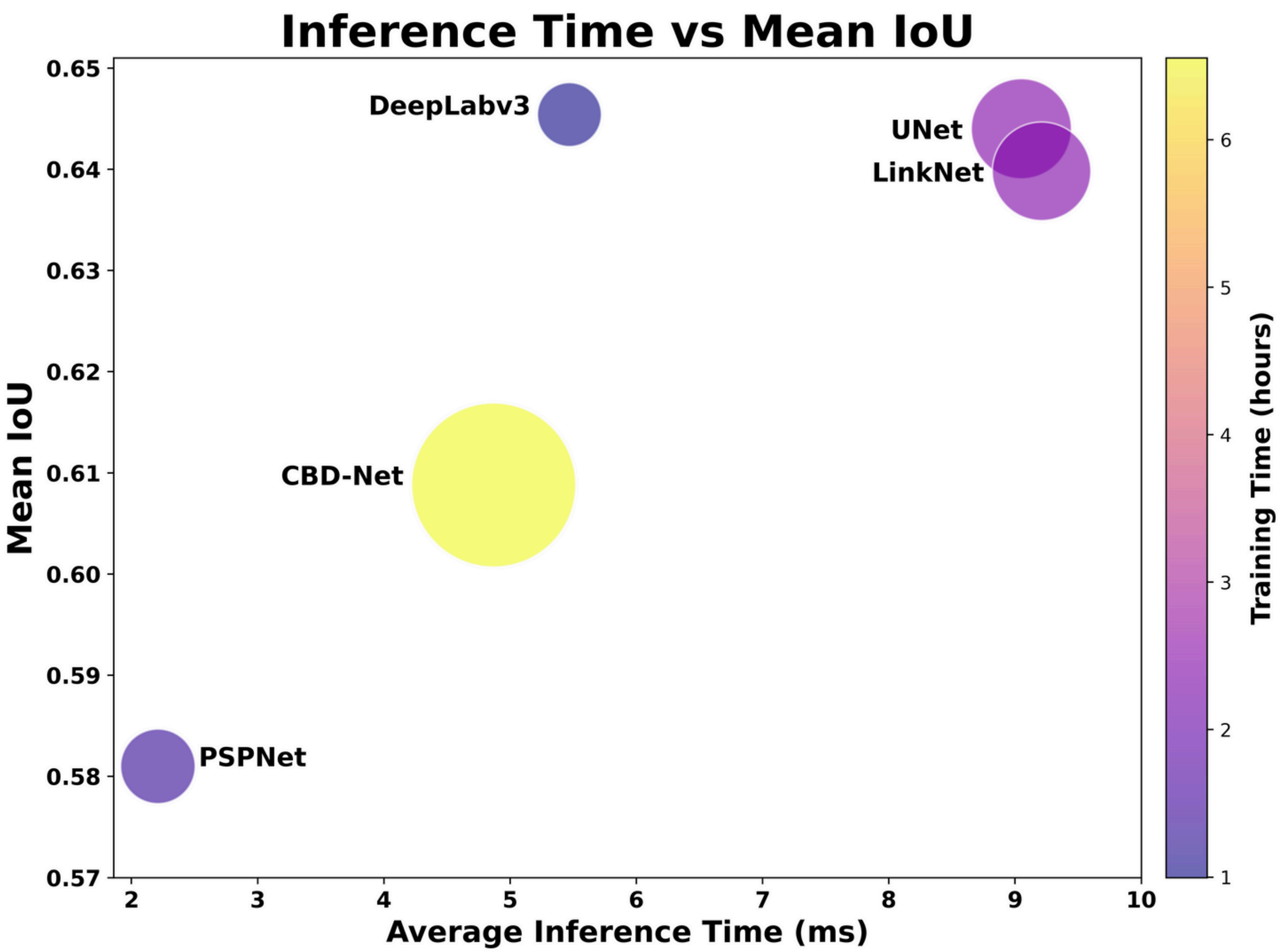


The graph shows the running average IoU of the models over 20 training epochs.

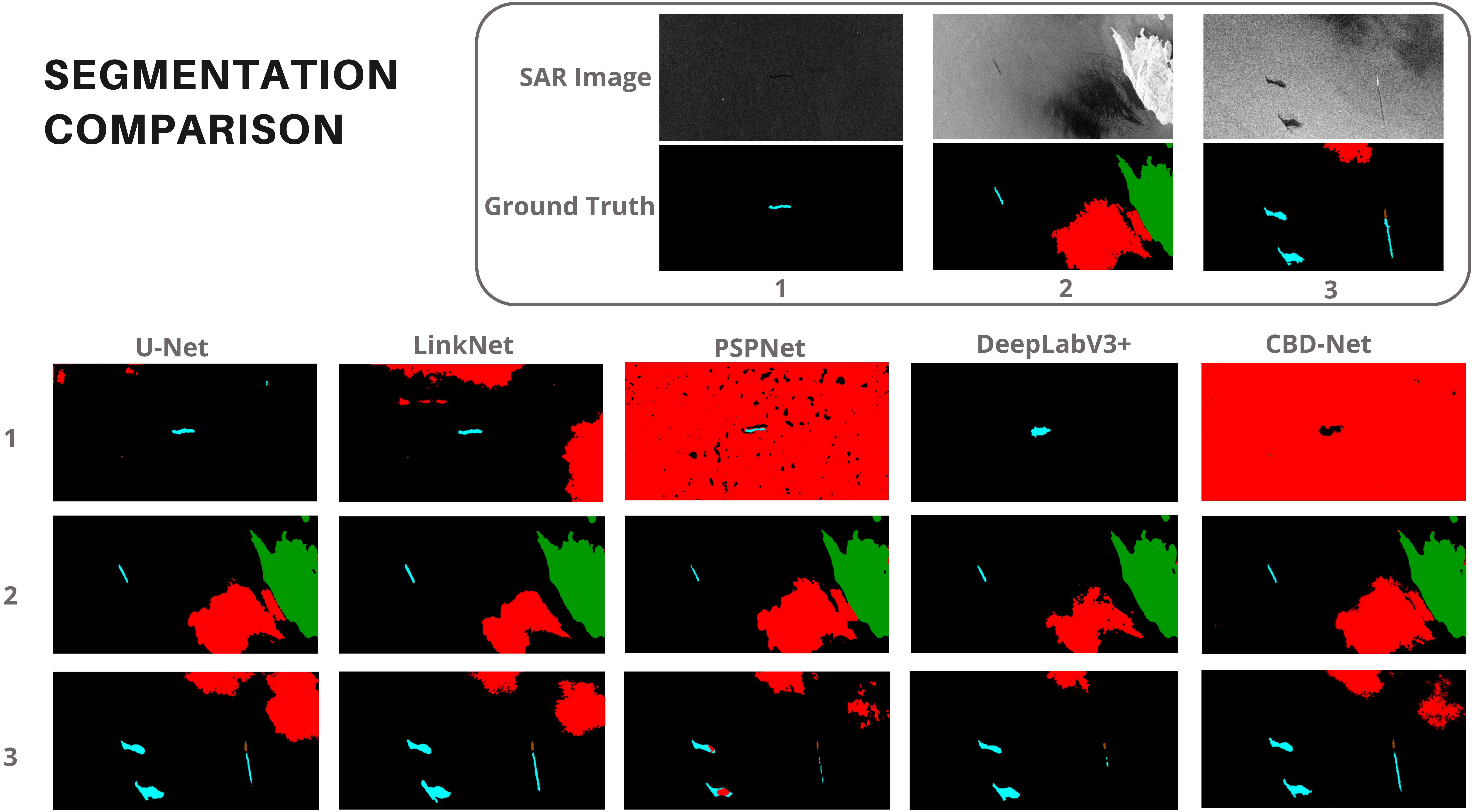
TEST RESULTS

	U-Net	LinkNet	PSPNet	DeepLabV3+	CBD-Net
Sea Surface	0.9555	0.9527	0.9327	**0.9609**	0.9437
Oil Spill	**0.5554**	0.5485	0.4444	0.5262	0.5261
Look-alike	**0.4918**	0.4247	0.3652	0.4874	0.4461
Ships	0.2672	**0.3405**	0.2141	0.3131	0.2588
Land	**0.9500**	0.9326	0.9485	0.9392	0.86.96
Mean IoU	0.6440	0.6398	0.5810	**0.6454**	0.6088

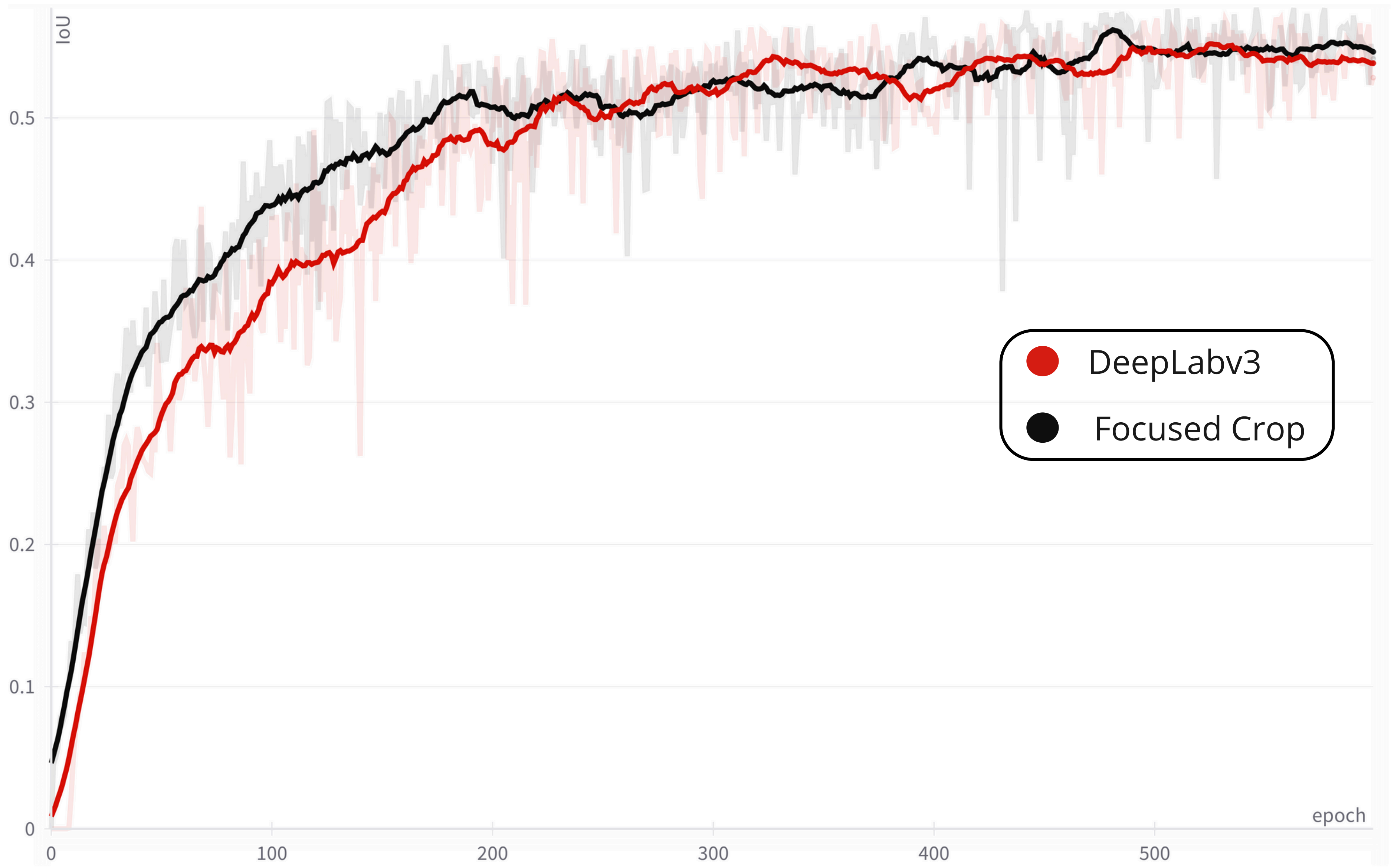
MODEL EVALUATION



Model	Mean IoU	Avg Inference Time (ms)	Training Time
U-Net	0.6440	9.05	2h 26m 40s
LinkNet	0.6398	9.21	2h 22m 6s
PSPNet	0.5810	**2.21**	1h 21m 19s
DeepLabv3	**0.6454**	5.47	**59m 47s**
CBD-Net	0.6088	4.87	6h 44m 16s


SEGMENTATION COMPARISON
SAR Image
Ground Truth
1
2
3
U-Net
LinkNet
PSPNet
DeepLabV3+
CBD-Net
1
2
3

EXTENSION RESULTS



	DeepLabV3+	Focused Crop	Sliding Window
Sea Surface	**0.9609**	0.9555	0.9400
Oil Spill	**0.5262**	0.4971	0.4539
Look-alike	**0.4874**	0.4748	0.3277
Ships	0.3131	**0.3288**	0.2551
Land	**0.9392**	0.9217	0.8863
Mean IoU	**0.6454**	0.6356	0.5726

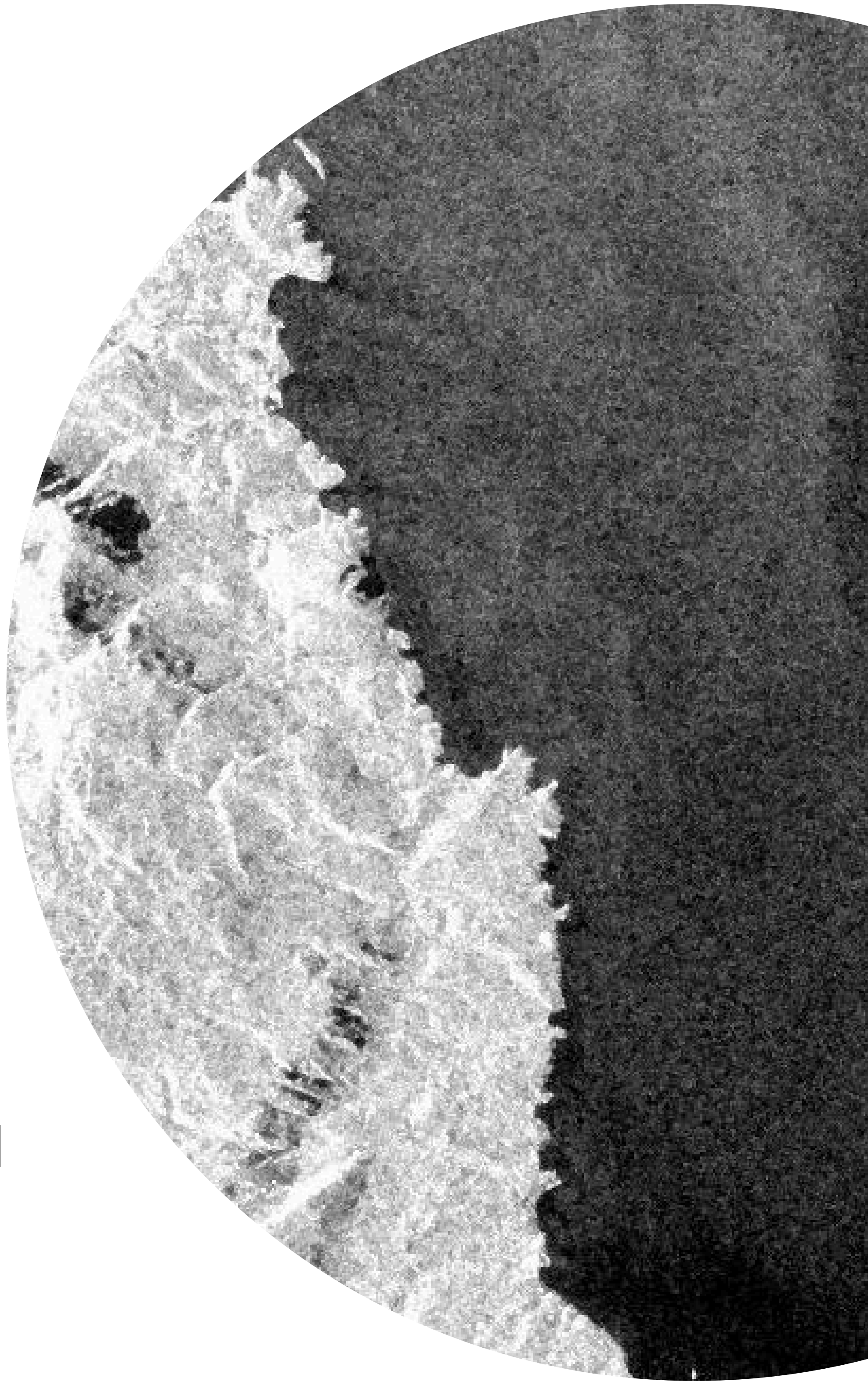
CONCLUSIONS

Key remarks from our study:

- We achieved promising results in identifying oil spill regions.
- DeepLabv3+ proved to be the most suitable model for the task among those evaluated, guaranteeeing the best trade-offs between accuracy and efficiency
- Challenges in segmenting underrepresented classes, particularly ships.
- Targeted cropping emphasized relevant features, leading to faster training convergence, without significantly compromising performance.

Future Directions:

- Noise Reduction: Develop advanced despeckling techniques for addressing the inherent noise present in SAR imagery.
- Class Imbalance: Develop synthetic data to address underrepresented categories.
- Hybrid Approaches: Combine CNNs with transformers for more robust solutions.
- Open Source development: We advocate for the creation of an open source, foundational dataset of SAR imagery to address current challenges and fostering research in the field of oil spill detection.



Thank you for your attention

Any questions?

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For further information, visit our GitHub repository!