Neural Networks for SAR Oil Spill Detection

Applied Data Science Project

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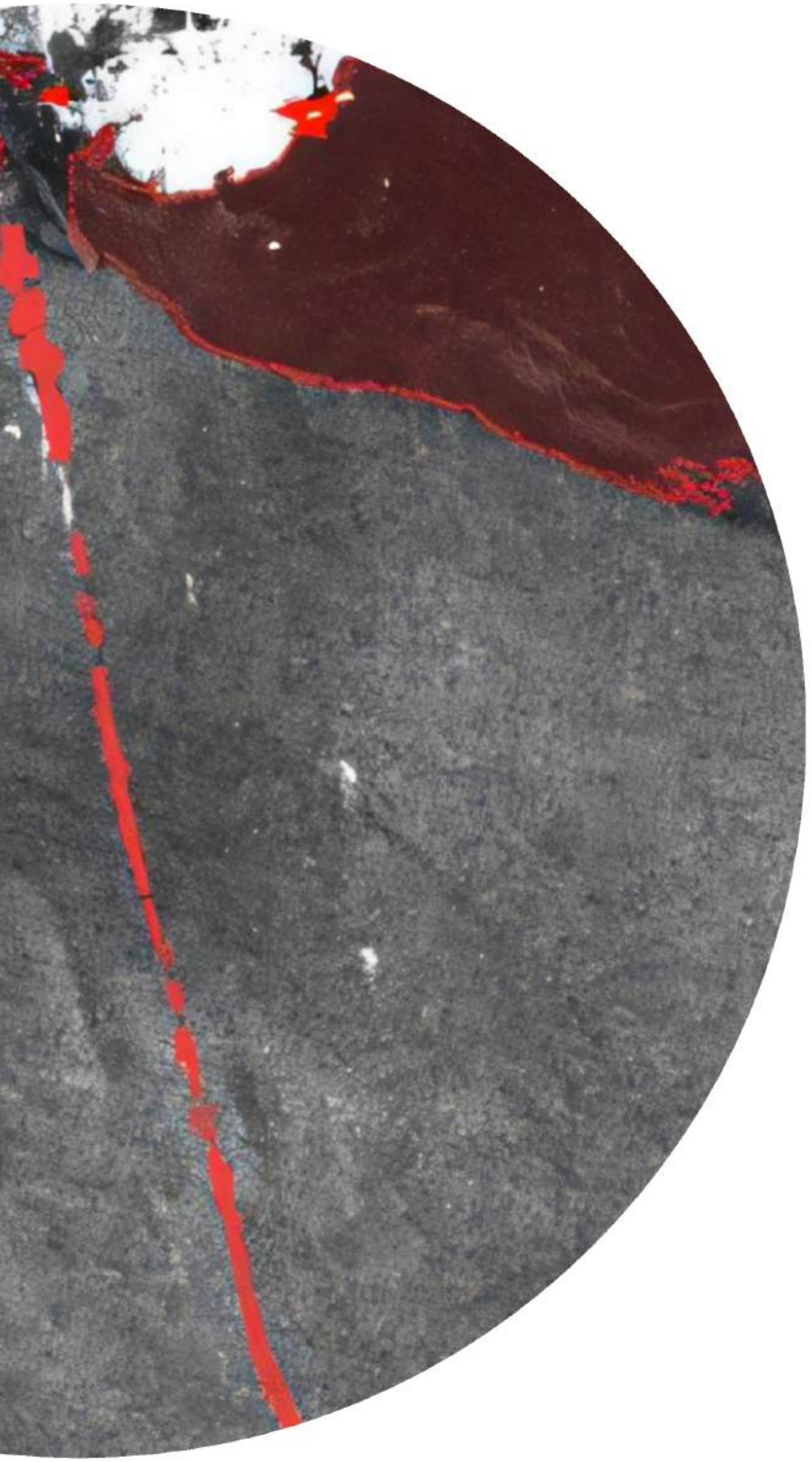
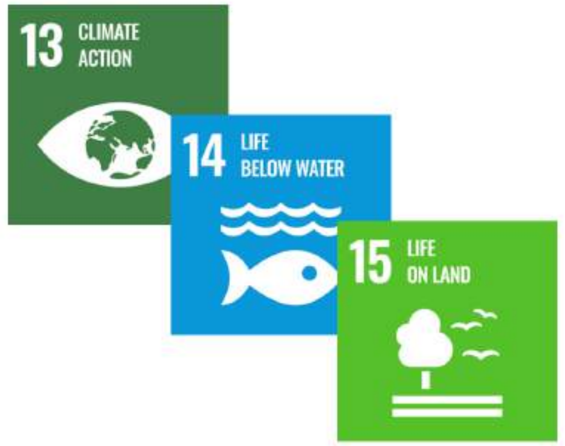
VALUE PROPOSITION



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

TASKS

Introduction:

- Understand the oil spill issue
- Review reference papers and resources

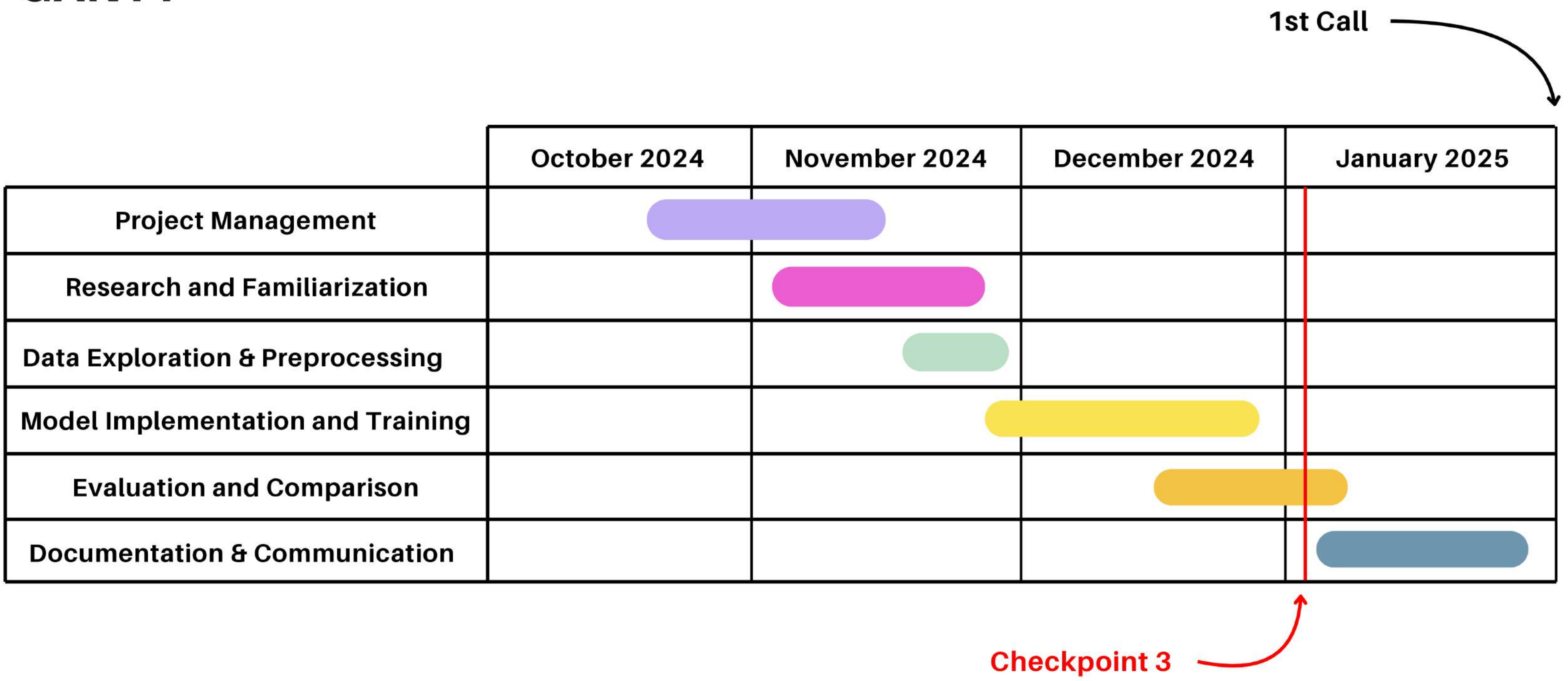
Paper replication:

- Explore the dataset
- Build a functional pipeline
- Apply paper-specific augmentations
- Reproduce all models
- Evaluate and compare results

Development of improvements:

- Design and test tailored augmentations
- Implement and test CBDNet

GANTT


1st Call
October 2024
November 2024
December 2024
January 2025
Project Management
Research and Familiarization
Data Exploration & Preprocessing
Model Implementation and Training
Evaluation and Comparison
Documentation & Communication
Checkpoint 3

RESEARCH QUESTIONS

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?

DATA AUGMENTATION

How does augmenting SAR images influence the detection of oil spills?

- Which augmentation techniques lead to more effective oil spill detection?

COMPUTATIONAL EFFICIENCY

Balancing accuracy and efficiency:

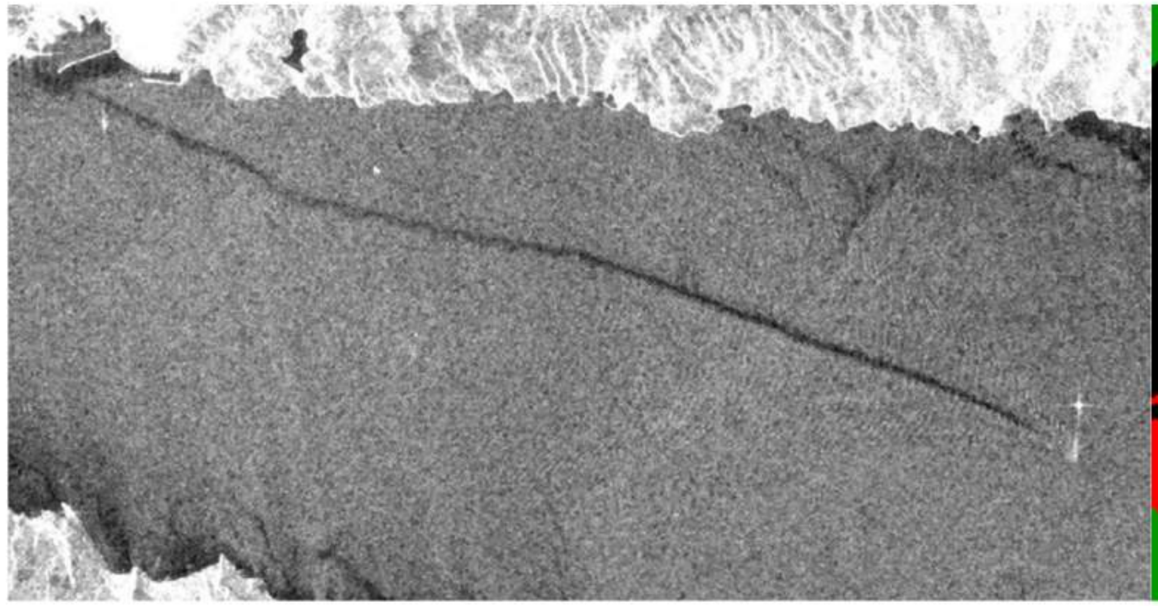
- What are the trade-offs?
- Can lightweight models achieve competitive accuracy?


DATASET
EXPLORATION

Images are taken by the ESA Satellite Sentinel-1

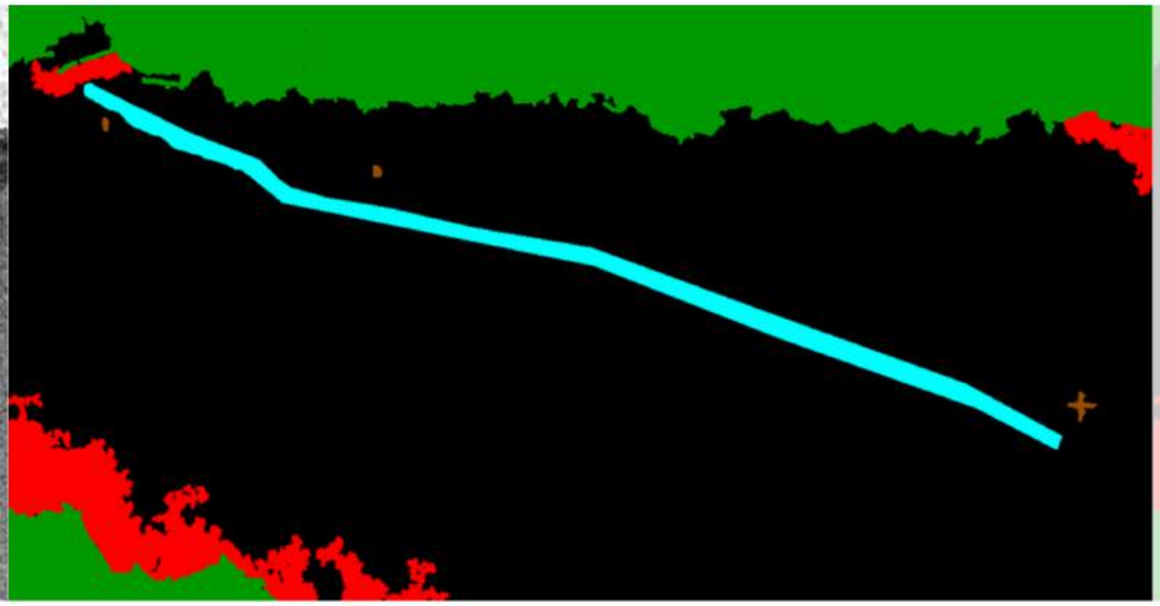
All images have dimensions *1250 x 650*

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



Original SAR image

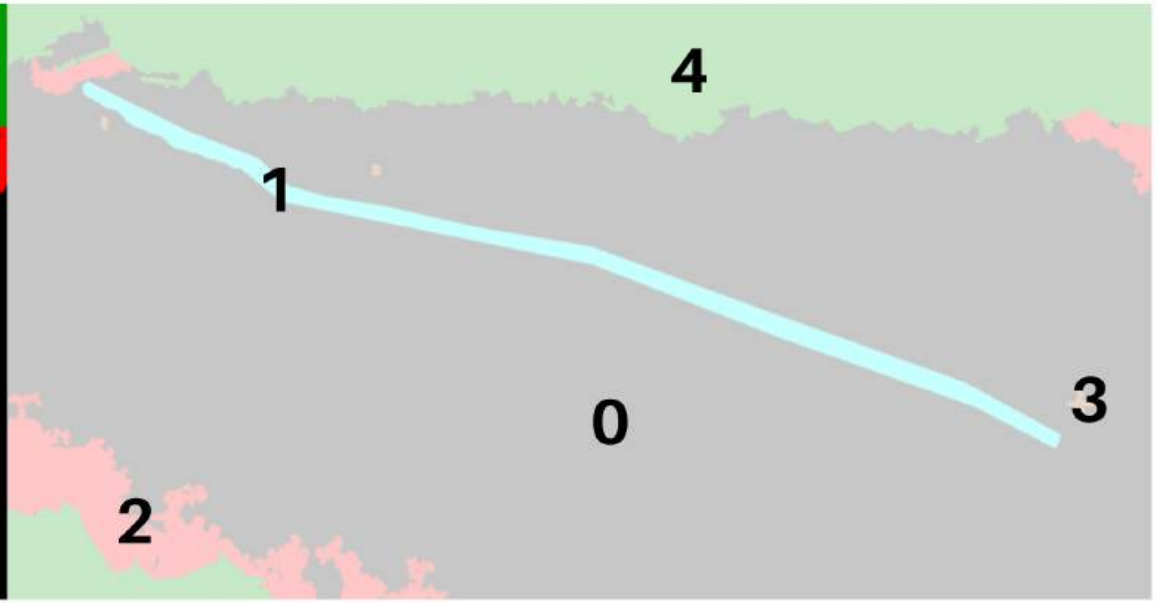
3 greyscale identical channels



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

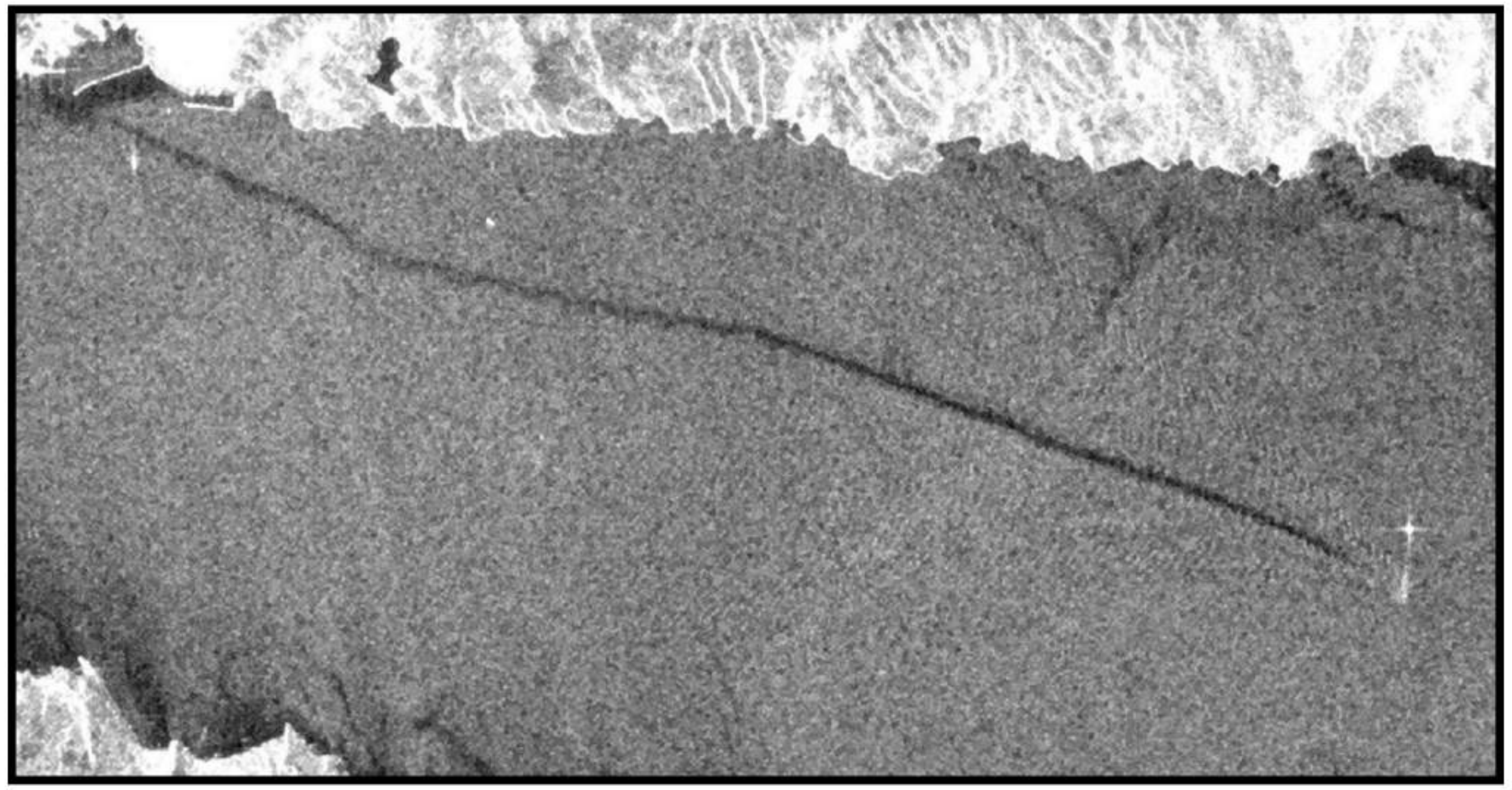
DATA PREPROCESSING

PAPER AUGMENTATIONS

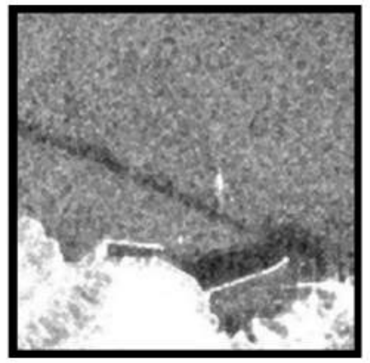
Starting from the original image, the original paper performs:

- **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



PAPER AUGMENTATIONS

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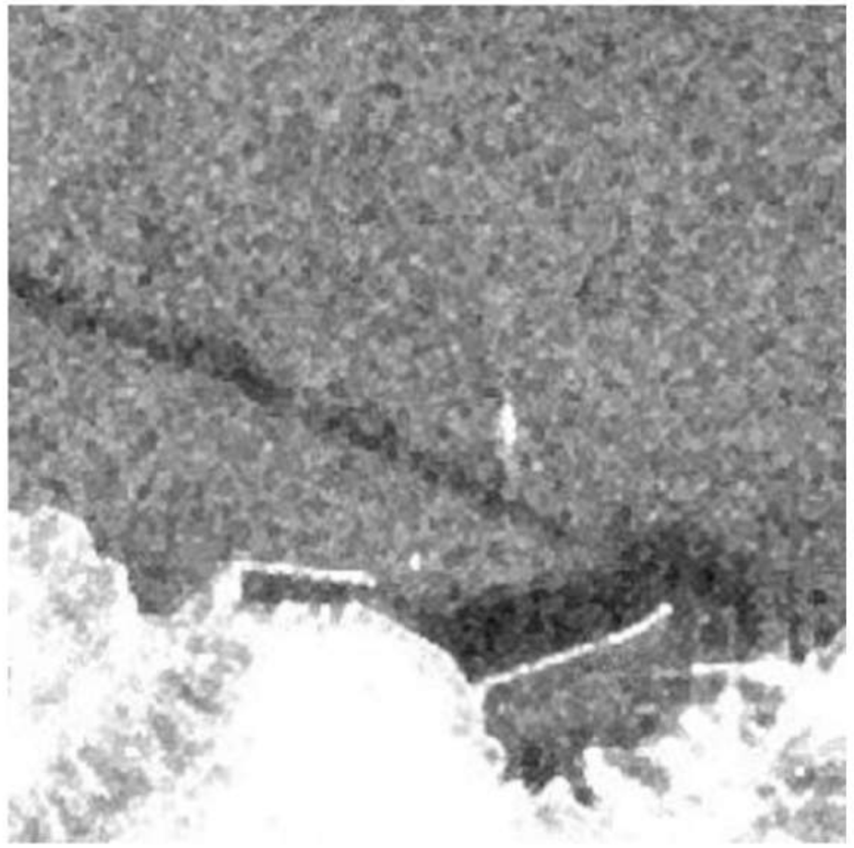
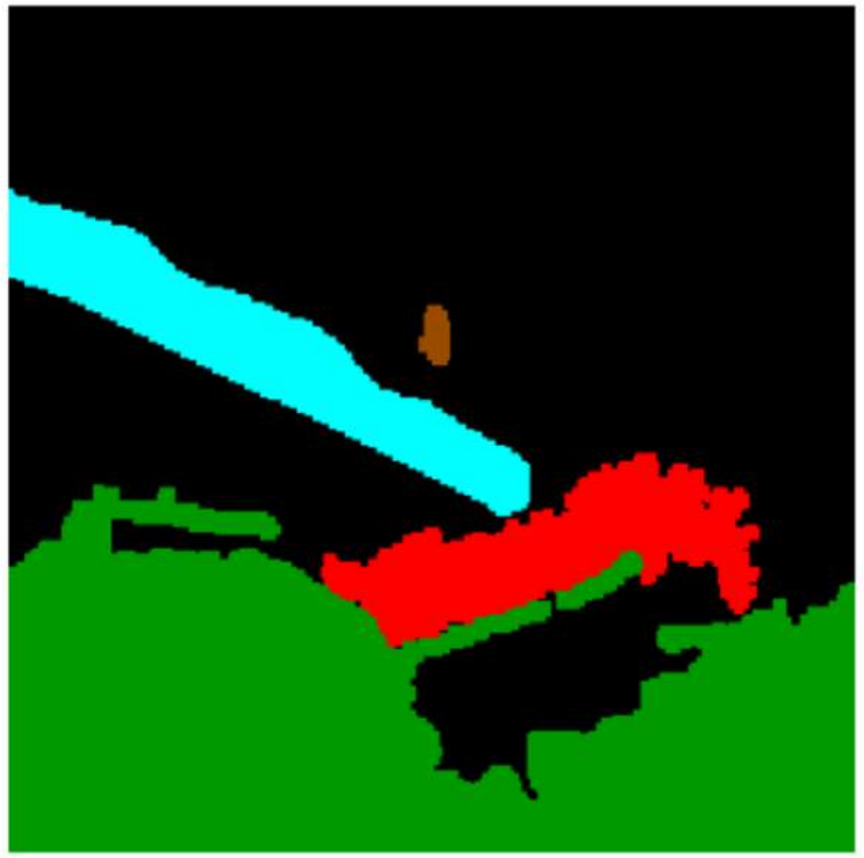
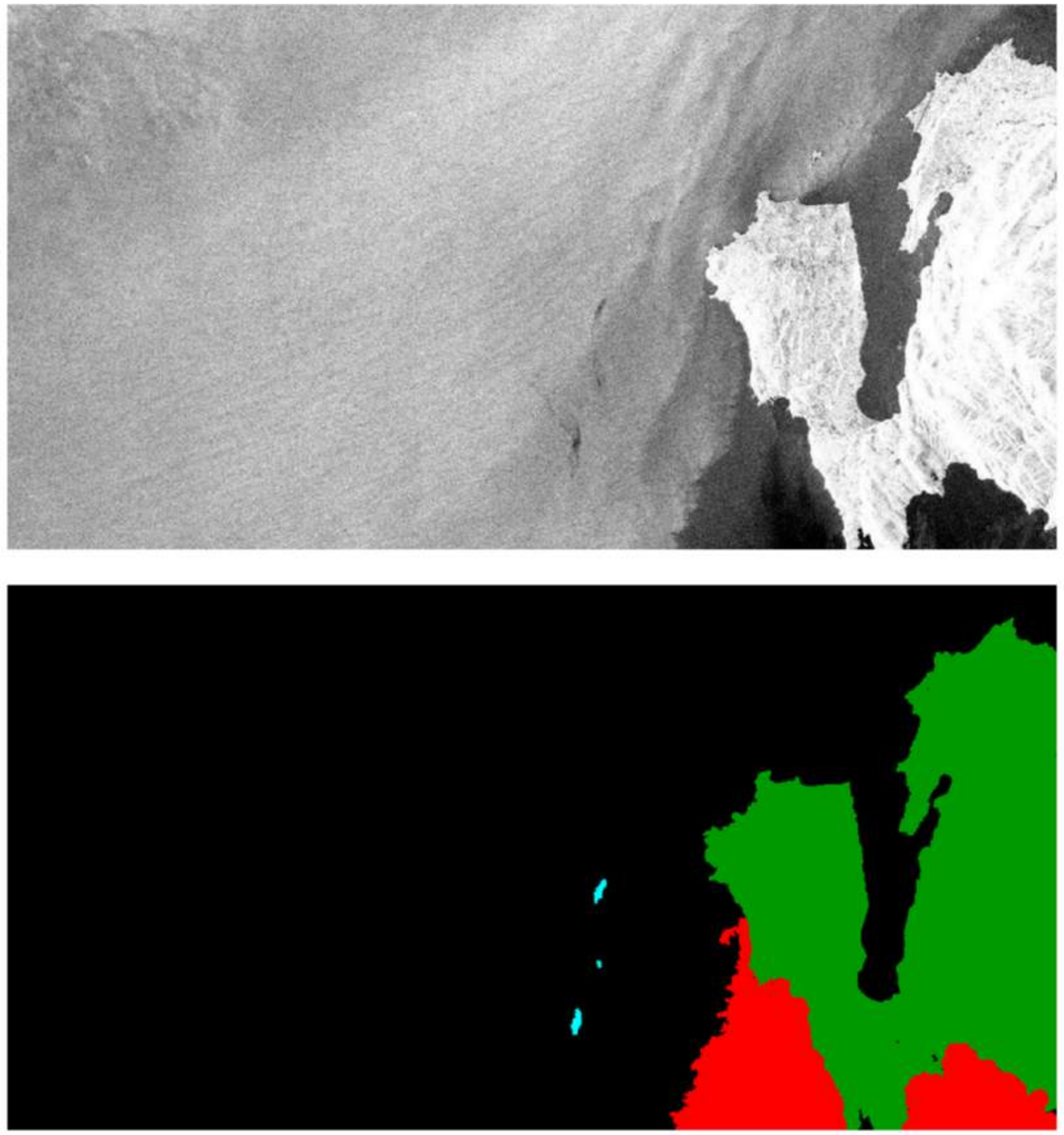




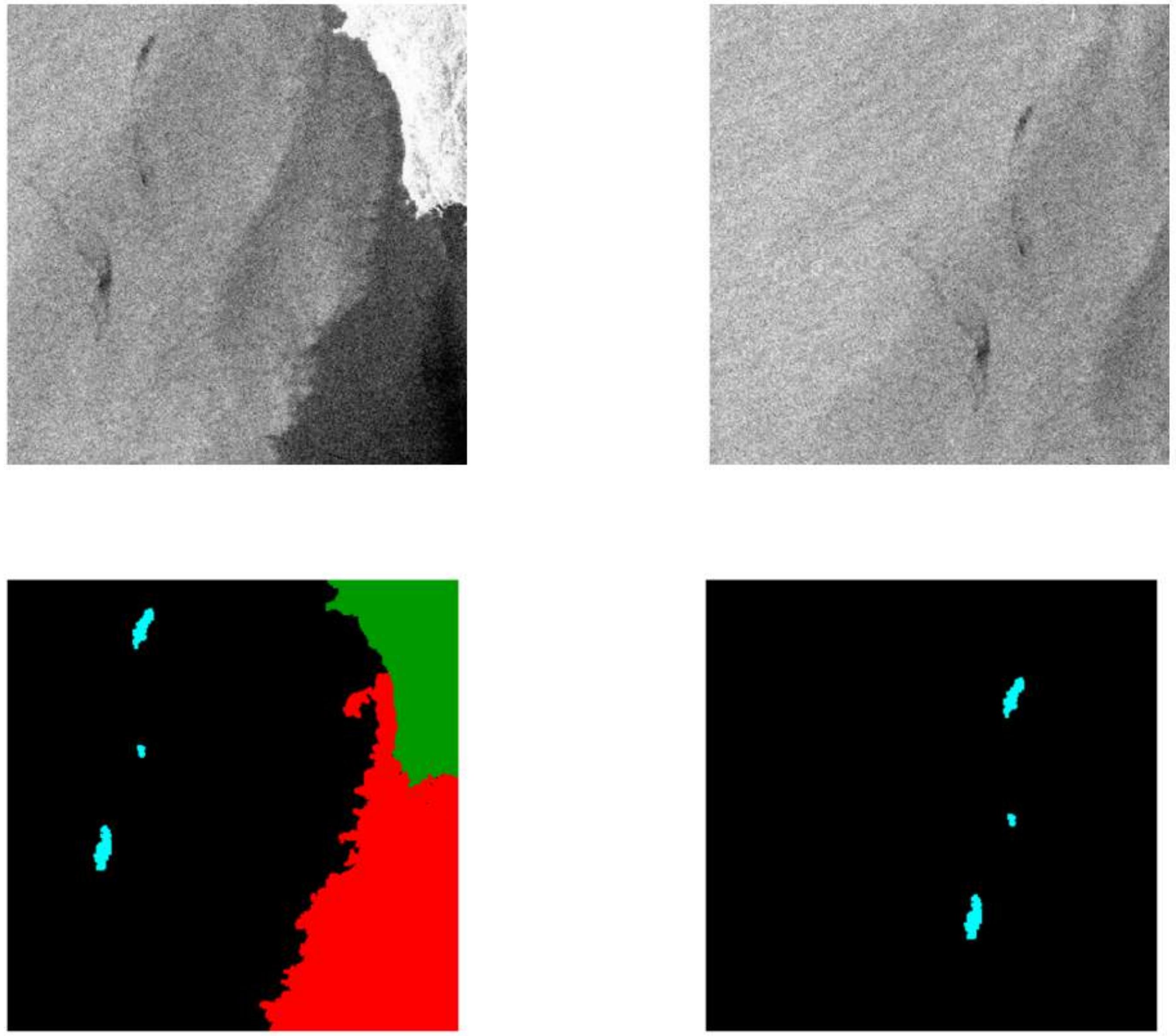
PROPOSED AUGMENTATIONS

- **Focused Crop on Oil Spill**

Original Image



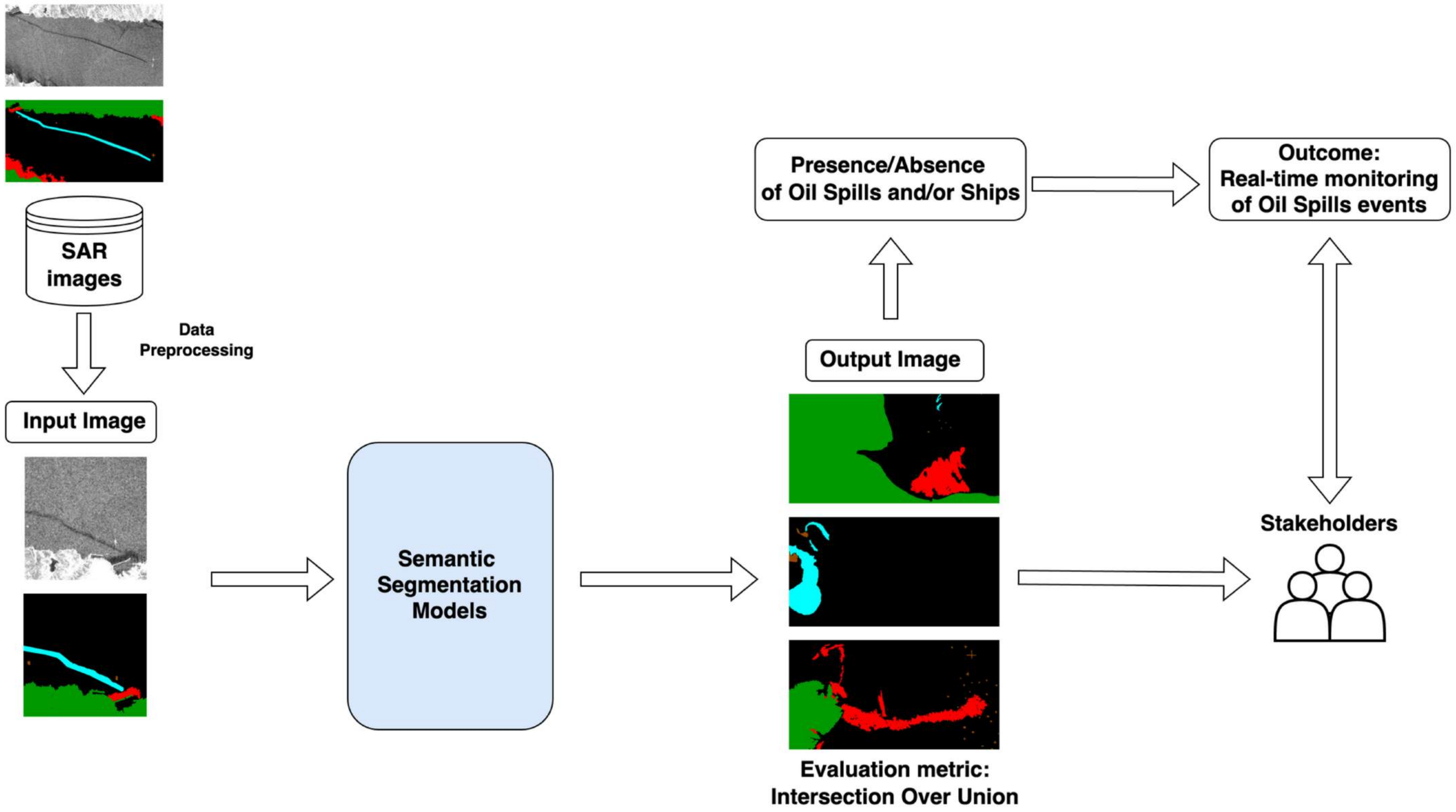
Focused Crop Examples



- **Sliding window for the Crop**
- **Despeckling**

IMPLEMENTATION & TRAINING

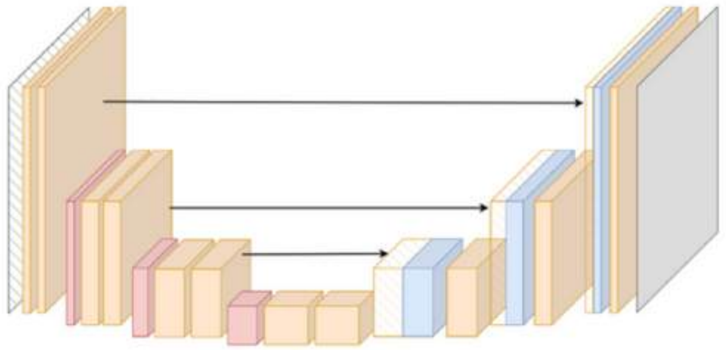
GENERAL OVERVIEW



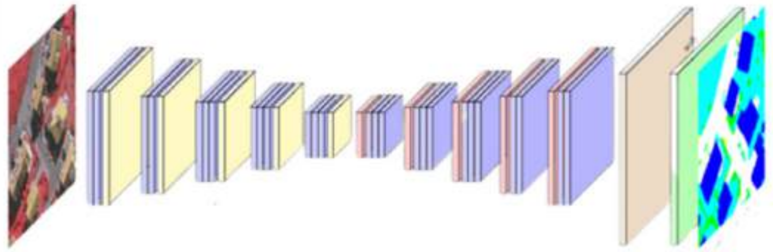
MODELS

Semantic Segmentation Models

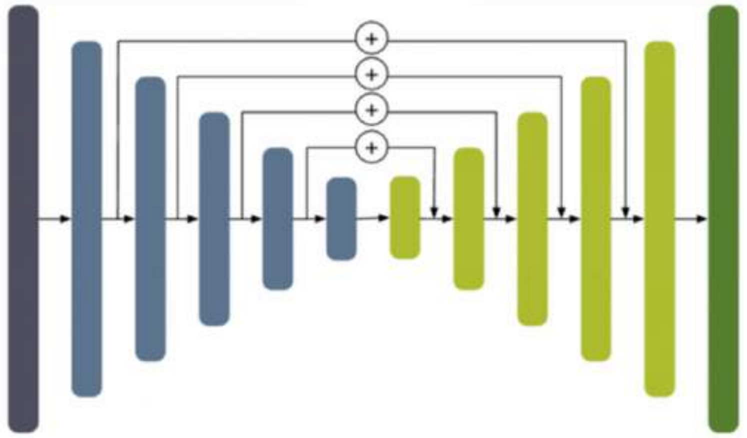
UNet



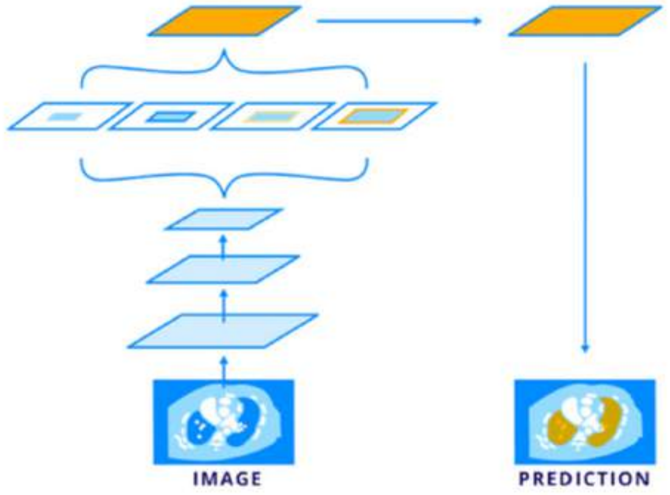
PSPNet



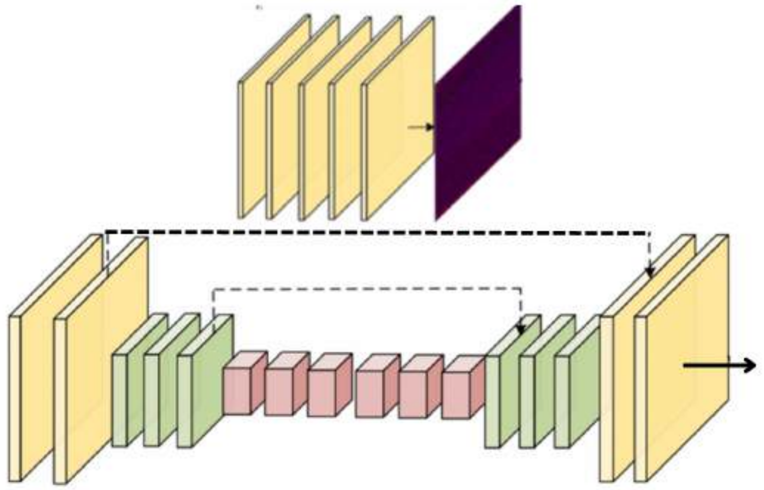
LinkNet



DeepLab



CBDNet



TRAINING METHOD

- **Training framework:** PyTorch Lightning

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

- **Model Details:**

Model	Backbone Architecture	Learning rate
U-Net	ResNet-101	0.0001
LinkNet	ResNet-101	0.00005
PSPNet	ResNet-101	0.0001
DeepLab3	MobileNet3	0.0001

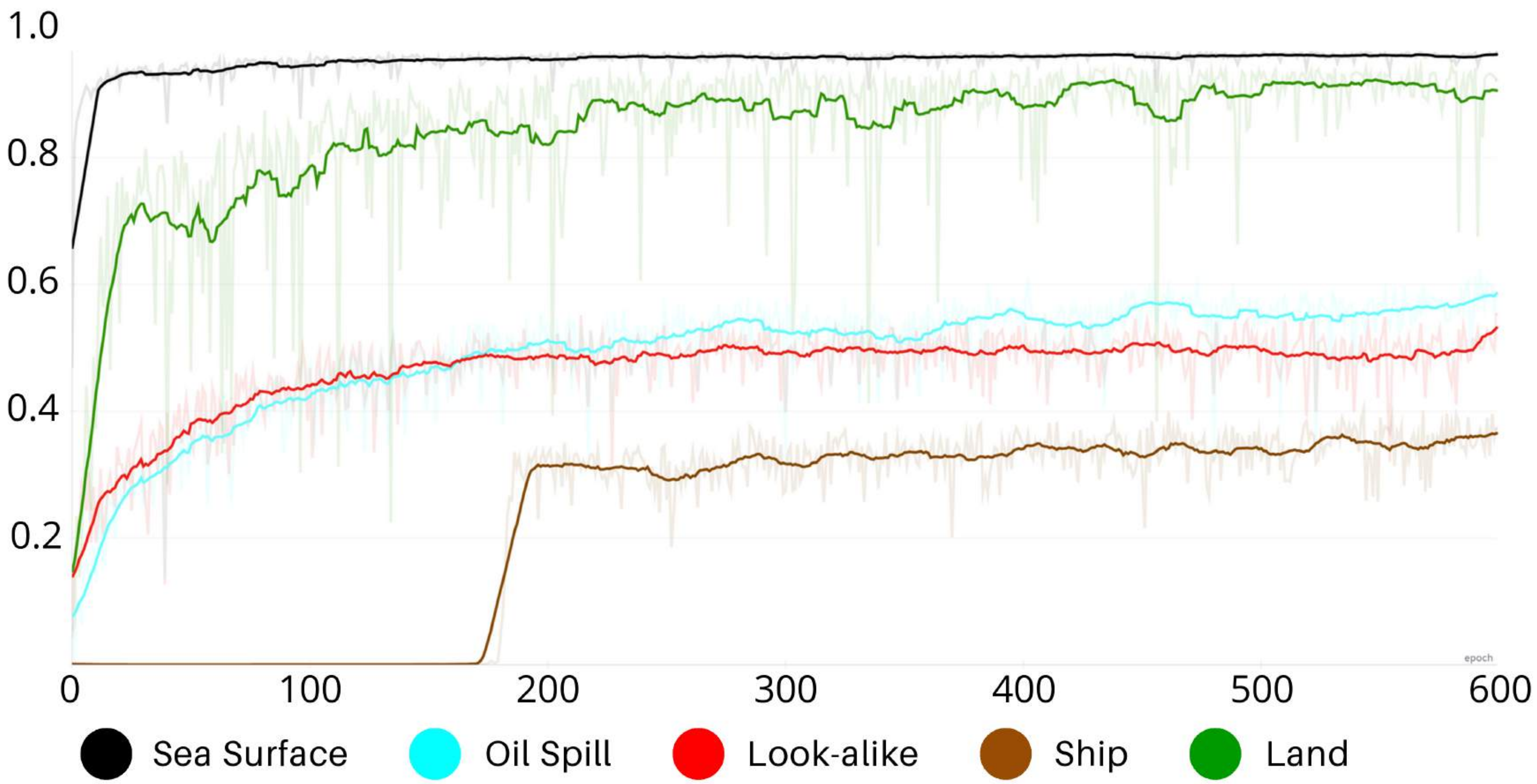
- **Dataset:**

  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

UNET



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

Class Label	IoU Score
Sea Surface	0.9555
Oil Spill	**0.5554**
Look-alike	0.4918
Ships	0.2672
Land	0.9500
Mean IoU	**0.6440**

Metrics from test set predictions

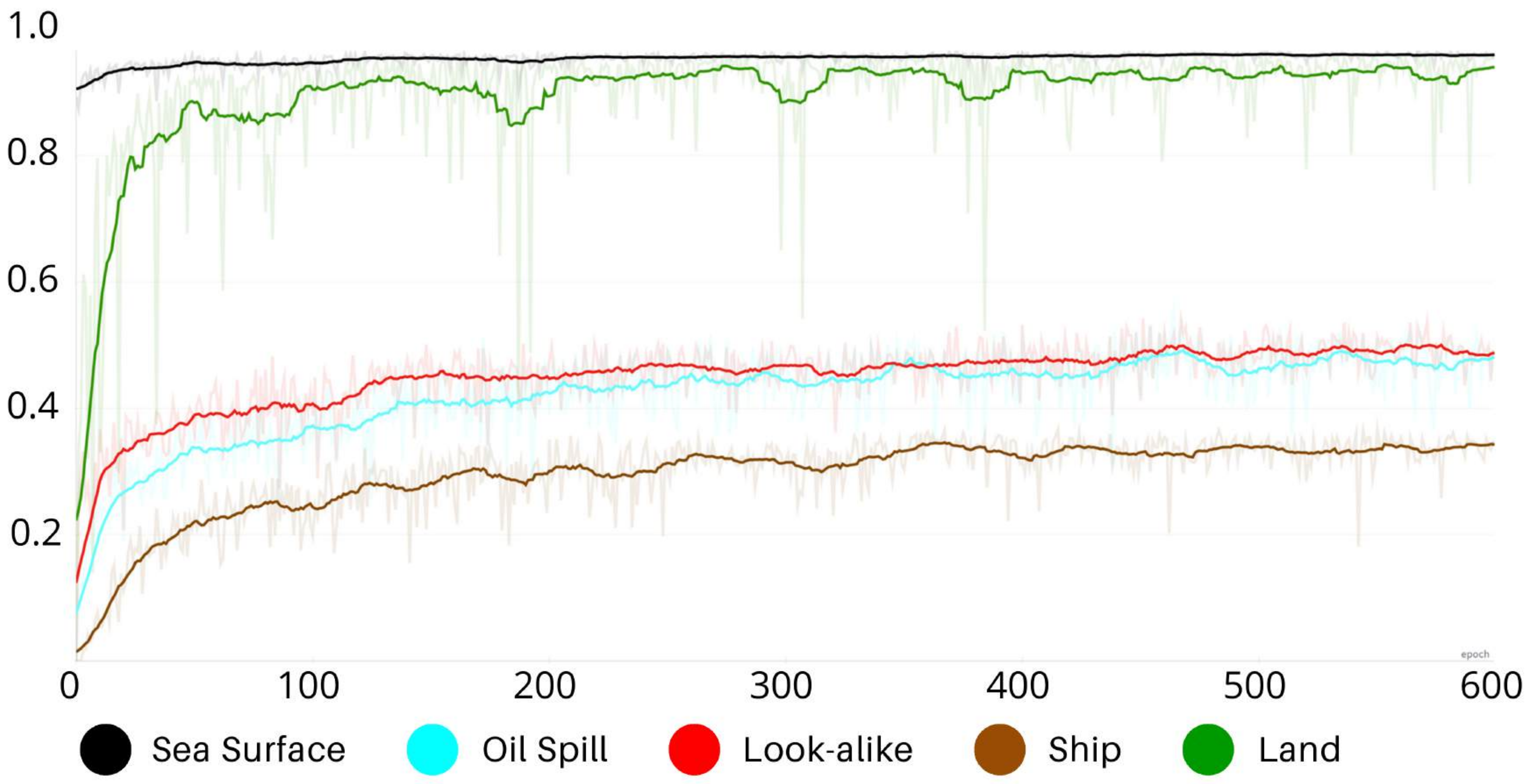
Total Training Time: *2h 26m 40s*

LINKNET

Class Label	IoU Score
Sea Surface	0.9527
Oil Spill	**0.5485**
Look-alike	0.4247
Ships	0.3405
Land	0.9326
Mean IoU	**0.6398**

Total Training Time: *2h 22m 6s*

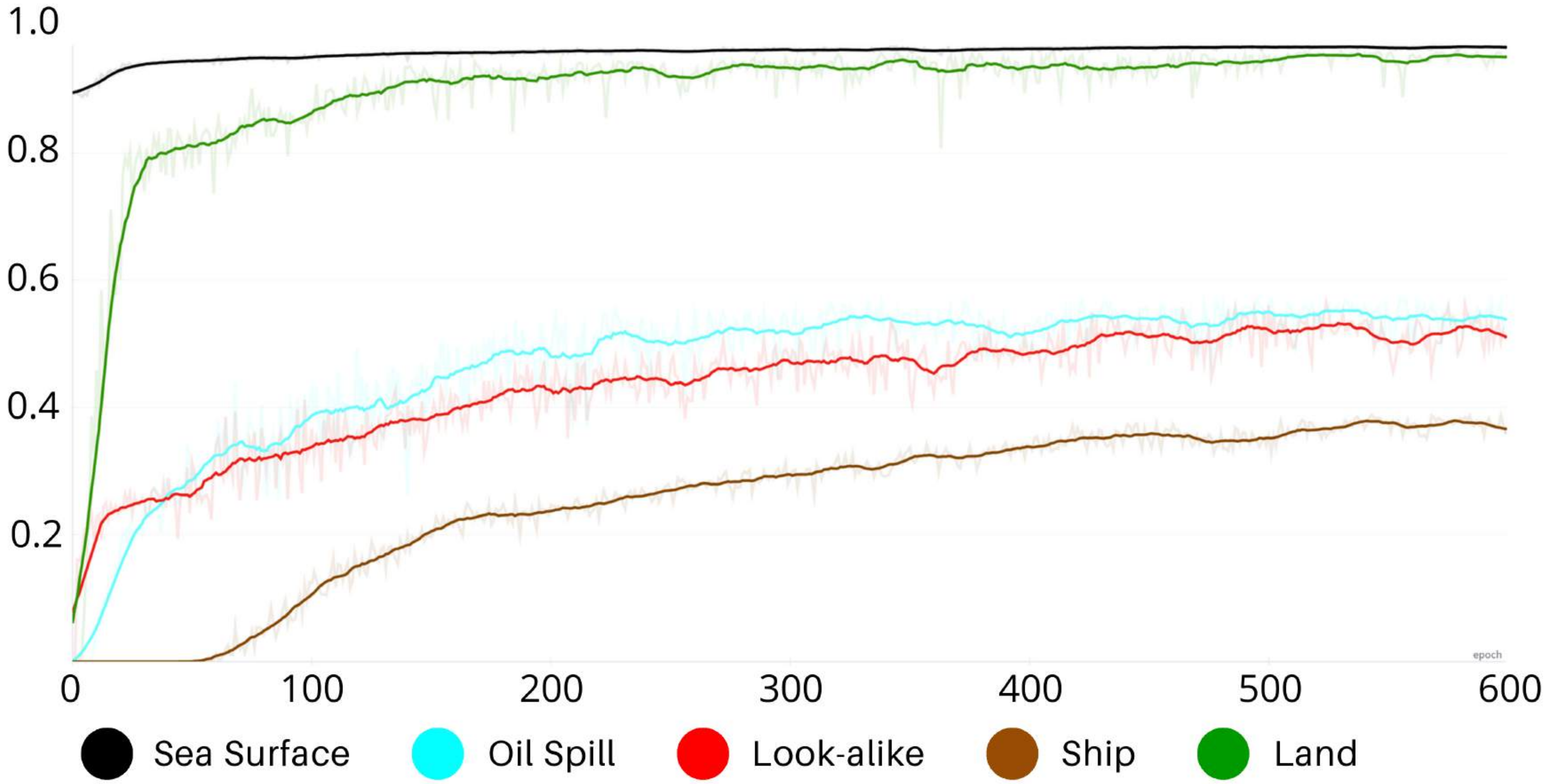
PSPNET



Class Label	IoU Score
Sea Surface	0.9327
Oil Spill	**0.4444**
Look-alike	0.3652
Ships	0.2141
Land	0.9485
Mean IoU	**0.5810**

Total Training Time: *1h 21m 19s*

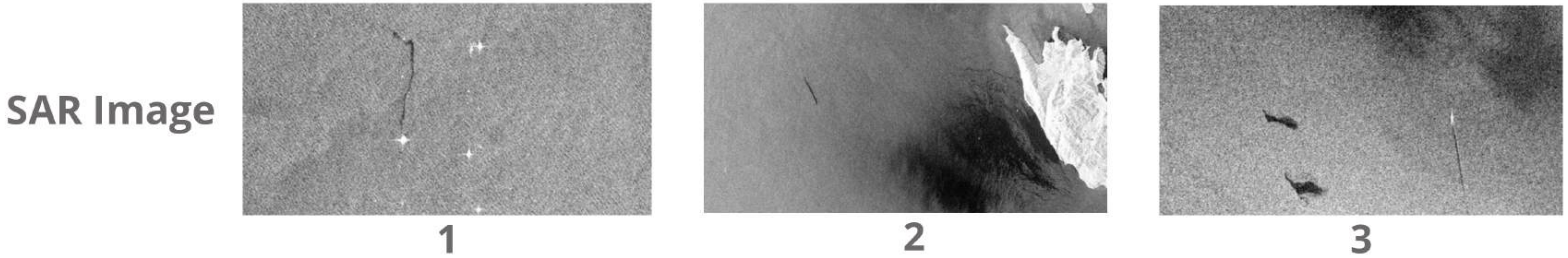
DEEPLAB

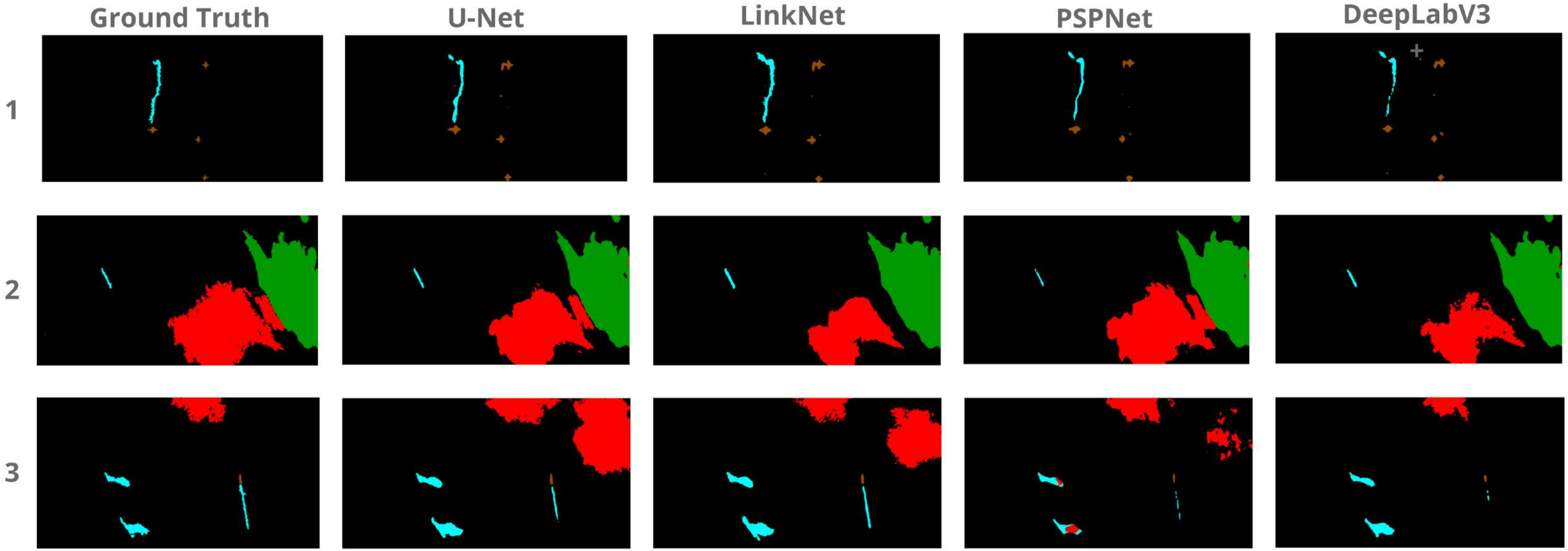


Class Label	IoU Score
Sea Surface	0.9609
Oil Spill	**0.5262**
Look-alike	0.4874
Ships	0.3131
Land	0.9392
Mean IoU	**0.6453**

Total Training Time: *59m 47s*

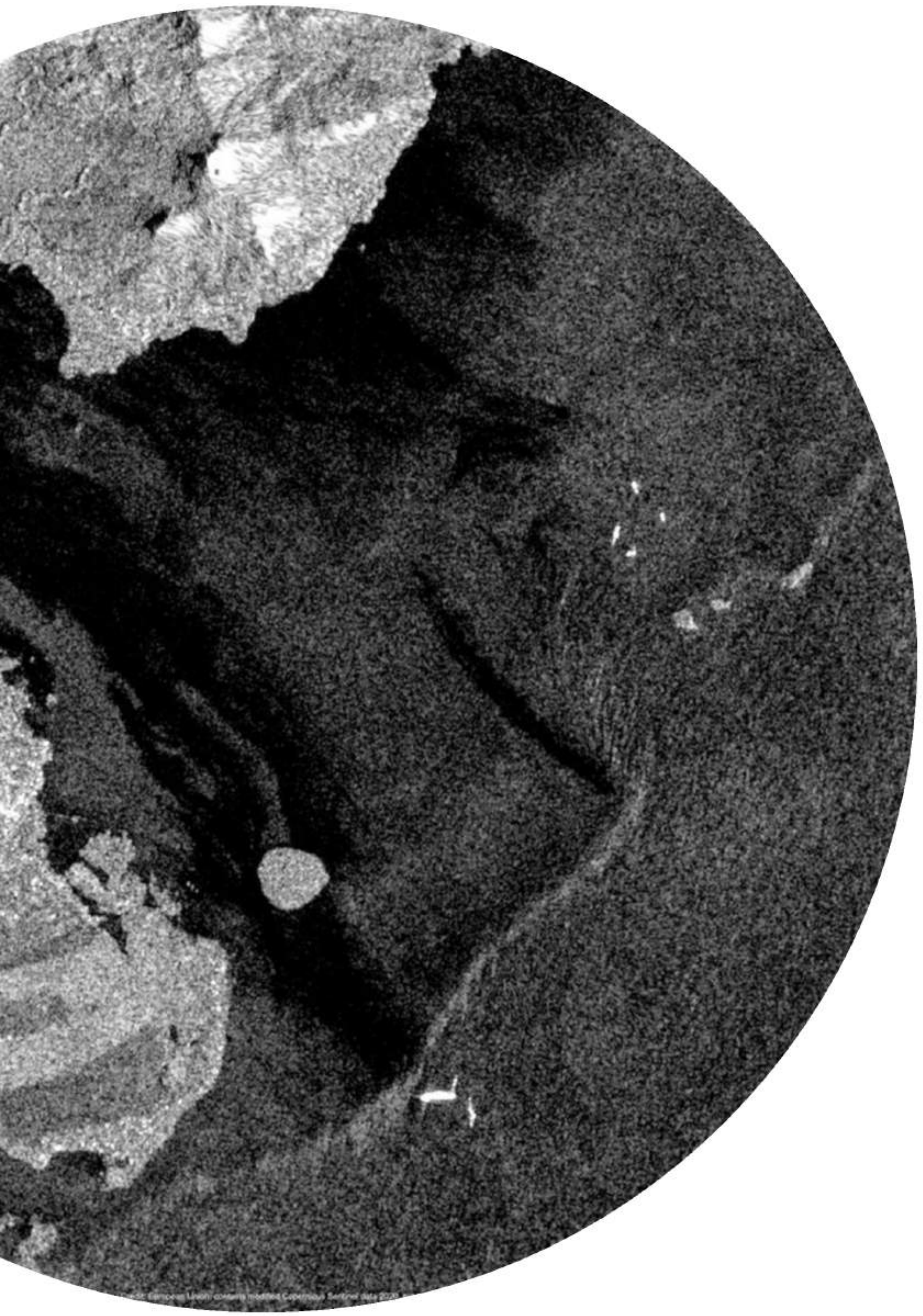
SEGMENTATION COMPARISON





FINAL COMPARISON

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



Thank you for your attention

Any questions?

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