A DEEP NEURAL NETWORK FOR OIL SPILL SEMANTIC SEGMENTATION IN SAR IMAGES

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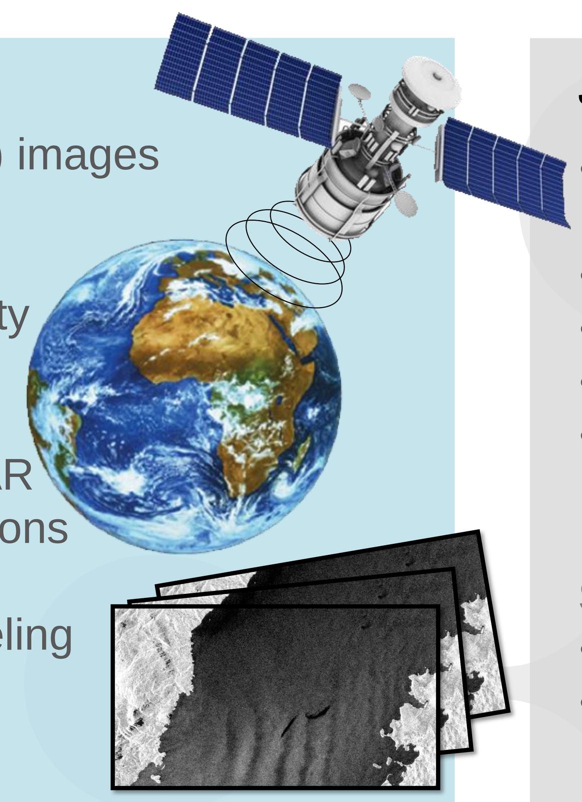
1. Introduction

Satellite Synthetic Aperture Radar (SAR) images
- High resolution representations
- Large areas coverage
- Light and weather condition invariability

Typical approach for oil spill detection
- Detection of the dark formations in SAR
- Feature extraction for the dark formations
- Feature classification
- Decision making model for object labeling

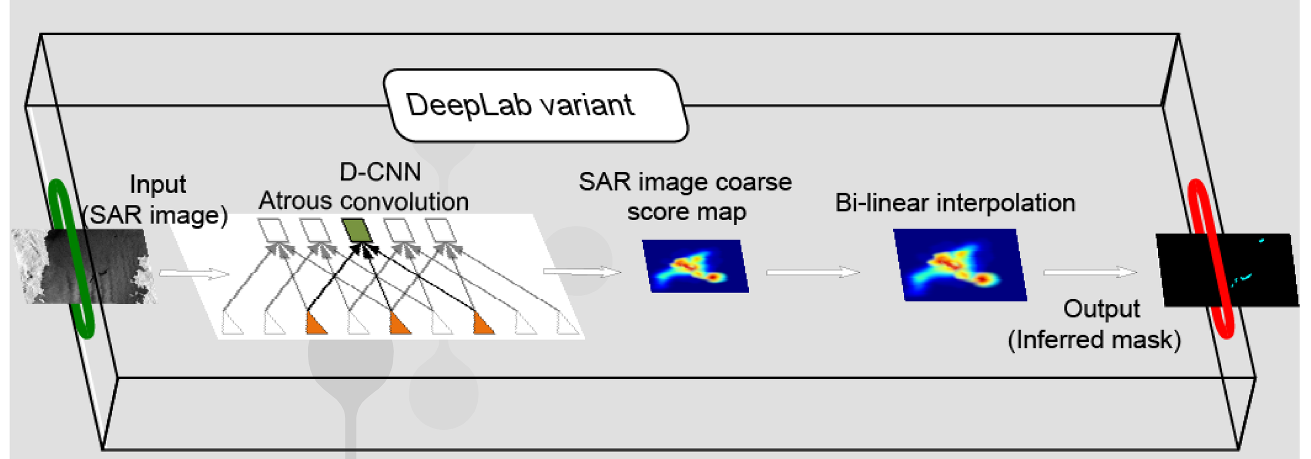

SAR images

Main drawbacks
- Selection of specific features
- Feature extraction is required
- Single label assignment to each input image
- Two-class classification problem

Advantages of using deep convolutional neural networks
- No feature extraction
- Simple extension to a multi-class problem
- No image patches is required
- Robust and accurate solution
- Simple model expansion and modification

2. Methodology

- A DeepLab[1] model variant was deployed
- Backbone model: ResNet-101 model
- The model was redefined, properly trained and fine-tuned for oil spill identification.
- Satellite images include large operational amplitudes
  - R-CNN spatial pyramid pooling (ASPP) method
  - Cropped images in various sizes to simulate height variations
- No CRF due to vague optical limits in SAR images



[1]Chen, L. C., Papandreou, G., Kokkinos, I., Murphy, K., & Yuille, A. L. (2018). Deeplab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected crfs. IEEE transactions on pattern analysis and machine intelligence, 40(4), 834-848.

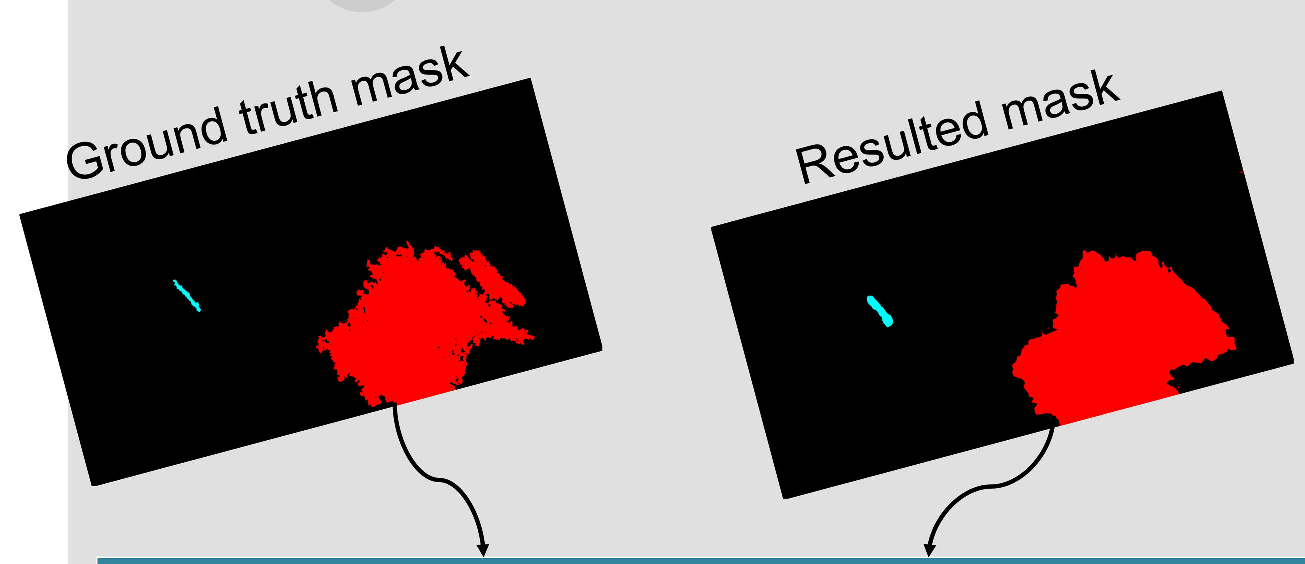
3. Dataset

- Geographical coordinates for confirmed oil spills were provided from European Maritime Safety Agency (EMSA)
- CleanSeaNet service: 28/09/2015 up to 31/10/2017
- European Space Agency (ESA) services for SAR images
- Copernicus Open Access Hub 1
- Training and evaluation set: 571 and 106 images, respectively

SAR Data Preprocessing
- Oil spills were localized
- SAR representations were cropped to include objects of interest
- Rescale to resolution of 1252x609 “SAR pixels”
- Radiometric calibration
- Speckle filtering to suppress sensor noise
- Additional 7x7 mean filter was applied
- Linear transformation from db to luminosity values

4. Experimental results

- Two foreground classes (oil-spills and look-alikes)
- One background class
- Measured performance
  - Pixel intersection-over-union (IoU) averaged across all classes mIoU.
  - IoU for every class
  - Image classification accuracy for a number of patches cropped from each sample



Intersection-over-Union (IoU)

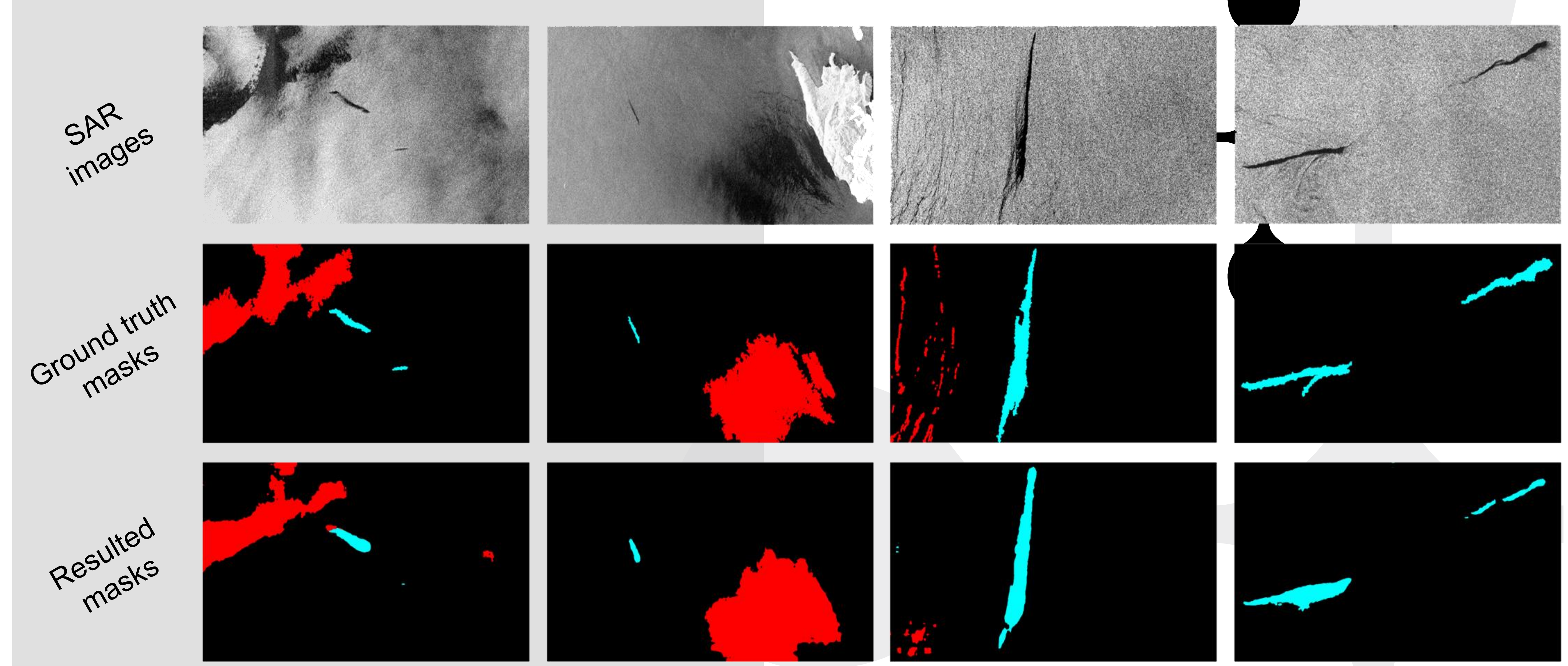
mIoU	Oil spills	Look-alikes	Background
0.6098	0.4130	0.4564	0.9599

4. Experimental results (cont.)

Patch classification precision results

	Overall	Oil spills	Look-alikes
No Patches (3,3)	0.8063	0.8621	0.7588
No Patches (5,3)	0.8166	0.8932	0.7540

Examples



4. Conclusions

- New approach for oil spill detection with SAR images
- No similar approach addresses similarly the problem
- Incorporated into a larger detection pipeline
- No feature extraction is required
- Improving the automated oil spill detection

5. Future work

- Utilization of more advanced datasets
- Evaluation of multispectral satellite images
- Fine tuning the existing model
- Test relevant DCNN architectures for both object detection and semantic segmentation

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