A Multisensory SAR-based approach for melt ponds retrievals

Summary of methodology performed and first main results using PolarTEP

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polar tep

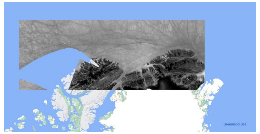
NoR ID 3c06w7

Methodology 1: Preparation preparation of training datasets

1) Acquisition

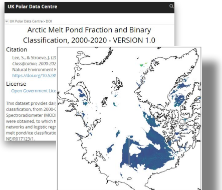
Sentinel-1

- Through EE
- Selected angles between 31 and 45 degrees
- Selected only HH band
- Daily average
- Over same area:



MPF (Lee et al.)

- Data acquired at ramadda.data.bas.ac.uk



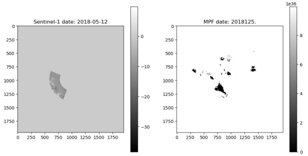
2) Processing

Reprojected to 'EPSG:6931'

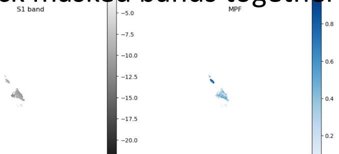
- NetCDFs converted into GeoTIFFs using a Lambert Azimuthal Equal-Area Projection (EPSG 6931)

3) Stacking & Masking

- Aligning and stacking MPF file and S1 reprojected using GDAL commands for warping, followed by creating a VRT to combine them into a single entity
- Translating them into a GeoTIFF (COG) format

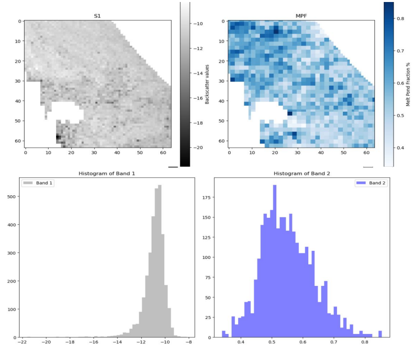


- Masking invalid values (9.969e+36) (NaN) in each band, creating a new binary band indicating where the S1 is valid
- Stack masked bands together



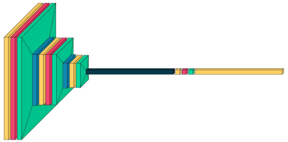
4) Cropping into patches

- Every COG is divided into tiles of 64 by 64 and saved as a separate TIFF. If all pixels in a tile are either all NaN or all Zero, that tile/patch is not save.



Methodology 2: Preparation 3 different AI workflows: CNN, UNET and SegNET

CNN



Consists of convolutional layers followed by pooling layers and fully connected layers.

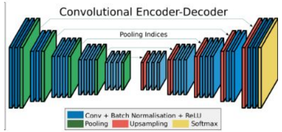
Pros:

- Effective in capturing spatial hierarchies in data due to the use of convolutional layers.
- Automatically learns hierarchical patterns from the input data.
- Suitable for a variety of tasks such as image classification, object detection, and segmentation.

Cons:

- Requires a large amount of data for training, which can be computationally expensive.
- Prone to overfitting, especially with complex architectures and insufficient data augmentation.
- Interpretability might be challenging due to the complexity of the learned features.

SegNET



Employs an encoder-decoder architecture with skip connections. Utilizes skip connections to retain spatial information during decoding.

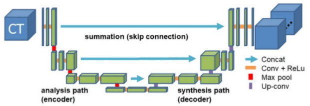
Pros:

- Utilizes a hierarchical encoder-decoder architecture which enables capturing fine details.
- Incorporates skip connections to retain spatial information during the decoding process.
- Effective for tasks like image segmentation where preserving spatial information is crucial.

Cons:

- May suffer from vanishing gradients during training, especially in deeper architectures.
- Requires careful tuning of hyperparameters and architecture design to prevent overfitting.
- Computationally intensive due to the use of multiple convolutional layers and upsampling operations.

U-NET



Features a U-shaped architecture with symmetric encoder and decoder paths. Incorporates skip connections to facilitate feature propagation and precise localization.

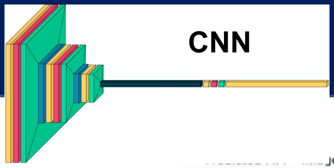
Pros:

- Incorporates a U-shaped architecture with symmetric encoder-decoder paths, facilitating better feature propagation.
- Enables precise localization of objects due to skip connections that preserve spatial information.
- Widely used and proven effective for medical image segmentation and other tasks requiring precise delineation.

Cons:

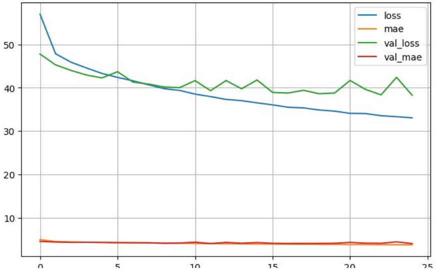
- Can be memory-intensive, especially for larger input sizes and deeper architectures.
- Training can be slow due to the large number of parameters, especially in the bottleneck layers.
- May struggle with class imbalance if not properly addressed during training.

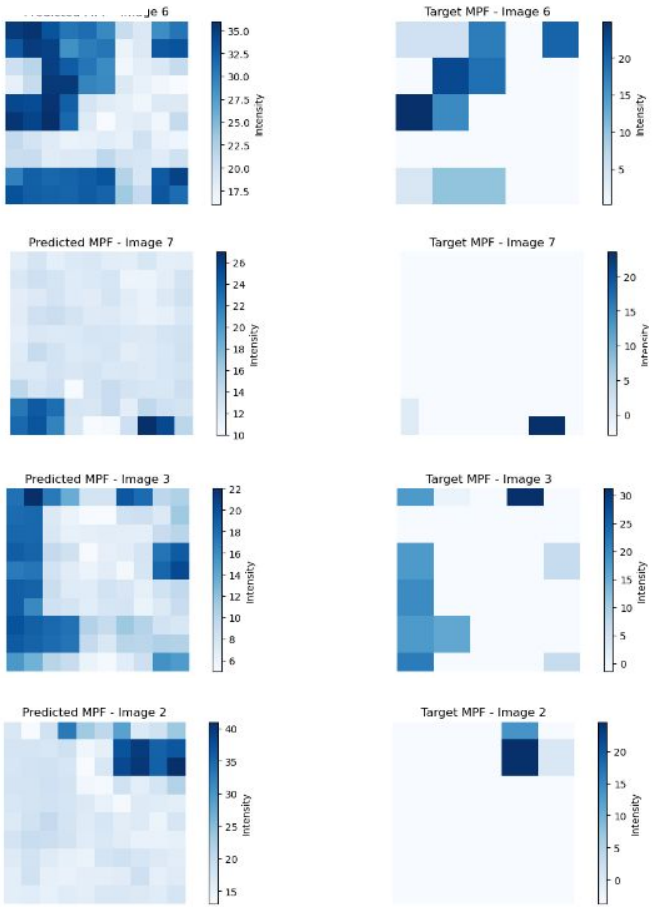
Results 1: OLCI ISTOMINA-dataset



No Filter

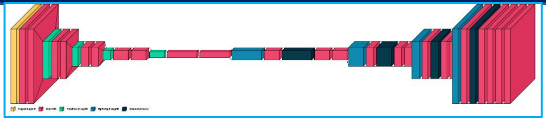
10 x 10 input image
38054 instances

Loss and metrics	Loss: MSE Metric: **MAE**
NaN handling	X =0
CNN	Model A
Epochs	25
Normalization	no data normalization
Results	Model evaluation is [38.27766418457031, 4.0326619148254395] 

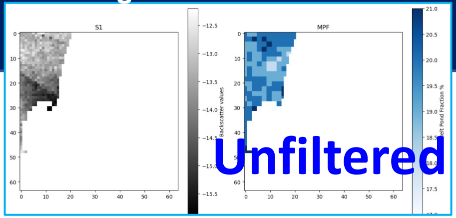


Results 2: OLCI ISTOMINA-dataset

First trials with UNET

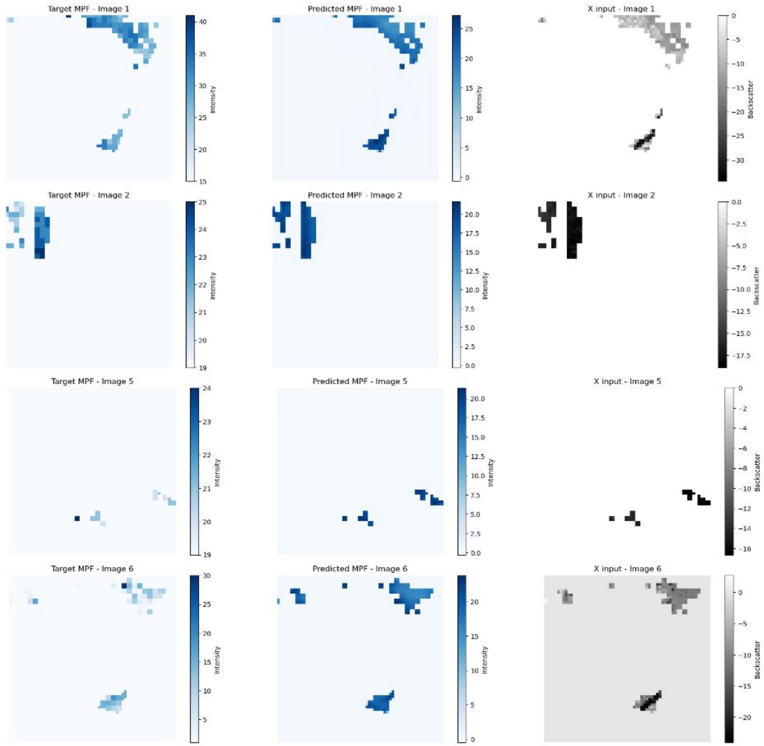


Training datasets w/ NaNs

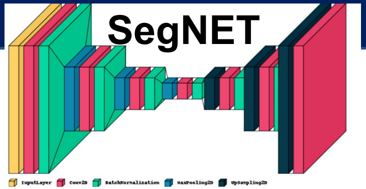


64 x 64 input image
2862 instances

Loss and metrics	Loss: MSE Metric: **MAE**
NaN handling	X[nan] = 0 images with NaNs
CNN	SegNet 1
Epochs	15
Normalization	without normalization
Results	loss: 10.1952



Results 3: OLCI ISTOMINA-dataset



64 x 64 input image
1302 instances

Lee Filtered

Loss and metrics	**Loss: MSE** **Metric: MAE**
NaN handling	X[nan] = 0 images with NaNs
CNN	SegNet 1 with sigmoid
Epochs	25
Normalization	y/100
Results	loss: 0.0014 - ma