This leads to further melting of surrounding areas, resulting in a positive feedback loop / rapid changes of the ice surface properties.

Later: Melt Ponds: Accumulations of melt water on lower surface areas.

[5] Perovich et al 2002

[6] Eicken et al 2004

[7] T.C. Grenfell & Maykut 1977

[8] T. Grenfell & Perovich 1984, 2004,

[9] Perovich 2002

[10] Maslanik et al 2007

[11] Nicolaus 2010

[12] Polashenski et al 2012

**Introduction**

melt ponds have a significant influence on the amount of sea ice melt [[*Perovich et al.*, 2002a](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2011JC007869#jgrc12461-bib-0033); [*Tschudi et al.*, 2008](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2011JC007869#jgrc12461-bib-0050)], on Earth's radiation balance [[*Maslanik et al.*, 2007](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2011JC007869#jgrc12461-bib-0026); [*Perovich et al.*, 2007](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2011JC007869#jgrc12461-bib-0035); [*Nicolaus et al.*, 2010](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2011JC007869#jgrc12461-bib-0028)], and the potential loss of a multiyear ice coverage [[*Maslanik et al.*, 2007](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2011JC007869#jgrc12461-bib-0026); [*Perovich et al.*, 2007](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2011JC007869#jgrc12461-bib-0035); [*Nicolaus et al.*, 2010](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2011JC007869#jgrc12461-bib-0028); [*Kwok and Untersteiner*, 2011](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2011JC007869#jgrc12461-bib-0020); [*Serreze and Barry*, 2011](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2011JC007869#jgrc12461-bib-0046)] (https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2011JC007869)

The Arctic region is warming almost four times faster than the rest of the world [3]. During the summer months, sea ice begins to melt and pools of water form on its surface. These melt ponds can cover up to about 50-60% of the sea ice surface as the season progresses [2][5][6]. Melt ponds are of major importance for the Arctic energy budget as they are darker than snow and ice and absorb significantly more sunlight ([2][7][8][9][10][11]). This leads to further melting of surrounding areas and rapidly changing surface structures [12]. Moreover, they change light transmission into ocean water, affecting the underlying ecosystem.

* Measuring melt pond fraction is critical to study the Arctic sea ice dynamics, climate feedbacks, modelling and ecosystem impacts.
* Accurate estimation of melt pond fraction is crucial in climate models that simulate and predict Arctic climate system / melt pond fraction is used to simulate the impact of melt ponds on the energy budget of the sea ice / melt pond fraction is a important parameter in models that predict future sea ice evolution
* Impacts on marine ecosystem: ecological implications for the Arctic marine ecosystem: Habitat for various organisms, light availability for photosynthesis and productivity of ecosystem. (transmission of incident irradiance through ponded ice is up to an order of magnitude greater than through bare ice (Frey et al, 2011; Ehn et al, 2011) (Anhaus et al 2021
* A method that could accurately retrieve melt pond fraction helps to improve the understanding of complex Arctic processes and enhance the ability to predict and respond to changes in this rapidly changing region.
* ‘A quantification of the overall distribution of melt ponds would be helpful to constrain the role of sea ice for the Arctic amplification and Earth's climate system [e.g., [*Holland et al.*, 2006](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2011JC007869#jgrc12461-bib-0015); [*Eisenman and Wettlaufer*, 2009](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2011JC007869#jgrc12461-bib-0007); [*Notz*, 2009](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2011JC007869#jgrc12461-bib-0029); [*Serreze*, 2011](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2011JC007869#jgrc12461-bib-0045); [*Serreze et al.*, 2011](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2011JC007869#jgrc12461-bib-0047); [*Kurtz et al.*, 2011](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2011JC007869#jgrc12461-bib-0019); [*Perovich et al.*, 2011a](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2011JC007869#jgrc12461-bib-0038)]’
* Until now, statements about the melt pond distribution in the Arctic can only be made from the attempts to model melt ponds [[*Lüthje et al.*, 2006](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2011JC007869#jgrc12461-bib-0023); [*Pederson et al.*, 2009](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2011JC007869#jgrc12461-bib-0030); [*Scott and Feltham*, 2010](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2011JC007869#jgrc12461-bib-0044); [*Skyllingstad et al.*, 2009](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2011JC007869#jgrc12461-bib-0048); [*Flocco et al.*, 2010](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2011JC007869#jgrc12461-bib-0011)]. A realistic presentation of melt pond fractions in the Arctic is only be possible with observations on a large scale over at least one melting period. Therefore, it is important to use remote sensing techniques that are applicable to detect the evolution of melt ponds. To survey melt ponds Arctic-wide, approaches regarding the use of satellite data have been developed by[*Markus et al.* [2003]](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2011JC007869#jgrc12461-bib-0024); [*Tschudi et al.* [2008]](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2011JC007869#jgrc12461-bib-0050); [*Rösel and Kaleschke* [2011]](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2011JC007869#jgrc12461-bib-0040) and [*Rösel et al.* [2012]](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2011JC007869#jgrc12461-bib-0041).

Observing melt ponds is of major importance. Quantifying their extent over time provides insights “into the seasonal and interannual variability of Arctic sea ice, contributing to our understanding of long-term trends and climate change impacts” (chatgpt).

Melt ponds play a significant role for sea ice evolution, making them crucial for models that try to understand and predict the Arctic climate system (Flocco et al., [2010](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015569#jgrc23831-bib-0008); Perovich, [2005](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015569#jgrc23831-bib-0020); Perovich et al., [2002](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015569#jgrc23831-bib-0024); Perovich & Polashenski, [2012](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015569#jgrc23831-bib-0022); Schröder et al 2014). Gaining an understanding about

Melt pond fraction can be used to validate those models “(e.g., as in Hunke et al., [2013](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015569#jgrc23831-bib-0012); Zhang et al., [2018](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015569#jgrc23831-bib-0041)) and to understand trends in the energy balance of the Arctic Ocean (e.g., Perovich et al., [2008](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015569#jgrc23831-bib-0025))”. 🡪 segmentation.

Processing images to derive fraction requires the extraction of different surface classes.

Given the major importance of melt ponds for climate models and studies concerning …

Melt Pond fraction is a crucial factor in predicting future sea ice evolution.

Melt Pond fraction is a crucial factor for future sea ice evolution in climate models (Flocco et al 2010; Flocco et al 2012; Hunke et al 2013). However, accurate prediction of melt pond coverage is still lacking of accuracy

An important factor in understanding melt ponds and their impact on the Arctic climate requires a method that can accurately extract melt pond fraction. So far, there are still a lot of uncertainties in doing so.

Retrieving the **spatial coverage** of melt ponds is of special importance. So far, there are still a lot of uncertainties in Melt Pond modelling. “It is important to observe the spatial coverage of ponds across the Arctic”. (to be able to better understand Arctic climate processes…)

Melt pond observation is of major importance but still undertaken by a lot of uncertainties [1]. Developing a method that can accurately extract melt pond fraction is crucial to understanding and modelling Arcitc climate processes, future sea ice evolution and will lead to a better understanding of processes underlying global climate change.

Developing a method that can accurately extract melt pond fraction is needed.

**Studying Melt Ponds**

Observing melt ponds is challenged by the remoteness of the Arctic ocean. Melt pond coverage has been studied by ground-based measurements (Eicken et al 1994; Perovich and Tucker 1997; Tucker et al 1999, Perovich et al 2002; Tschudi et al 1997, 2001 and Tschudi et al 2008; coverage: Eicken et al., [2004](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015569#jgrc23831-bib-0006); Landy et al., [2014](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015569#jgrc23831-bib-0014); Perovich et al., [2003](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015569#jgrc23831-bib-0021); Polashenski et al., [2017](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015569#jgrc23831-bib-0026), [2012](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015569#jgrc23831-bib-0027)). However, these methods are locally restricted to small areas. Remote Sensing techniques collect data at a distance which allows for retrieving melt pond coverage from a larger scale. While satellite images can cover major parts of the Arctic at a regular scale, they often lack of resolution. One pixel can contain many ponds which makes accurate pond retrieval challenging (Kim 2013, [4]). Airborne images that are taken by helicopters provide the opportunity to observe melt ponds on a more detailed scale while still providing spatial coverage. They can be used to provide an accurate estimation for particular areas and later improve satellite imagery (validate and supplement algorithms utilizing data from other RS platforms).

(+ satellite TIR images only for lower latitudes)

(Airborne limited in spatial extent)

Observation on a detailed scale provided by airborne imagery can help to improve “understanding of sea ice melt processes and MP properties”

State advantages / disadvantages of satellites and airborne. Later: IR on satellites only available for lower latitudes (ask Gunnar if true) 🡪 IR on high-resolution satellites could provide a level of detail plus wider coverage of pond fraction.

Unmixing algorithms based on multi-spectral optical data are a promising method for retrieving large-scale pond fraction but they have quite large uncertainties due to prevailing clouds and cannot derive detailed pond geometry (size and shape) which is important to understand the melt pond development. High-resolution satellites (e.g. SAR) provide more accurate all-weather ice-surface information (Yackel and Barber 2000; Kim 2013; Mäkynen 2014; Scharien 2014) but their narrow swath and inability to discriminate between melt ponds and leads enclosed within interconnected ice floes limits their ability to retrieve a basin-scale surface fraction. Landsat’s low temporal resolution and incapability of cloud penetration hampers its usage in obtaining a daily or weekly datasets of melt pond coverage (Markus 2003). <https://www.cambridge.org/core/journals/annals-of-glaciology/article/melt-pond-distribution-and-geometry-in-high-arctic-sea-ice-derived-from-aerial-investigations/8770BFD400443CB8704AE5B32D3577AE>

To retrieve melt pond fraction from image data, surface classes need to be extracted. This is the task of semantic segmentation. Recent work has mainly focused on detecting ponds in optical images that capture the amount of sunlight reflected by surface objects in the visible range. However, optical images are affected by clouds (<https://www.researchgate.net/publication/341944175_Machine_learning_approaches_to_retrieve_pan-Arctic_melt_ponds_from_visible_satellite_imagery>) and are not available at winter or night during polar night when no sunlight is available. Unaffected by these conditions are thermal infrared images that capture the thermal radiation emitted by objects, corresponding to their surface temperature emitted by the underlying object.

Melt Ponds extracted from IR images could be applied for seasonal prediction from temperature anomalies in winter more accurately as in (<https://agupubs.onlinelibrary.wiley.com/doi/epdf/10.1029/2022GL101493>)

* Higher resolution thermal infrared satellite images are not available for the polar regions (Linda). Helicopter borne images can cover this.
* Topography is included to large extent in the surface temperatures while temperatures contain additionally thermodynamic surface information
* Simple thresholding is sensitive to different environments and even does not work for some images (Beispiel, in dem melt ponds einmal heller, einmal dunkler)
* Measured brightness temperature is close to actual surface temperature, thus adding additional information about thermal properties of the surface structures observed.
* (Reference for sea ice surface temperature = brightness temperature)

To the best of the authors knowledge, no method so far explicitly encountered IR images. Challenging for the task of semantic segmentation are temporally and spatially varying surface temperatures.

Simple temperature-based thresholding methods are therefore not applicable and more complex methods must be applied that can detect characteristic shapes.

This works focuses on building a Deep Learning approach to extract melt pond fraction from IR helicopter images. This method can be applied to extract melt ponds from infrared images and computing melt pond coverage on a small spatial scale. Fast prediction time will allow to calculate and observe the melt pond fraction on time-series helicopter data and can thus be extending to a larger scale. Ideally, the method will be temperature-independent and can be applied to different IR dataset (also winter), such as on-board measurements and meaningfully applied to future melt pond research.

**Background**

Spatially and temporally changing surface temperatures make automated segmentation of melt ponds from IR images challenging.

Prior algorithms for segmenting melt pond images have mainly focus on optical image data.

Thresholding / color based detection / pixel-intensity based segmentation:

A very simple method consists of setting a threshold value on single or multiple color channels and classifying accordingly. Some approaches use thresholding of single color channels (…) or combinations of channels (…). This is not applicable for IR images. (Thielke et al) prone to many errors, requires careful manual threshold choices that need to be adjusted for different environments and seasonal changes. Even within one flight, temperatures change for different surface features and even within one image, differences can occur (Figure 2). (changing temperatures due to changing atmospheric conditions, affected by flight).

<https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015738> classified surface types with color-based segmentation and thresholds based on color channel combinations (= color-based segmentation)

<https://www.cambridge.org/core/journals/annals-of-glaciology/article/melt-pond-distribution-and-geometry-in-high-arctic-sea-ice-derived-from-aerial-investigations/8770BFD400443CB8704AE5B32D3577AE> , Perovich 2002, Inoue 2008, Lu 2010, 2011, Krumpen 2011): manually selecting red, green and blue RGB thresholds based on color distribution histograms of each image independently 🡪 time-consuming and does not work because of color-based

<https://agupubs.onlinelibrary.wiley.com/doi/full/10.1002/2015JC011030> (**thresholding** and then consideration of neighbouring pixels intensities, high-resolution satellite)

<https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/2000JD900275> (Tschudi 2001)

<https://agupubs.onlinelibrary.wiley.com/doi/epdf/10.1029/2022GL101493> (Linda; used thresholding for IR 🡪 exhaustive and prone to errors and small variations in surface temperatures)

Supervised approaches:

[https://www.researchgate.net/publication/341944175\_Machine\_learning\_approaches\_to\_retrieve\_pan-Arctic\_melt\_ponds\_from\_visible\_satellite\_imagery (2020](https://www.researchgate.net/publication/341944175_Machine_learning_approaches_to_retrieve_pan-Arctic_melt_ponds_from_visible_satellite_imagery%20(2020)) (used a neural network to perform pixel-wise classification, however, this cannot take larger features into account and is equally unsuitable as thresholding).

<https://zenodo.org/record/7548469> (PASTA ice Github Repo Niels Fuchs; uses pixel-wise RF classifier)

<https://tc.copernicus.org/articles/8/2163/2014/tc-8-2163-2014.pdf> (decision tree)

Other work proved successful with Edge-based segmentation.

<https://tc.copernicus.org/articles/12/1307/2018/> “use an image segmentation algorithm to divide the image into objects which are then classified with random forest machine learning” (code: Wright 2017). Image segmentation algorithm: Edge detection to find boundaries between surface types, watershed to build complete objects based on edge locations and intensity.

<https://www.researchgate.net/publication/272365874_Regional_melt-pond_fraction_and_albedo_of_thin_Arctic_first-year_drift_ice_in_late_summer> (boundary segmentation with Otsu (chooses threshold to minimize intra-class variance of black and white pixels), boundary tracing with Moore-Neighbor tracing algorithm, thresholding in red channel).

In IR images, boundaries are often not sharp enough to encounter for accurate edge detection / However, accurate edge detection requires clear boundaries of surface structures which is not given in IR images (see Figure).

The impracticality of existing approaches requires to develop a new method that can detect more complex features and takes shapes into account. In recent years, major improvements in image classification and segmentation could be achieved with CNN-based architectures, have been applied in the sea ice domain (<https://www.mdpi.com/2077-1312/8/10/770>;

CNN???

<https://tc.copernicus.org/articles/13/2421/2019/> (Neural Network to estimate snow depth on Arctic sea ice with microwave radiometry satellite data)

<https://ieeexplore.ieee.org/abstract/document/9443178> (Used an ensemble neural network segmentation approach for ship-based images 🡪 (very complex approach, not easy to determine effects of single components))

<https://ieeexplore.ieee.org/abstract/document/7122229> (Neural Network for pixel-based classification of SAR

meltpondnet

**Melt Pond optical properties**

<https://www.cambridge.org/core/journals/annals-of-glaciology/article/melt-pond-distribution-and-geometry-in-high-arctic-sea-ice-derived-from-aerial-investigations/8770BFD400443CB8704AE5B32D3577AE>

Generally <10m in size. (of order 10m² in area at melt onset (Perovich 2002)

The geometric appearance of melt ponds is relevant for detection.

Can vary in shape, ranging from circular or oval to irregular or elongated (influenced by factors such as the underlying topography), size and area (small ponds to large expanses covering significant portions of the ice surface). Some ice floes with lots, some without. Surface temperature (influenced by depth). Melt ponds can be interconnected, forming a network of channels and pools on the ice surface. Generally, they occur as warmer pools on the top of ice floes, although this cannot be universalized.

These characteristic properties are hoped to be detected by feature extractor of neural network.

**U-Net**

Two main parts: Feature extractor or backbone which takes an image as input and progressively reduces the feature space’s dimension, producing a highly nonlinear representation of the image. Second, the upsampling part / decoder, which utilizes features from the feature extractor and outputs a segmentation mask.

**Training Data**

Neural Network architectures generally perform better

**Patch Extraction**

**Augmentation**

**Pretraining**

The thesis is structured as following.

**Methods**

Flow-chart of image processing

**Data**

Each pixel corresponds to a specific temperature value. Warmer objects appear brighter, while cooler objects appear darker.

Helicopter-borne imaging TIR. Study area. VarioCam HD head 680 camera with a brightness temperature precision of 0.02K and accuracy of 1K (reference). Gridded surface temperatures at 1m resolution. Focus on data from 18 August that was mostly unaffected by atmospheric conditions (as has been done in <https://www.nature.com/articles/s41597-022-01461-9.pdf> ???)

(additionally optical during polar day, Lena AWI)

The surface classes captured in the infrared image have different spectral signatures. A IR camera has one spectral band at wavelengths of around …nm. The digital number of a pixel (DN) contains part of the spectral signature of the different classes. In IR, this digital number encodes the brightness temperature and strongly correlates with the surface temperature of the respective class.

Dataset Selection

Within Flight 9, images have been selected according to having a lot of variation and making the model able to analyse a large variety of images. In future, even more Flight should be taken into account to account for a larger diversity in the dataset.

CLASS IMBALANCE (network will be biased towards the majority classes 🡪 oversampling?)

* Make loss decision due to class imbalance
* <https://www.cv-foundation.org//openaccess/content_cvpr_2016_workshops/w19/papers/Kampffmeyer_Semantic_Segmentation_of_CVPR_2016_paper.pdf>

**Annotation**

To encounter for better visibility during annotation, the images have been clipped to a temperature range of [273, 276] allowing for a higher contrast.

To help for Gimp, masks have been aligned with the images. (describe Sobel Filter…) High gradient values correspond to abrupt changes in pixel intensity, which are likely boundaries between surface types. (no further noise detection and filtering of weaker edges). However, melt ponds in IR are often not clearly distinguishable by boundary, which led to further manual processing of several hours per image, to account for accurate training masks.

**Patch Extraction**

**Augmentation**

KOMBINIEREN MIT ORIGINALEN DATA DAMIT GRÖßERER DATENSATZ

* To make model more robust and prevent overfitting 🡪 make dataset more diverse
* Increase dataset size, good method to increase without manual labelling required (images and masks will be augmented accordingly)

Methods used:

* Noise injection (Gaussian noise)
* Flipping
* Rotation
* Blurring and sharpening
* Brightness contrast

Methods not used:

* Color augmentations (saturation)
* Multiple image augmentations (mixing strategies have been disregarded; mixup results in unrealistic outputs and label ambiguity; cutmix will distort object boundaries)

Images were taken of an overhead perspective and therefore require no specific orientation. Flipping, random rotation could be applied. Cropping and zooming were disregarded as augmentation techniques as patch extraction should be observed and this would have distorted effects achieved by patching.

Random brightness and contrast changes were applied. No absolute information from temperature values.

More advanced Multi image augmentation techniques that combine multiple images by blending or cropping like mixup or cutmix (successfully applied in recent studies) have been disregarded because this would have distorted the closed and unique shape of melt ponds.

Sharpening and blurring have been applied as these could imitate atmospheric effects of water vapour or changing camera quality.

(Robustness measures for varying quality) Image blur imitates snow, rain, water on camera lens; brightness decrease imitates changes in surface temperature due to different points in space or time; water vapour that results in blurring the IR image)

“During training, random image augmentations were performed on the images: Random flipping, rotation, zoom, brightness, contrast, (hue and saturation 🡪 optical). As temperatures are not consistent among the surface types, brightness change was still selected, imitating an even higher variability in environmental conditions. 🡪 diversify and enlarge training dataset”.

Cropping and zooming were disregarded as augmentation methods because it would have distorted the effect of different patch sizes, which was under study.

‘Albumentations is a fast and flexible Python tool for image augmentation. It is widely used in ML competitions, industry and research to improve the performance of DL”

**Model Training**

Adam Optimizer: <https://arxiv.org/abs/1412.6980>

**Model Evaluation**

Model Evaluation is a important method to estimate the models performance and be able to compare different hyperparameter settings. Train test splits allow to detect overfitting.

Model Evaluation has been done using a train test split of 70 / 15 / 15 (random selection; splits only calculated once and reused for all experiments to allow for comparibility. However, note that it results in different training and testing sets for the different patch sizes). As the training set is very small, for some patch sizes, this results in a test set that is only one image and therefore likely to be highly biased (reference). Hyperparameter Optimization is dependent on the evaluation metric. K-cross validation allows to overcome this issue but results in heavy training. Therefore, k-cross validation has been performed on a default hyperparameter setting, the results compared to a simple train test split.

(k was chosen as five because it achieves a balance between the number of images in the validation sets and number of folds for cross-validation). 🡪 Divide into six parts of nearly equal size, use first five for cross-validation and set sixth fold aside as test set.

<https://ieeexplore.ieee.org/abstract/document/9443178> (histogram to make sure that class distribution among folds is equal).

**Pretraining**

A common method to pretrain U-Net is exchanging the encoder with a pretrained classification backbone as Resnet34 or VGG16.

Commonly, networks are pretrained on Imagenet. This has been given successful results even for sea ice domain (Petersen et al 2009), however,

Note that the results are not directly comparable between plain U-Net, pretrained with ResNet and pretrained autoencoder, as the ResNet is used as backbone.

(Training: The pretrained backbone was frozen, only the upsampling part was trained). For UNet, Keras implementation was used and adjusted. Autoencoder was implemented with inspiration from…

**Optical Training Data**

<https://www.sciencedirect.com/science/article/pii/S0165232X09000032?casa_token=CYND2U8oJU0AAAAA:6uob_5DIJWHREBWz8ahxK8E66WT1tM6QzkleGjuZjCISKrkklNT6760zYytnieMroBIcTE9E_XUz> used kmeans to classify into different ice types (successful given appropriate image conditions and environment (e.g. illumination, visual clarity, snow cover).

Important: are the aerial images preprocessed / normalized (think so)

**Hyperparameter Optimization**

**Results**

**Evaluation Metrics**

5-fold cross-validation was used as evaluation scheme (to evaluate the model on each of the five validation sets, the neural network was trained on the remaining four validation sets).

Quantitative Performance indicators:

MeanIOU

( Accuracy (biased towards most frequent class) )

F1score

IOUc (for particular class)

Mean IOU has been selected as primary metric to make strict decisions possible, as standard in image segmentation literature

**Quantitative Results**

**Baseline**

**Ablation on patch size**

**Ablation on pretraining approach**

**Ablation on training dataset**

**Time Complexity**

**( Labeling Consistency )**

**Qualitative Results**

Qualitative Results contained visual inspection of segmentation results.

**Melt Pond Fraction**

Knowing Melt Pond Fractions sufficient for crudely estimating regional averages of albedo and surface ablation.

„Melt Pond fraction is the ponded area relative to the sea ice area (Webster 2015). We define MPF as the ponded percentage of the sea ice area:

MPF = ( MP / MP + ICE ) x 100, as has been done in (<https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015738>).

To allow for another evaluation metric, MP fraction has been calculated for RGB and predicted IR images and compared to MPF calculated with … method.

**Discussion**

<https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015738> (discuss factors that lead to misclassification in RGB images color-based)

Difficulties of manual segmentation: Although done very carefully, some melt ponds could not be detected.

Problem with unsupervised kmeans segmentation: Produce inconsistent, non-intercomparable results (fixed k, even if not all features are present).

Distinction melt ponds and open leads. “Submerged ice (resulting from lateral melting) presented at some ice floe edges are classified as melt ponds and melt holes (melt ponds that penetrated through the underlying sea ice cover) are classified as leads, partly because of similar optical and physical properties between submerged ice and pod, and between hole and lead (Inuoe 2008) <https://www.cambridge.org/core/journals/annals-of-glaciology/article/melt-pond-distribution-and-geometry-in-high-arctic-sea-ice-derived-from-aerial-investigations/8770BFD400443CB8704AE5B32D3577AE> . Fraction of these features are very small compared with the melt ponds and image coverage, resultant errors with the mean value of pond statistics for one image are likely to be small (Perovich 2002) 🡪 (but might be too large for training data).

Notice that the aerial photograph is highly distorted, and hence, the sizes of melt ponds in the aerial photograph cannot be directly compared with those in the airborne SAR image acquired in this study.

IR data was fed in ungridded. This was encountered by using the image centers that generally are less distorted. However, this could effect model performance by learning wrong shapes.

Necessary to label more images, also from different flights and possibly different seasons.

Future work: Work more on alignment of optical an IR images, improve classification method of optical (apply discriminant analysis to find highly discriminative features while reducing the dimensionality of the feature space).

Implement different loss function, further tune hyperparameters, extract different number of patches from images.

Different architectures such as PSP-Net (uses pyramid pooling module to aggregate multiscale context information in different subregions). DeepLabV3+ combines encoder-decoder structure with SPP to better capture multiscale contextual information and produce sharper object boundaries by gradually recovering spatial information. However, they are more complex and require more training time.

**Conclusion**

The objective of this work was to develop a deep learning-based approach to segment helicopter-borne IR image data containing three classes (ocean, sea ice, melt pond) that can later be used as validation data for satellite imagery.

The results can be summarized the following:

* … classes and … could be detected well, other poorly.
* Pretraining with … could outperform pretraining with IR images (on average and in per-class IOU).

To be applicable in future and derive correct MPF, data needs to be gridded.

“Further applications include calculation of partial and total concentrations, melt-pond feature size assessment

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