**Introduction**

The Arctic region is warming faster than the rest of the world [1]. 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][3][4]. 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][5][6][7][8][9]. This leads to further melting of surrounding areas and rapidly changing surface structures [10]. Moreover, they provide habitat for various organisms (…) and change light transmission into ocean water, having effects on the underlying marine ecosystem (Frey et al 2011, Ehn et al 2011, Anhaus et al 2021).

Quantifying the distribution of melt ponds is crucial to study the Arctic sea ice dynamics and ecosystem impacts. Accurate estimation of melt pond fraction is required for models that simulate and predict the Arctic climate system (Flocco et al 2010; Perovich 2005; Perovich 2002; Perovich & Polashenski 2012; Schröder 2014; Flocco 2012; Hunke 2013), overall contributing to our understanding of long-term trends and climate change impacts. Melt pond fraction, the ratio of melt pond to sea ice, can be derived from image data. Methods are needed that separate images into melt pond, sea ice and ocean classes, respectively.

**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 and don’t allow for a realistic representation of melt pond fraction in the entire Arctic. Remote Sensing techniques collect data at a distance which allows for retrieving melt pond coverage on a larger scale. While satellite images can cover major parts of the Arctic at a regular frequence, they often lack of resolution. In low-resolution satellite images, one pixel can contain many ponds which makes accurate pond retrieval challenging (Kim 2013 [4]). High resolution satellite imagery only exists for certain spectral bands and …. Airborne images that are taken by helicopters are limited in spatial extent but provide the opportunity to observe melt ponds on a more detailed scale. They can be used to provide an accurate estimation for particular areas and later improve satellite imagery, as has been done previously.

To retrieve melt pond fraction from image data gathered, surface classes need to be extracted. This is a 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 often affected by clouds (…) and not available during polar night in the absence of sunlight. Mostly unaffected by these conditions are thermal infrared images (IR) that capture the thermal radiation emitted by surface objects. Additionally, surface temperature contains information about thermal properties of the object measured. A specific application is seasonal prediction of temperature anomalies, as in (Linda).

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 methods that rely on information provided by pixel temperature only cannot be applied. As TIR (high-resolution?) satellite imagery is only available for lower latitudes (Linda), helicopter-borne imagery is regarded.

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**

**Related Work**

Spatial and temporal variations in surface temperature make automated segmentation of melt ponds from IR images a challenge. Existing methods designed for optical data are not applicable. Previous work on melt pond segmentation has mainly focused on (1) thresholding and other colour-based methods or (2) edge-based segmentation.

Thresholding involves setting a threshold value on a single or multiple colour channels to separate instances that lie below and above that value. [] manually selected thresholds based on colour distribution histograms. This works for optical images where surface types can generally be distinguished by their pixel intensity, but often requires independent threshold settings for each image due to changing lighting conditions.

Thielke et al applied thresholding to a winter IR dataset. In winter, when sea ice is much colder, surface classes are better distinguished by their temperature (**CITATION**). As mentioned above, this is not the case for summer datasets, when melt ponds appear. Other than that, the method still required careful choice of thresholds and was prone to error.

Colour-based segmentation methods apart from thresholding include pixel-wise supervised approaches such as random forest classification or feed-forward neural networks. These methods use a set of labelled training examples to infer classes on unseen pixels. However, existing methods are likewise dependent on single pixel values only and therefore impractical for changing conditions.

Edge-based detection refers to automated approaches that identify object boundaries. [] implemented a Sobel filter that calculates the gradient magnitude of each pixel and detects edges due to rapid changes in pixel intensities. [] did with Otsu. In IR images, boundaries are often not sharp enough to encounter for accurate edge detection. Especially melt ponds are often disregarded as exemplified by Figure 1.

The impracticality of existing approaches requires to develop a new method that takes context into account. In recent years, major improvements in image classification could be achieved with deep convolutional neural network (CNN) architectures (references). CNNs apply filter kernels to input data, extract local features by convolutions and reduce spatial dimensions by pooling. This enables extraction of meaningful features across different scales and effective learning of complex image patterns. When replacing classification layers with a decoder, spatial information can be restored and the architecture used for segmentation tasks.

that excel at extracting meaningful features from images. A major strength of CNN is that they can efficiently detect contextual features on different scales of the images, thus melt pond and ice floe shapes [].

CNN architectures have been efficiently applied in remote sensing tasks and the sea ice domain.

The hope is that feature extraction can effectively detect pond and sea ice shapes. When connected to a decoder, image localization can be restored and the architecture used for segmentation. This work investigates U-Net as architecture.

Figure 1: Changing brightness temperatures for different images. Note the marks in image 1 that show that even within one image, melt ponds can appear brighter or darker than sea ice and ocean. Corresponding optical image for comparison.

Figure 2: Application of Sobel Filter on IR image can detect only some surface boundaries.

**Melt Pond optical properties *(later)***

[Arctic sea-ice conditions and the distribution of solar radiation during summer | Annals of Glaciology | Cambridge Core](https://www.cambridge.org/core/journals/annals-of-glaciology/article/arctic-seaice-conditions-and-the-distribution-of-solar-radiation-during-summer/DFD79CB3D5D156B68EB54A88CDAF8812)

**U-Net**

**Training Data**

As deep learning method, CNN-based architectures do not require manual feature engineering and automatically adjust to erroneous predictions.

**Patch Extraction**

**Augmentation**

**Pretraining**

**References**

[1] Rantanen, M., Karpechko, A.Y., Lipponen, A. *et al.* The Arctic has warmed nearly four times faster than the globe since 1979. *Commun Earth Environ* **3**, 168 (2022). <https://doi.org/10.1038/s43247-022-00498-3>

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