“Melt Ponds form on sea ice in summer when the snow melts and water accumulates in the lower locations on the ice floes. Melt ponds are very important for the Arctic energy budget because they strongly change the sea ice brightness and thus the amount of solar energy absorbed by the ice. There are still large uncertainties in models to predict melt pond evolution, especially their parameterization of size, depth, and effect on light transmission (Flocco et al., [2012](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2022GL101493#grl65489-bib-0010); Light et al., [2008](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2022GL101493#grl65489-bib-0023); Webster et al., [2022](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2022GL101493#grl65489-bib-0038))”.

\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

o. Eicken et al.(2002) and Lei et al. (2016) detailed the evolution of melt ponds inseveral stages. In the first stage (initial melt phase), as the ponds be-gin to form, melt water accumulates on the rather impermeable ice, ex-panding spatial pond coverage. Melt pond elevation is generally abovesea level because the outflow pathways under themelt pond are limited. During the second stage (drainage phase), pondelevation remains close to sea level because of increased outflow. Manyponds are created during this stage and the spatial coverage of pondsexpands. As the melt season progresses, melt ponds may drain throughthe ice. In the third stage (mature pond phase), ponds still remain nearsea level with high ice permeability and open macroscopic flaws. Manyponds may melt through to the ocean during this stage. The last (refreez-ing phase), is not limited to the end of the melt season but can occuranytime during summer once air temperatures drop below freezing. Athin layer of ice may form on top of the pond during initial freezing andmay open again if air temperatures rise above freezing or enough solarradiation is available. Eventually, the winter season sets in and pondscompletely freeze.   
*(14) (PDF) Machine learning approaches to retrieve pan-Arctic melt ponds from visible satellite imagery*. Available from: <https://www.researchgate.net/publication/341944175_Machine_learning_approaches_to_retrieve_pan-Arctic_melt_ponds_from_visible_satellite_imagery> [accessed May 24 2023].

it has been widely theorized that melt ponds cover a larger fraction of first year ice than of multiyear ice because flat, undeformed pans of first year ice allow melt water to spread horizontally, while the rough surface of multiyear ice contains melt water in well-defined ponds (Eicken et al., [2004](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015569#jgrc23831-bib-0006); Fetterer & Untersteiner, [1998](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015569#jgrc23831-bib-0007)). As the Arctic sea ice cover transitions from one dominated by thick multiyear ice toward a seasonal ice cover (Maslanik et al., [2007](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015569#jgrc23831-bib-0016); Rigor & Wallace, [2004](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015569#jgrc23831-bib-0029)), the coverage of melt ponds and their role in albedo feedback is likely changing. The importance of melt ponds, and the changes they are likely experiencing, demand we observe seasonal and long-term trends in their prevalence.

Flight was performed in August which means… phase… coverage…

Processing high-resolution sea ice imagery to derive use-  
ful metrics quantifying surface state, however, remains a ma-  
jor hurdle. Recent years have seen numerous publications  
demonstrating the success of various processing techniques  
for optical imagery of sea ice on limited test cases (e.g., In-  
oue et al., 2008; Kwok, 2014; Lu et al., 2010; Miao et al.,  
2015; Perovich et al., 2002b; Renner et al., 2014; Webster  
et al., 2015). None of these techniques, however, have been  
adopted as a standard or been used to produce large-scale  
datasets, and validation has been limited. Furthermore, no  
single method has been used to process data from multi-  
ple sensor platforms or documented and released for wide-  
spread community use. These issues must be addressed to  
enable in large-scale production-type image processing and  
use of high-resolution imagery as a sea ice monitoring tool.

“The observation of melt ponds is primarily motivated by the need to better understand the processes and changes in Arcitc climate.”

* Studies that have focused on detecting melt ponds using HR imagery such as WV and SAR (Divine et al 2015, Fors et al 2017, Wright and Polashenski 2018). Understand trends in pond coverage
* Expanding the collection of high-resolution (satellite) imagery over sea ice is necessary to monitor melt pond coverage with the accuracy needed by the scientific community ([1]) *There is a need for high resolution datasets compared to low resolution MODIS data*
* Accurate classification from high resolution (airborne) data that is only partly available can be seen as ‘true’ estimates to validate melt pond models
* Used to: inform/improve/test spectral unmixing and ML techniques that seek to determine MP coverage from more widely available, but lower resolution optical satellite imagery (e.g. MODIS)
* Validate large-scale models of melt pond evolution (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)). Recent advances in global climate models have implemented explicit parameterization of melt pond formation and evolution processes as a component of calculating sea ice surface albedo, with the goal of increasing physical realism, accuracy, and model resiliency under changing conditions (e.g., Hunke et al., [2013](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015569#jgrc23831-bib-0012)). In these models, pond coverage is an intermediary in calculating the albedo.
* MPs influence the sea ice energy balance (Maslanik et al 2007, Perovich et al 2007, Nicolaus et al 2010), the amount of light available under and within sea ice (Nicolaus et al 2012),… In climate model simulations, melt ponds have been found to play an important role in future sea ice evolution (Flocco et al. 2010; Flocco et al. 2012, Hunke et al. 2013) and may also play a role in forecasting how much ice melts each summer. In particular, Schröder et al (2014) found that MP fraction in May provided good predictive skill for the September Arctic sea ice extent minimum.
* Melt pond coverage retrieval: Flocco et al., [2010](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015569#jgrc23831-bib-0008); Hunke et al., [2013](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015569#jgrc23831-bib-0012); Lüthje et al., [2006](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015569#jgrc23831-bib-0015); Zhang et al., [2018](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015569#jgrc23831-bib-0041)
  + Precise pond coverage over small domains and short time periods using ground based studies (e.g., 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))
  + those using aerial photography (Miao et al., [2015](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015569#jgrc23831-bib-0017); Perovich, [2002](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015569#jgrc23831-bib-0023); Webster et al., [2015](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015569#jgrc23831-bib-0038); Wright & Polashenski, [2018](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015569#jgrc23831-bib-0039)), high-resolution optical satellite imagery (Wright & Polashenski, [2018](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015569#jgrc23831-bib-0039), and other citations therein), and C-band SAR imagery (Scharien et al., [2014](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015569#jgrc23831-bib-0032)) to quantify pond coverage explicitly over multi-kilometer domains at snapshots in time
  + those attempting to determine pond coverage over extensive spatial and temporal scales from lower resolution remote sensing by de-convolving the pond-related signals from other contributions to the surface signature (Rösel et al., [2012](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015569#jgrc23831-bib-0031); Rösel & Kaleschke, [2011](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015569#jgrc23831-bib-0030); Tschudi et al., [2008](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015569#jgrc23831-bib-0034)).

To date, these efforts have not met the need for a spatially and temporally continuous data set that would serve as a climatological data record suitable for examining trends in pond coverage or as a basis against which to validate model predictions.

* Algorithms to detect melt ponds: (Miao et al., [2015](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015569#jgrc23831-bib-0017); Miao et al., [2016](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015569#jgrc23831-bib-0018); Webster et al., [2015](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015569#jgrc23831-bib-0038); Wright & Polashenski, [2018](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015569#jgrc23831-bib-0039))
* ‘Recent advances in processing high-resolution optical imagery of sea ice provide high-accuracy measures of the state of the sea ice surface’. However, these images capture only part of the information that can be revealed from melt ponds.
* In the infrared domain, surface structures are not easily distinguishable only by color anymore. Why. The shape is important
* Shape of melt ponds (geometry of melt ponds)
* oversimplified melt pond modeling, which is related to the albedo parameterization in the climate model (Flocco et al., 2010, Scott and Feltham, 2010)

Optical methods exist 🡪 IR not 🡪 IR more difficult.

‘High-resolution imagery of Arctic sea ice enables direct observations of melt ponds because their size and shape are explicitly resolved and most pixels represent only one surface type. The fraction of a scene coveres by melt ponds can be determined by classifying which surface each pixel represents and counting those that represent pond-covered areas’.

Semantic Segmentation with Deep Learning: Theoretical Basis

Supervised methods use a set of labelled examples… Can produce fixed surface type definitions, improve in skill as more training data is added, feature extractor that regard shapes.

‘Artificial Neural Network has been widely used for the classification of remote sensing images over various surfaces (Chang and Islam, 2000; Hong et al., 2004; Yu et al., 2017), including sea ice and snow (Bogdanov et al., 2005; Rösel et al., 2012; Ressel et al., 2015; Braakmann-Folgmann and Donlon, 2019; Liu etal. 2019).’

Limitations and Challenges faced in this work

[1] <https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC015569> (2020, 6 cit)

* Open Source Sea Ice Processing algorithm to classify surface features in submeter resolution optical satellite imagery ([3])

**Geometry of Melt Ponds**

**Infrared Melt Ponds: Figure of reflectivity MP in IR?**

**Why airborne?**

Current technologies to detect melt ponds include high spatial resolution synthetic aperture radar (SAR) (Kim et al., 2013, Scharien et al., 2007), low or medium spatial resolution optical satellite images such as MODIS and LandSat ETM + (Markus et al., 2002, Markus et al., 2003, Rosel and Kaleschke, 2011, Tschudi et al., 2008), and high spatial-resolution airborne images (Inoue et al., 2008, Lu et al., 2010, Perovich et al., 2002, Renner et al., 2013, Tschudi et al., 2001). The MODIS or LandSat ETM + imagery showed potential in measuring melt pond fraction, but it cannot derive detailed pond statistics due to the limitation of spatial resolution (Markus et al., 2003, Rosel and Kaleschke, 2011). Furthermore, the optical bands of satellite imagery were easily blocked by the pervasive cloud coverage during the Arctic summer (Kim et al., 2013). Even high spatial resolution SAR images failed to detect most small melt ponds since all pond polygons with less than 25 pixels were excluded as they were difficult to be derived consistently (Kim et al., 2013). On the other hand, aerial photographs, especially taken by helicopters during the icebreaker expeditions can avoid cloud blockage to the maximum extent by flexible flight mission and low flight height (usually below 300 m). Although the field of view is limited and sampling bias exists since aerial photographs are usually taken along or near the ship tracks, they are still valuable in Arctic research, because they could provide a detailed and accurate estimation of sea ice and melt ponds for the particular areas, and further extract sea ice physical parameters due to its typical sub-meter spatial-resolution.

The Arctic region is warming three times faster than the rest of the world. During the summer months, rising temperatures lead to the formation of melt water ponds on the surface of sea ice. They begin to appear around mid-May and can occupy up to about 50-60% of the sea ice surface as the summer season progresses. Melt Ponds are important for the Arctic energy budget as they are darker than snow and ice and thus absorb significantly more sunlight. This leads to further melting of surrounding areas and results (mündet) in a positive feedback loop, possibly having a large effect on sea ice loss (Schröder et al (2014)). Moreover, Melt Ponds change the light transmissity of sea ice,…

Observing Melt ponds therefore plays a major role in understanding and modelling Arctic climate processes. Melt pond fraction can provide information about… Developing a method that can accurately predict melt pond fraction is crucial to understanding future sea ice evolution, further extending to a better understanding of global climate change.

Observing melt ponds therefore plays a major role in understanding ice-albedo feedback that govern annual ice retreat (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)).

(Melt Ponds can form and disappear quickly, leading to a highly dynamical system and energy budget).

There is a need for high resolution datasets [1].

Observing melt ponds is challenged by the remoteness of the Arctic ocean. Melt Ponds have been studied by in situ 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). However, these methods are locally restricted to small areas. Remote Sensing techniques allow for observing melt ponds on a larger scale. While satellite images provide good temporal coverage, ponds are often to small to extend the pixel level and it is challenging to retrieve accurate results from recent data. Airborne imagery that are taken by helicopters on Arctic expeditions provide the opportunity to observe melt ponds on a more detailed scale. They can only cover parts of the whole region but can be used to later improve satellite imagery (…).

To extract the melt pond fraction from image data gathered, images need to be processed and different surface types extracted. Recent work has mainly focused on visible data.

As all surface structures, melt ponds have a special spectral reflective behaviour, reflecting specific parts of the sunlight to a certain amount. This behaviour makes them distinguishable from surface structures such as sea ice or ocean. Visible for the human eye are wavelengths in the visible spectrum, which is why they have been often studied in this spectral area. However, visual data is affected by clouds and can not be gathered when there is no sunlight available. Images taken in the Thermal Infrared spectrum (TIR) provide information about the surface temperature and are independent from night or polar night. TIR are mostly unaffected by clouds. Further, they can be used for predicting surface temperatures.

The reflectance behaviour of melt ponds is distributed over several bands. Recent work has focussed on extracting melt ponds from optical wavelengths, allowing for Visual bands allow for optical interpretation of the surface structures. However, visual data is affected by clouds and can not be used at night (Furthermore, the optical bands of satellite imagery were easily blocked by the pervasive cloud coverage during the Arctic summer (Kim et al., 2013)). Thermal Infrared Images (TIR) allows to predict the surface temperature of features measured. While melt ponds have been studied optically (…, …., …) no work has been done in investigating their fraction based on infrared images.

This work aims to build and improve a Deep Learning model to extract melt pond fraction from IR helicopter images. This model can be used to detect melt ponds, calculate their spatial coverage/ fraction.

The following contributions / requirements:

Ideally, the algorithm can later be used for other image data.

--------------------------------------------------------------------------------------------------------------------------------------

Extracting image data into meaningful features is task of semantic segmentation.

Recent work has focused on developing algorithms for extracting melt ponds from satellite imagery and airborne visual bands (Divine et al 2015, Fors et al 2017, Wright and Polashenski 2018). Many of the methods used a combination of unsupervised Random Forest approaches … could provide a highly accurate segmentation model for melt pond extraction. (However), most of the studies are based on color-segmentation, thresholding… (and thus not applicable to surface temperature data).

TIR images are especially challenging for semantic segmentation as their information restricts to one wavelength and surface temperature is characterized by high variability among the surface features. Due to the salinity of ocean water, the melting point decreases under zero degrees. It is therefore possible that sea ice reaches higher surface temperature than ocean water. Surface features vary heavily in their absolute temperatures, as well as in their ordering (can neither be classified due to their temperature odering nor to absolute values). Classical methods applied for optical imagery, such as thresholding (…), unsupervised clustering (…) or … do not work. Temperatures vary a lot due between the images so not much information can by retrieved not only by the threshold value.

Show different temperatures of IR.

GEOMETRY OF MELT PONDS. (characterized by small round shapes, interconnected – refer to stage of melt ponds at time of data retrieval).

Methods exceeding threshold- and color-based segmentation include edge detection and texture based segmentation. Simple edge detection algorithms are prone to errors, texture is not inclusive. Recent advances in image processing and feature extraction has been made by Deep Neural Networks. CNNs have been shown to be able to successfully recognize features and could thus be used to detect shapes of melt ponds. This work investigates the possibility by using UNet as a Artificial Neural Network inspiration.

As other methods, UNet consists of an encoder and a decoder. They are additionally interconnections. UNet has originally been introduced in 2016 for medical image segmentation, but successfully been applied to remote sensing tasks. Although more advanced methods like PSPNet or DeepLab have been developed and applied since then, UNet remains a state of the art method due to its fastness, relatively simple architecture. UNet has been chosen for this work as a benchmark architecture that provides the ability to be finetuned later on as it has been done by (UNet2, UNetPlus…).

Graphic of UNet.

As a supervised method, there remains a huge challenge in training the network: The requirement of labelled training data. In image segmentation tasks, this means mask extracting the features on which the model can learn patterns.

TRAINING DATA

Unlike large computer vision tasks like ImageNet or… , remote sensing tasks lack of labelled training data.

PATCH EXTRACTION

AUGMENTATION

TRANSFER LEARNING

Segmentation, RF classification (Miao et al 2015; Wright and Polashenski 2018)

Threshold / brightness based (Webster 2015)

In addition, as the most representative supervised DL model, convolutional neural networks (CNNs) [43] have outperformed most algorithms in visual recognition. The deep structure of CNNs allows the model to learn highly abstract feature detectors and to map the input features into representations that can clearly boost the performance of the subsequent classifiers. (<https://ieeexplore.ieee.org/abstract/document/7486259?casa_token=OyaF4Id1TQEAAAAA:AcJIHDODrVPZM8RzDx71RMrXqnMx1rK6urhLFZEV5PtrTGKDIqqloRVf2kN7zNDU9jQe4F9H>)

“Current technologies to detect melt ponds include high spatial resolution synthetic aperture radar (SAR) (Kim et al., 2013, Scharien et al., 2007), low or medium spatial resolution optical satellite images such as MODIS and LandSat ETM + (Markus et al., 2002, Markus et al., 2003, Rosel and Kaleschke, 2011, Tschudi et al., 2008), and high spatial-resolution airborne images (Inoue et al., 2008, Lu et al., 2010, Perovich et al., 2002, Renner et al., 2013, Tschudi et al., 2001). The MODIS or LandSat ETM + imagery showed potential in measuring melt pond fraction, but it cannot derive detailed pond statistics due to the limitation of spatial resolution (Markus et al., 2003, Rosel and Kaleschke, 2011).”

* Threshold based methods are prone to changes in illumination conditions (Lu et al., 2010), that are natural in airborne photography

References based on: <https://www.sciencedirect.com/science/article/abs/pii/S0165232X15001433>