Machine Learning for the Detection of Arctic Melt Ponds from Infrared Imagery

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INTRODUCTION

- Melt Ponds are pools of water on Arctic sea ice that **significantly influence the Arctic energy budget and accelerate ice melt** by reducing surface reflectivity.
- Accurate retrieval of melt pond coverage is **crucial to understand and predict the rapidly changing Arctic** and its role in the global climate system.
- **Melt pond data are limited.** The remoteness of the Arctic Ocean limits in situ measurements. Small melt ponds can not be captured by most satellite products.

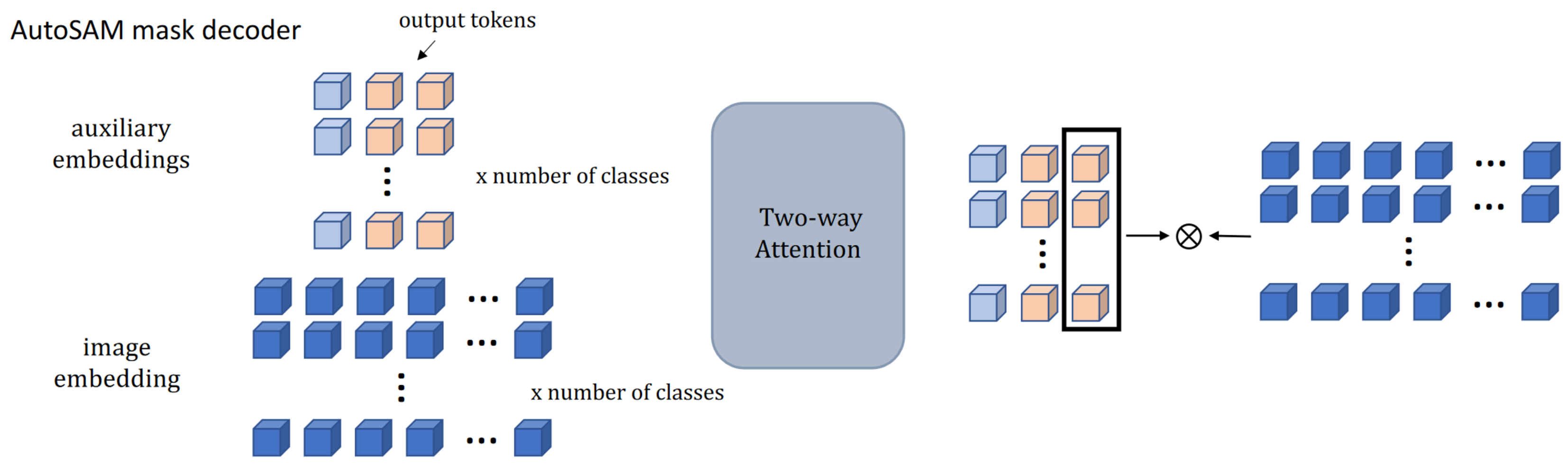
- Our project: enhance melt pond data by developing a method to segment **high resolution helicopter-borne thermal infrared (TIR) imagery** into melt pond, sea ice, and ocean classes. We rely on machine learning to handle temporally and spatially varying temperatures.

DATA

- Existing approaches mostly use optical imagery.
- TIR has the advantage of being less dependent of lighting conditions.
- We collected TIR data from 16 helicopter flights conducted in the marginal ice zone of the Fram Strait region in July and August 2022 (PS131 ATWAICE Campaign [1][2]).
- Broadband infrared radiation (7µm-14µm) at 1m resolution.
- The data are gradient and drift corrected.
- 640 x 480 pixels per image.

METHOD

- Temporally and spatially varying surface temperatures challenge traditional segmentation methods that rely on hand-crafted features.
- We approach segmentation by fine-tuning AutoSAM [3], an automated version of the Segment Anything (SAM) model [4]: Building on the pre-trained SAM encoder, AutoSAM introduces a mask decoder for prompt free multiclass segmentation.
- We manually annotate 21 images with diverse surface structures from flights with good atmospheric conditions.



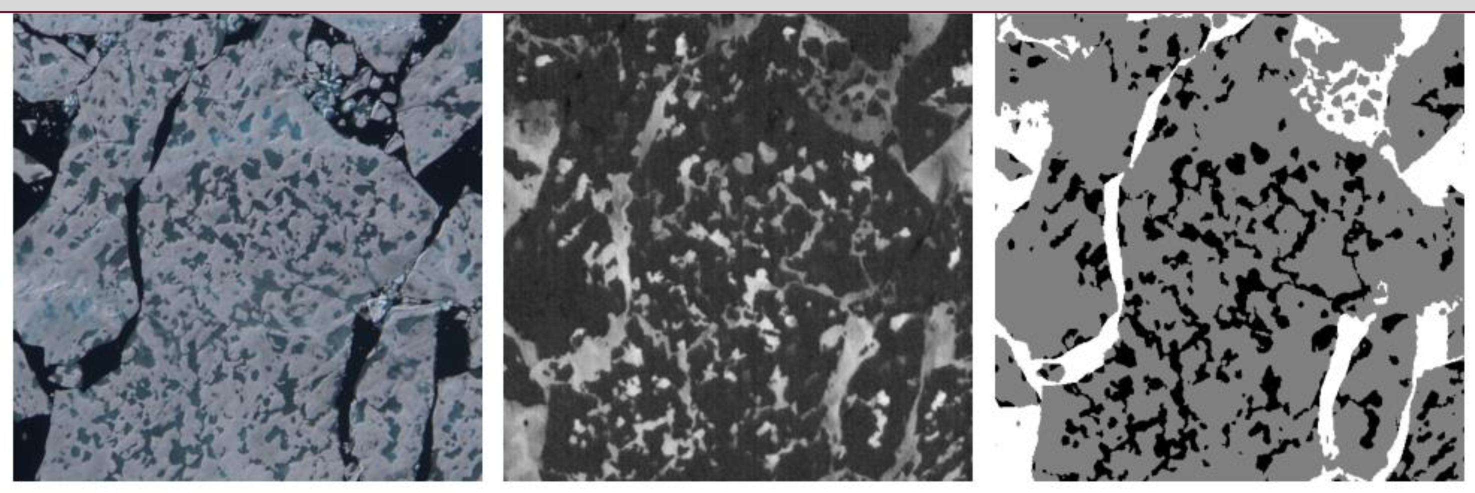
AutoSAM mask decoder based on the SAM model. Prompt tokens are removed and embeddings are copied to match the number of classes. Credits for architecture and figure to Xinrong Hu et al. [3].

REFERENCES

[1] Thorsten Kanzow. The Expedition PS131 of the Research Vessel POLARSTERN to the Fram Strait in 2022. Ed. by Horst Bornemann and Susan Amir Sawadkuhi. Bremerhaven, 2023. doi: 10.57738/BzPM_0770_2023.
[2] PS131 ATWAICE, expedition grant AWI_PS131_02.
[3] Hu, Xinrong, Xiaowei Xu, and Yiyu Shi. "How to efficiently adapt large segmentation model (sam) to medical images." arXiv preprint arXiv:2306.13731 (2023).
[4] Kirillov, Alexander, et al. "Segment anything." Proceedings of the IEEE/CVF International Conference on Computer Vision. 2023.

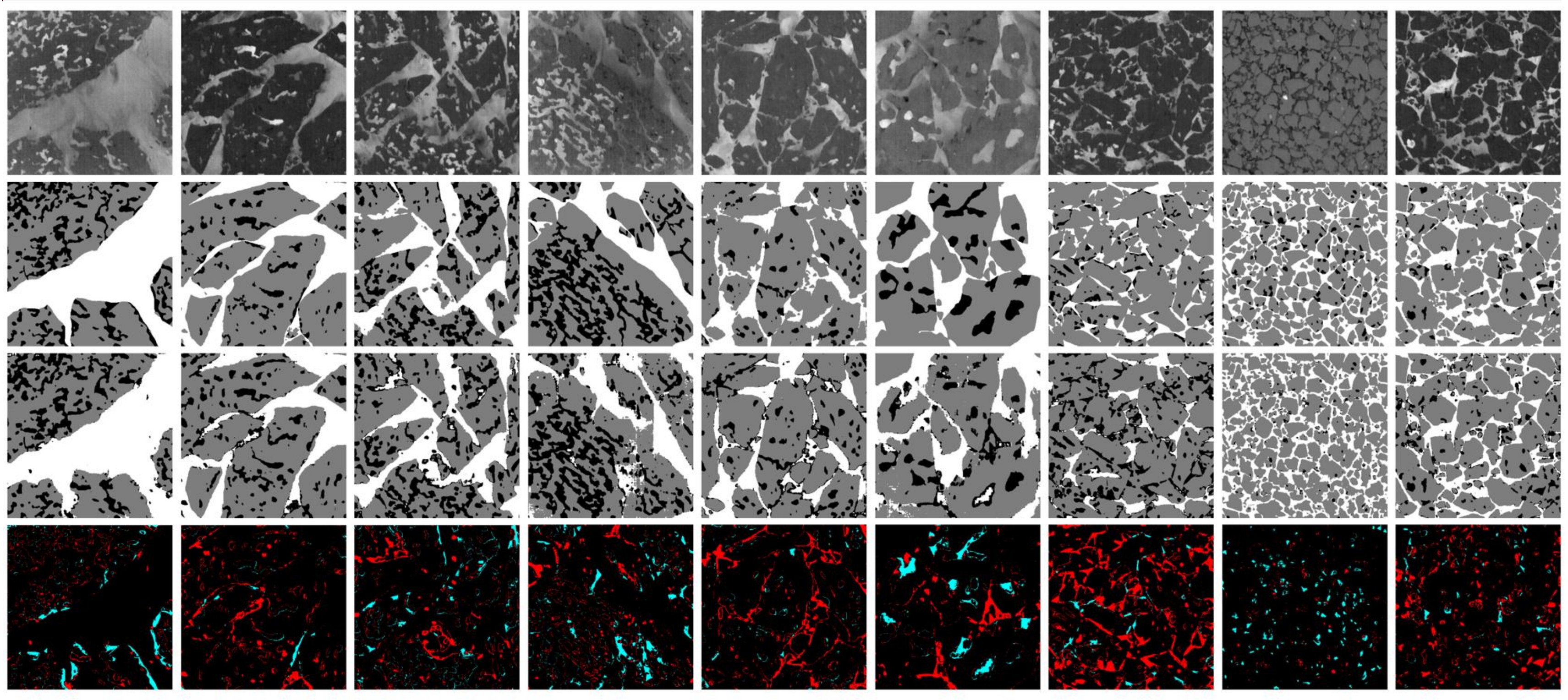
CONCLUSION

- TIR has the potential to extend current sparse melt pond data with light-independent imagery, further enhancing the study of the Arctic climate system and links to global climate change.
- Machine learning can help to predict varying surface conditions.
- Results are preliminary: With AutoSAM, we obtain **0.667 mean IoU** and **0.435 melt pond IoU** on a limited sized test set.
- Simultaneous VIS images are available, but have not been matched due to different camera positions and parameters. Future efforts include VIS and TIR fusion to enable multimodal parameter retrieval.



Left to right: Optical image for reference [2], TIR image, annotation.

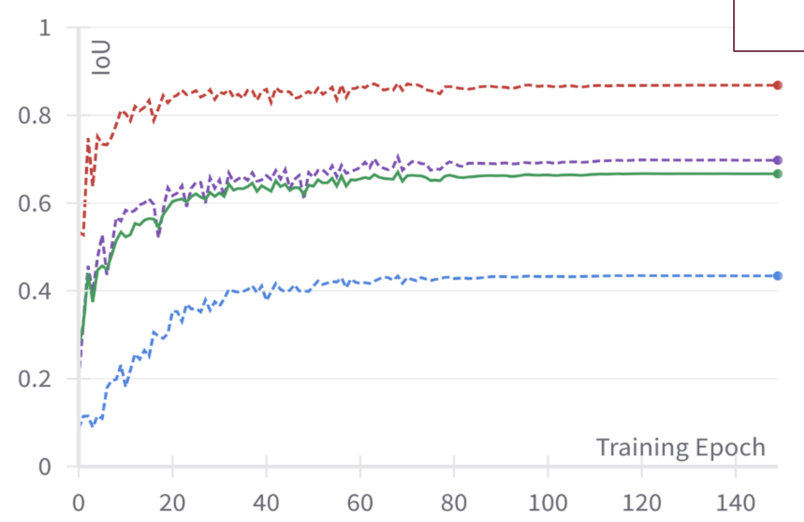
RESULTS



AutoSAM prediction results on validation images. Top to bottom: validation input images, ground truths, predictions, error map (shows melt pond false positives in red and melt pond false negatives in blue).

- AutoSAM captures varying surface types independent of their relative temperature difference.
- High inter-class variability in performance, presumably due to class imbalance in the training data.
- Good performance on images with large ice floes, worse on smaller floes and fuzzy boundaries.
- Misidentification occurs at floe edges and within correctly delineated melt ponds.

	mean	melt pond	sea ice	ocean
AutoSAM	0.667	0.435	0.868	0.698
U-net	0.582	0.320	0.823	0.602



Mean IoU (green), melt pond IoU (blue), ocean IoU (purple), sea ice IoU (red).

MATERIAL

Access to code and training data:

https://github.com/marlens123/autoSAM_pond_segmentation

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