Can operational Ice Charts help to train AI for Sea Ice properties retrieval?

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Motivation

Satellite based Sea ice observation has been subject to intense attention over the last few decades, recently also at higher resolution, thanks to wide spread availability of open access Synthetic Aperture Radar images. Besides the scientific interest in sea ice to understand the detailed geophysical properties of sea ice and its interaction with microwave signals, the operational aspect of high resolution (~100 m scale) ice charting is becoming important due to increasingly ice-free Arctic waters, resulting in growing navigational possibilities. As of now, widely used daily pan-Arctic sea ice concentration maps are derived from space-borne microwave radiometer data with a typical spatial resolution of dozens of kilometres, which are rather inadequate for navigational purposes. Since last few years, Sentinel-1a/b and recently Radarsat Constellation Mission (RCM) have been providing unprecedented spatial and temporal coverage over the entire Arctic in C-band with their respective 'Wide Swath' modes. Despite proven AI based sea ice classification achievements on 'Wide Swath' mode images where training data was generally derived manually due to the scarcity of ground truth information, a fully automated, operational classifier has not yet been established due to large variation in the geometry and bulk properties of sea ice, and incidence angle induced impacts. Here we propose a methodology for basin-wide (e.g. Baltic Sea, Eastern Greenland Sea) sea ice type retrieval using Sentinel-1 (EW, HH-HV) dataset, where we take advantage of the vast archive of existing operational ice charts to train an AI based algorithm.

Data Preparation

The processing chain accounts for the thermal/systematic noise and incidence angle related effects. The proposed supervised classification algorithm consists of the following steps: The first step comprises pre-processing (noise removal, calibration and reprojection) and texture based (GLCM) feature extraction to build a 3-D array of 27 layers consisting of HH and HV backscatter, Incidence angle and GLCM based textural features (both from HH and HV) information. In the second step we collect the spatially and temporally overlapping ice charts from two different operational services, US National Ice Center for Arctic Wide ice charts and BSH ice charts for the Baltic sea, which are provided in shape file and S-411 format respectively. For generating the training labels, we utilize the 'Stage of Development' information present in the ice chart. In order to reduce the complexity, we merged together some closely related 'Stage of Development' types from the original charts to produce five classes of 'Stage of Development'. Those five classes are Open Water/Ice Free/Leads, New Ice, Young Ice, First Year Ice and Old Ice. After spatially and temporally aligning the SAR images and rasterized ice charts, we extracted a comprehensive amount of training and testing data, a total of 100000 points from which 80% were used for training and 20% were used for testing (mutually exclusive). In order to increase the reliability of the training and testing dataset we only use ice charts produced within plus or minus 3 days of the SAR image acquisition.

Analysis Methodology

The extracted training dataset is then used to train a TensorFlow based classifier. As the local neighbourhood textural features are already calculated for each pixel in step 1, a shallow neural network with only one hidden layer containing 64 nodes is all that is required to classify each pixel from the 27 feature values. The implementation uses a Bayesian architecture, replacing the weights and biases of a traditional neural network with probability distributions, and making use of the efficient in-built Monte Carlo estimator. Training is achieved by minimizing the sum of the negative log-likelihood (in this case, the same as the cross-entropy loss) and the Kullback-Leibler divergence of the prior and posterior distributions for the weights and biases. The network output is probabilistic, driven by the internal variable distributions. The result is similar to averaging the results of a large ensemble of neural networks. When applying the classifier, the posterior is constructed using repeated passes of each pixel as input. This method has advantages over an equivalent deterministic network. The posterior distribution over the classes provides the means to access the uncertainty on the class determination for each pixel. Furthermore, the posterior for data beyond the scope of the training dataset has a very large variance allowing pixels that do not belong to any of the five classes to be flagged as such.

Prior on model parameters: $p(\boldsymbol{\theta}) = \frac{1}{\sqrt{2\pi}} e^{-\boldsymbol{\theta}\cdot\boldsymbol{\theta}}$

Model training:

$$\min_{\boldsymbol{\theta}}[-\ln p(y_D|x_D,\boldsymbol{\theta}) + D_{KL}|q(\boldsymbol{\theta})||p(\boldsymbol{\theta})|]$$

where $q(\boldsymbol{\theta}) \rightarrow p(\boldsymbol{\theta}|D)$ the posterior

Model prediction: generate $p(y|x,D)$

Marginalise over $\boldsymbol{\theta}$ by sampling from $p(\boldsymbol{\theta}|D)$

Median:

$$\hat{\boldsymbol{p}} = N_{50}[p(y|x,\boldsymbol{\theta}_n)p(\boldsymbol{\theta}_n|D)]$$

Quantile spread:

$$\Delta\boldsymbol{p} = N_{80}[p(y|x,\boldsymbol{\theta}_n)p(\boldsymbol{\theta}_n|D)] - N_{20}[p(y|x,\boldsymbol{\theta}_n)p(\boldsymbol{\theta}_n|D)]$$

Results and Future Work

Figure 1 shows the original Sentinel-1 images, ice chart and output prediction for two example scenes of the ocean between Greenland and Iceland acquired in 2021. A visual inspection confirms the well defined open water vs ice delineation. An initial assessment of the proposed algorithm via the test dataset, which is mutually exclusive from the training dataset, shows around 70% of overall accuracy with respect to the ice charts. The ice charts produce imperfect pixel labels; however, this problem is effectively countered by the limited capacity of the neural network and overall size of the training dataset, which minimise the danger of over-fitting. The true accuracy will require more detailed comparison with *in situ* measurements.

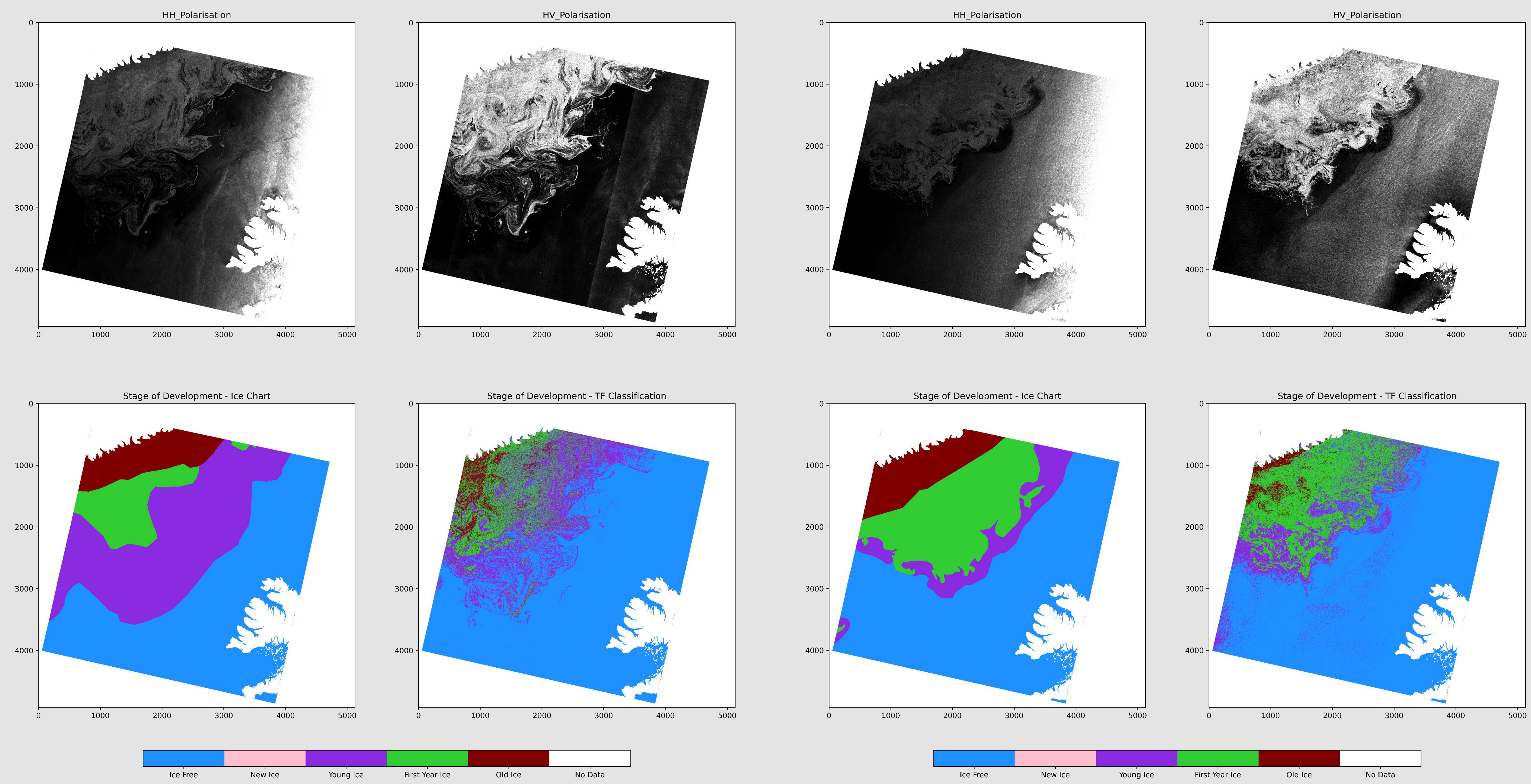

Fig. 1. (Top Left and Top Right) Sentinel-1 HH and HV backscatter acquired on 3rd January 2021 (Left Panel) and 10th of March 2021 (Right Panel). (Bottom Left): Rasterized operational ice chart provided by US National Ice Center (Modified Ice Stage of Development). (Bottom Right) Ice Chart generated using proposed TensorFlow based classifier.

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