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Advanced Iceberg Surveillance Using RCM

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ABSTRACT

The RADARSAT Constellation Mission (RCM) has delivered an exceptional volume of satellite imagery, significantly enhancing maritime and ecosystem monitoring in recent years. C-CORE has been performing RCM data analysis to support the Newfoundland offshore industry with iceberg and sea ice products. Having sufficient amounts of data assimilated, it became possible to develop and apply machine learning (ML) algorithms that automate large portions of image analysis with the intent to accelerate processing and employ the RCM data to the full extent. This paper presents an overview of iceberg detection and classification algorithms developed for single image analysis, spatial distribution of detection probabilities, collected multi-image iceberg tracks, and an ML-based iceberg drift model trained using the tracks. For the 2022 and 2023 iceberg seasons, the classification algorithms were trained using almost 10000 iceberg and ship targets and demonstrated 92% accuracy. A total of 59 iceberg drift tracks consisting of 391 detections were collected. The developed drift model demonstrated an 11.7 km average error. These results mark significant progress toward an integrated approach for automated iceberg detection, classification, and drift forecasting, offering iceberg management support regardless of weather or visibility conditions. This work was supported technically and financially by Equinor Canada.

KEY WORDS: Iceberg management; Machine learning; RADARSAT Constellation Mission; Iceberg drift forecasting

INTRODUCTION

The Bay du Nord oil field is located in the Flemish Pass, about 500 km north-east of St John's, Newfoundland, Canada. The development is estimated to contain a total of one billion barrels of oil. Harsh conditions such as strong winds, waves, low temperatures, fog, icebergs, and sea ice pose challenges to development in the region. In addition, the region has much deeper waters (600-1200 m) compared to the developments in the Jean D'Arc basin (80-120 m). This requires innovative engineering and operational solutions for safe and cost-effective production.

A production and storage facility design implies a floater with disconnection possibilities and a significant role for iceberg management, in particular surveillance and tracking. Traditionally, iceberg surveillance upstream has been performed by reconnaissance flights, ship observations, and satellite imagery analysis. With recent advances in satellite technology, the role of satellite-based iceberg services has been growing. For example, International Ice Patrol have been incorporating satellite data into their operations and currently more than 85% of total iceberg detections are derived from publicly available and commercial satellites during the 2024 iceberg season (International Ice Patrol, 2024).

Compared to reconnaissance flights, satellite data is less costly, covers larger areas, does not place personnel at risk and does not result in incremental emissions. In addition, the radar-based instruments can sense during any weather, in the night, and through fog. However, detecting growlers and bergy bits is more challenging and requires a substantial amount of processing and commercial, high-resolution data.

The amount and quality of satellite products keeps growing. With the introduction of RCM, the revisit period is approaching 12 hours, which results in a massive amount of imagery (RCM, 2025). While the data has significant potential value, it is challenging to process every image with the current semi-automated approach. Modern computer vision algorithms based on Deep Learning provide an opportunity for faster and more accurate RCM image processing and target classification. Which, in turn, would utilize RCM imagery to its full potential, and, thus, improve iceberg surveillance.

First, a fast and reliable target detector and classifier is required to provide efficient image analysis. Second, with multiple images, iceberg tracking and forecasting will improve detection confidence and overall iceberg management performance. This becomes even more valuable when approaching the active iceberg management zone. It will positively affect tactical decisions, thus, reducing the risks and cost.

This paper presents our recent advances in improvement and automation of satellite-based iceberg services. The major tasks performed were training data collection, AI-based classification algorithm development, ML-based drift forecasting and tracking, and confidence mapping. This is an overview paper summarizing work and discussing its potential impact on the industry.

DATA

C-CORE performed routine satellite surveillance during the 2022 and 2023 iceberg seasons. A total of 244 RCM images were processed operationally by the analysts and resulted in final products containing locations and labels (among other attributes such as, for instance, estimated dimensions) for all the detected targets. These detections were integrated into a training dataset that served as a foundation for this study.

Upon RCM image arrival, an analyst goes through the following major steps:

- Automated detection;
- Land mask application;
- Correlation with AIS;
- Artifact removal;
- Classification;
- Manual Quality Check (QC).

Target detection is performed using a Constant False Alarm Rate (CFAR) with a sliding window. CFAR is a thresholding algorithm widely used in Synthetic Aperture Radar (SAR) imagery target detection (Færch et al., 2023; Finn and Johnson, 1968). It is robust, however, rough sea states, or presence of sea ice may degrade its performance.

After processing and RCM image, the targets are manually QC'd, which requires some experience, and relies on auxiliary data such as metocean data or previous detections. The last step may also take significant time to perform, especially when the number of detected targets is large. The resulting product comes out as a shapefile containing labelled targets and their characteristics.

All the product shapefiles collected through the seasons were concatenated and quality-checked once again. This resulted in a database containing 9,928 targets. Of which 7875 were icebergs (2690 small, 4288 medium, 640 large, and 257 very large), 1977 vessels (1083 AIS, 894 ships). The remaining 76 targets belonged to ice island fragments or were unidentified, and were removed from the dataset. Figure 1a shows the size distributions for icebergs and vessels. Out of 9,928 targets, 8009 were detected in the 2023 season and 1919 in the 2022 season. The largest number of targets was identified in July and June (4237 and 3146).

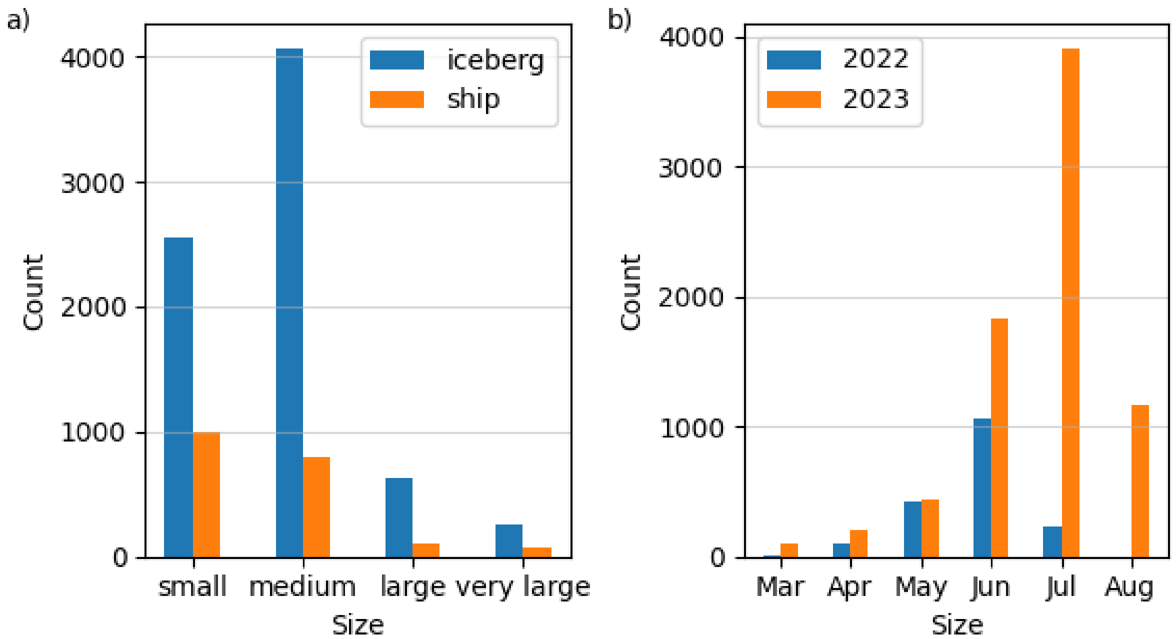

Figure 1. a) target distribution by size by type; b) iceberg distribution by month and by year.

Figure 1b shows the distribution of icebergs for 2022 and 2023 by month. The 2023 season lasted significantly longer with a large number of icebergs arriving late in July and August. It is worth noting that the reported number of icebergs crossing 48N by IIP were 22 and 385 for those years, respectively (International Ice Patrol, 2024, 2023).

After the database was created, for every target, small-size image "chips" were generated as training samples for the classification algorithms. Chip size was made no larger than the estimated largest iceberg size to suppress unnecessary information that could affect classification algorithm training.

CLASSIFICATION

Although icebergs constituted the majority of the detected targets, there were almost 2000 vessels as well. From an iceberg management perspective, vessels do not pose any threat, however, they may be plentiful in the region and cause a false alarm if classified as iceberg on an image (Figure 2). Therefore, it is important to accurately discriminate icebergs from vessels.

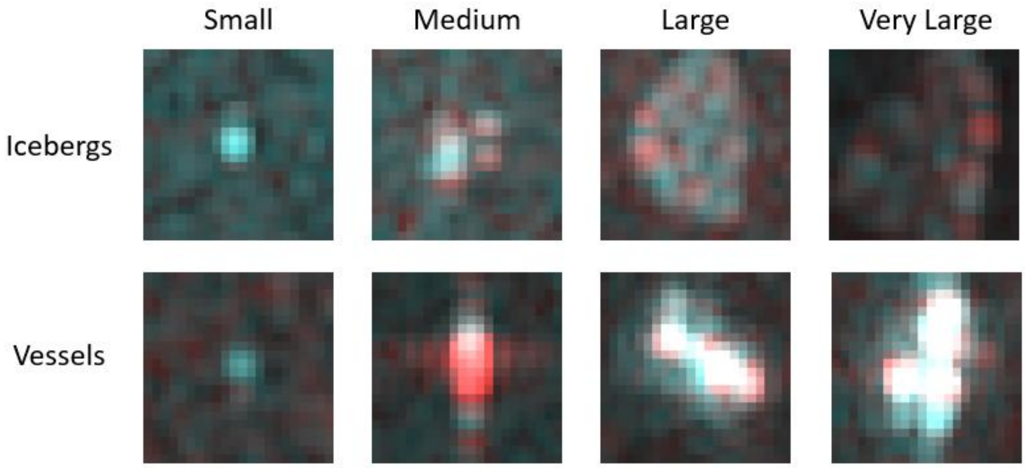

Figure 2. Examples of targets to classify. While larger targets are easier to classify, it is much harder to distinguish a small iceberg from a small vessel.

The task is not simple, in particular for smaller targets that appear indistinguishable to the human eye. A variety of state-of-the-art deep learning algorithms are capable of outperforming humans the classification task. One of the available classifiers was trained using the chips produced from 2022 and 2023 detections.

The binary classification approach was undertaken where chips had to be classified as vessels or icebergs. Stratified random sampling has been employed to overcome the unbalanced dataset. Thus, the resulting training dataset contained even fractions of each target class and uniform size distribution.

Original RCM images were supplied in dual channel, 16-bit per channel format. Normalization has been applied for each channel data to bring it down to 8-bit format. The pixel brightness values were normalized using the standard deviation approach. For the third channel, a combination of the first two channels was used. The models' performances were evaluated using overall accuracy (OA), F1 score and Cohen's Kappa. The former two are conventional metrics that are more robust for unbalanced datasets.

The individual classification accuracy was 93% for icebergs, and 90% for vessels after cross-validation. The resulting overall accuracy for the binary classification reached 92%, F1 score reached 92% and Cohen's Kappa was 0.82. The most challenging targets to classify are small icebergs and vessels, as can be expected. Due to their small size, they are represented by a small cluster of pixels and their brightness is not so high.

It was also found that using contextual information such as historical spatial distribution of icebergs may improve classification results. Bayesian calibration can be applied to the classifier, improving vessel discrimination accuracy by up to 4%.

CONFIDENCE

The probability of detection of an iceberg at a given location depends on local iceberg density, incidence angles, local surface conditions that impact backscatter, and detection algorithm performance. This spatial probability can be mapped into what we call a confidence map.

The confidence map was derived using kernel density estimation (Węglarczyk, 2018) for both HH and HV polarizations, then a combined confidence map was produced, showing the probability of a target being detected in any polarization for the whole image (Figure 3).

A few effects have been observed when deriving the confidence map. First, the HH component has incidence angle dependence. In addition, the HH component is more prone to wind-induced clutter. Due to the weaker cross-polarized clutter returns, HV channel had more banded artifacts that correspond to the sensor noise floor that become apparent in the right side of the image.

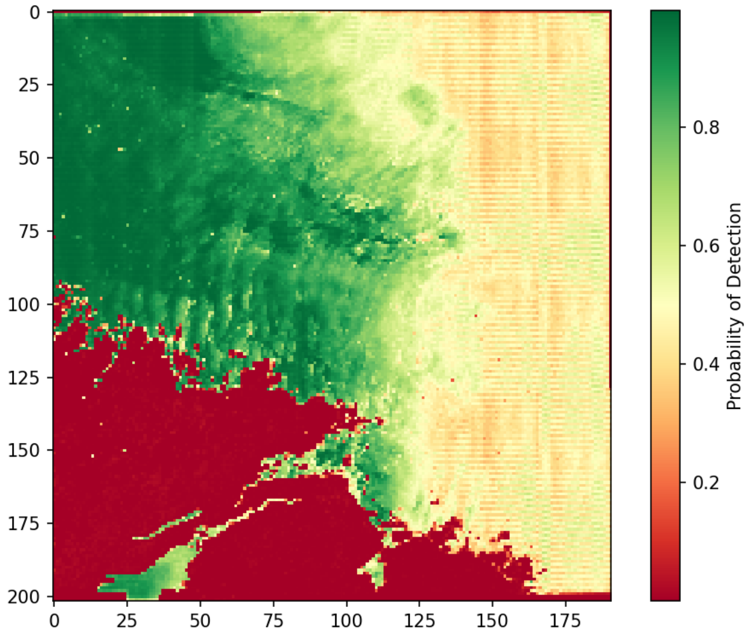

Figure 3. An example of a confidence map produced for southern Labrador

TRACKING

As mentioned earlier, the RCM revisit period is 12 h for these latitudes. With additional imagery from Sentinel 1 and Sentinel 2, the period between detections can shorten even further. This creates an opportunity to track icebergs between multiple consecutive images.

The 2023 and 2024 imagery have been manually analyzed to extract iceberg displacements between pairs of consecutive images (Figure 4). In general, the period between detections was not consistent due to multiple sources of imagery. However, when identifying the pairs, the priority was given to those separated by 12 or 24 hours. The majority of the detections in the tracks were medium-sized icebergs.

The drift track labeled dataset consists of 391 iceberg detections, belonging a total of 59 individual iceberg drift tracks. The tracks and points from 2023 and 2024 are shown in Figure 4. The longest track consisted of 11 points and was 28 days in duration; the shortest track consisted of only 2 points and was 11 hours long.

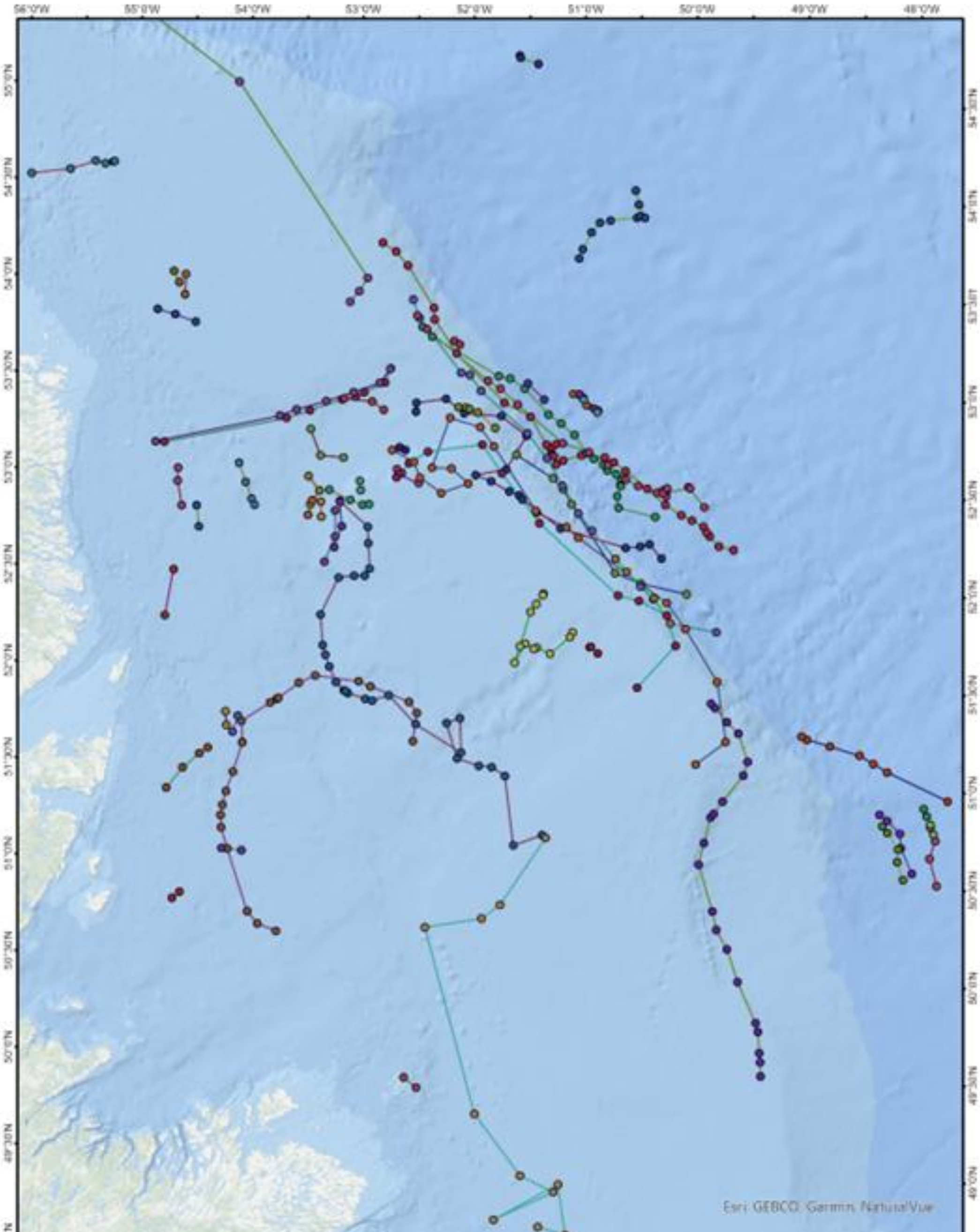

Figure 4. Drift tracks derived by target matching between consecutive satellite images.

The extracted drift tracks were used to develop and metricate an ML-based drift model. The model was required to be able to issue a forecast from a single point (a detection on a satellite imagery, or a field observation). The model had to be robust enough to issue up to 48 hours forecasts for a few hundreds of targets without delaying analysts' work. As new data would come in, the model should be possible to retrain on an updated dataset, thus, improving its accuracy. Since the iceberg detections in the tracks were separated by 12 or more hours, finer dynamical features were not expected to be resolved. For this reason, an approach similar to a dynamic-ML hybrid model (Yulmetov, 2021) could not be applied.

An LSTM neural network was chosen as the basis for the drift model due to its performance with time series and forecasting problems (Sak et al., 2014). For a single iceberg detection, the model receives a metocean forecast (12 hours of wind velocity and ocean current velocity predictions) and iceberg length at the detection location and produces a 12-hour iceberg displacement vector as a result. The metocean data was provided by ERA5 (Hersbach et al., 2020) for 10 m winds and Copernicus Marine dataset for ocean currents (Copernicus Marine Service, 2016). For 24-hour forecasts the model performed two 12-hour staged predictions.

The drift forecast performance is assessed using an error metric which is the distance between the forecasted and the actual iceberg locations. The leave-one-out approach is used to estimate average model performance. That is, the model is trained on all but one consecutive pairs of detections, and a single forecast error is estimated for that one pair. This process is repeated for every pair in the dataset and the error statistics (including average error) are derived.

The average performance of the new model compared to the conventional Leeway and the High-resolution ML applied to the same icebergs with the same metocean data is shown in Figure 5. The High-resolution ML model was previously trained on the in-house data consisting of iceberg logs and GPS tracks collected during the past 20 years. While the 12-hour error is comparable, the LSTM significantly outperforms the other two at the 24 hour mark. The average error of the LSTM model is 11.7 km in 24 hours. The high-resolution ML model underperformed compared to its originally reported error metrics collected, though, for a different dataset (Yulmetov, 2021).

The performance advantage may be explained by the dominant drift direction in the training dataset. As can be seen in Figure 4, the majority of the icebergs drifted south-east, following the shelf break.

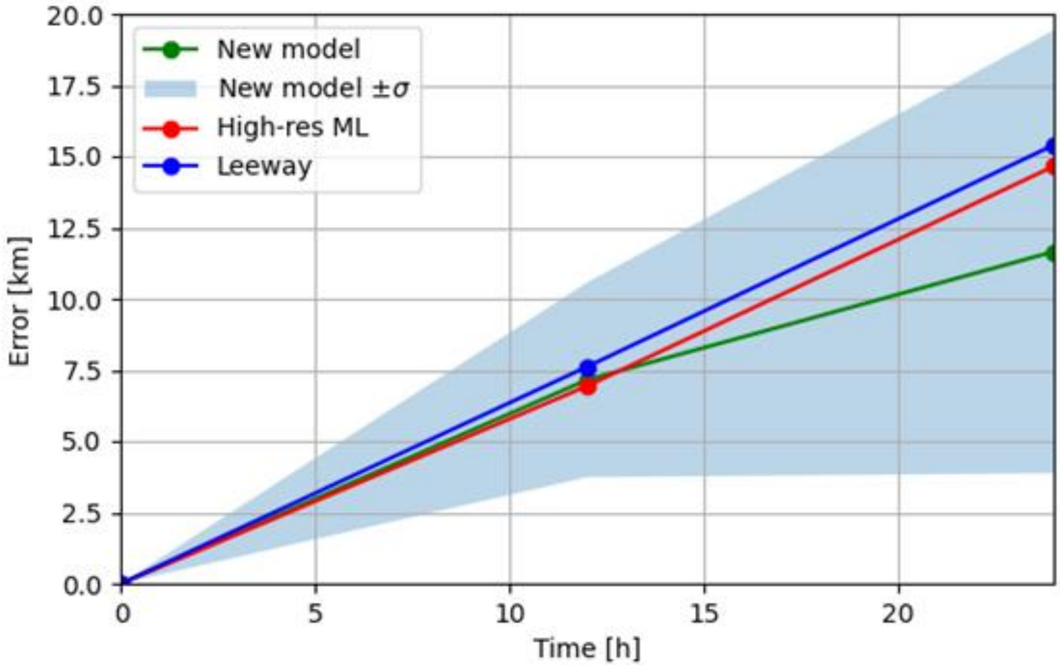

Figure 5. Average error curves compared for different drift models for 2023-2024 ice seasons

IMPLICATIONS TO ICEBERG MANAGEMENT

SAR imagery provides an advantage over conventional methods of surveillance. In particular, at Flemish Pass where reconnaissance flights upstream would require increased flight duration compared to Jean d'Arc Basin. SAR is not impacted by darkness and fog, which is frequent in the North Atlantic.

The developed advanced image processing algorithms allow for timely and accurate upstream iceberg detection, classification and discrimination from vessels. This can be done under operational time constraints given the revisit time period of 12 hours for RCM. With other publicly available imagery (for instance, from Sentinel 1 and Sentinel 2), the same iceberg can be followed with more than 2 detections daily. Then, with high-resolution commercial satellite imagery becoming more accessible, icebergs can be tracked with just a few hours between detections.

Classification algorithms in combination with confidence maps and drift forecasting provide an opportunity for automated tracking. Given two consecutive images, the targets corresponding to the same icebergs can be matched using visual target similarity, size, and distance to the corresponding forecasted locations. This opens up a possibility to automatically track hundreds of icebergs upstream, and dozens of them as they approach an iceberg management zone. Having constant eyes on icebergs extends tactical decision making beyond the facility radar limit. As the range to an offshore facility closes, there will be fewer targets to track, but more situational awareness and less uncertainty. Additionally, commercial satellites can be tasked to provide precise surveillance if needed. Thus, iceberg tracking using satellite imagery leads to a better understanding of iceberg-related risks, and more efficient planning of physical iceberg management actions.

In addition to the situational awareness, automated classification and tracking results in a large amount of new data that requires minimal QC and can be used to retrain the algorithms. Which, in turn, due to the larger training datasets will lead to more accurate classification and forecasting, and, thus, to improved operational decision making.

CONCLUSIONS

This paper provides a brief overview of recent and ongoing work to improve and automate RCM satellite imagery analysis and forecasting. The foundation for the study is a large target dataset collected during the 2022 and 2023 seasons. It consists of almost ten thousand identified vessels and icebergs of various sizes.

This massive dataset has been used to train a binary classifier to discriminate between vessels and icebergs. The classifier demonstrated impressive overall accuracy, reaching 90%, and being particularly accurate for larger targets. Another dataset consisting of pairs of consecutive detections belonging to the same icebergs was collected. It contained 59 iceberg tracks that were used to develop and train an ML-based drift forecasting model. The model is able to forecast from a single location, using no prior trajectory information. Using a leave-one-out approach, the model's average forecasting error was found to be approximately 12 km in 24 hours.

Combining a fast and reliable classifier, and drift forecasting enables efficient automated processing of RCM products to the full extent. Thus, it will improve maritime situational awareness, and overall performance of iceberg management in the Flemish Pass.

There is an ongoing development work occurring that attempts to automate iceberg tracking between images using a combined score of visual similarity, target length, and distance to forecasted location. In addition, a variety of classifiers are being assessed for an optimal performance.

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