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Reduction of False Alarms in Sea Ice Covered Ocean Regions Using Machine Learning

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IMPORTANT INFORMATIVE STATEMENTS

Abstract

Current ship detection algorithms for Synthetic Aperture Radar (SAR) imagery experience limitations due to false alarms that arise in sea ice conditions. The aim of this Scientific Report is to demonstrate how false alarms can be reduced by applying target discrimination algorithms. In this report, RADARSAT-2 Maritime Satellite Surveillance Radar (MSSR) images acquired in both Detection of Vessels Wide Far (DVWF) and Ocean Surveillance Very-wide Near (OSVN) modes are considered, because these are the operational modes used for ship detection. Training and testing data samples were collected in regions that include sea ice. Ship targets were identified using visual analysis and Automatic Identification System (AIS) data reported by ships. Sea ice targets were identified by removing detected ship targets, and ship-like targets were excluded via visual inspection. Testing data were kept independent from training data. Support Vector Machine (SVM), Autoencoder Neural Network (AENN), and Convolutional Neural Network (CNN) were applied to discriminate the false targets (i.e., sea ice) from ship targets. Preprocessing and feature extraction steps were applied to the SVM method but not to the AENN nor the CNN methods. AENN and CNN are deep learning neural networks. The results show that these methods can remove more than 93% of the false targets detected in DVWF and OSVN modes. However, a few of the ship targets were misclassified as sea ice targets in both the DVWF and OSVN modes. These methods should only be used in ocean regions in which sea ice is present.

Significance to Defence and Security

Many false alarms occur in SAR ship detection reports in the vicinity of sea ice. This report shows that false alarms can be reduced by applying SVM, AENN, and CNN methods to the detected targets. Use of these algorithms would save time in analysing detected targets by providing a more accurate ship detection product with fewer targets to evaluate.

Résumé

Les algorithmes actuels de détection des navires dans les images par radar à synthèse d'ouverture (RSO) sont confrontés à des limites à cause de fausses alertes qui surviennent en présence de glace de mer. Le but de ce rapport scientifique est de démontrer comment on peut réduire les fausses alertes en appliquant des algorithmes de différentiation des cibles. Dans ce rapport, on utilise des images de Radar de surveillance maritime par satellite (MSSR) RADARSAT-2 réalisées en mode DVWF et en mode OSVN, car il s'agit là des modes opérationnels utilisés pour la détection des navires. Les échantillons de données de formation et de mise à l'essai ont été prélevés dans des régions où il y a présence de glace de mer. Les navires cibles ont été identifiés par analyse visuelle et grâce aux données du Système d'identification automatique (SIA) transmises par les navires. Les cibles de glace de mer ont été trouvées en retirant les cibles de navire détectées, et on a retiré par inspection visuelle les cibles ressemblant à des navires. Les données de mise à l'essai ont été isolées des données de formation. On a appliqué une machine à vecteurs de support (SVM), un mécanisme d'encodage automatique à réseaux neuronaux (AENN) et des réseaux neuronaux convolutionnels (CNN) pour différencier les fausses cibles (p. ex., la glace de mer) des navires. Des étapes de prétraitement et d'extraction des caractéristiques ont été appliquées à la méthode SVM, mais pas à celles de l'AENN et des CNN, qui sont des réseaux neuronaux d'apprentissage profond. Les résultats obtenus démontrent que ces méthodes arrivent à retirer plus de 93 % des fausses cibles détectées dans les modes DVWF et OSVN. Cependant, quelques navires ont été mal classés en tant que glace de mer à la fois en mode DVWF et en mode OSVN. Ces méthodes doivent être réservées aux régions océaniques où il a présence de glace de mer.

Importance pour la défense et la sécurité

Les rapports de détection de navires du SIA contiennent de nombreuses fausses alertes lorsqu'il y a présence de glace de mer à proximité. Ce rapport indique qu'il est possible de réduire ces fausses alertes en traitant les cibles décelées avec la SVM, l'AENN et les CNN. L'utilisation de ces algorithmes permettrait d'augmenter la précision du produit de détection des navires et donc de réduire le nombre de cibles à évaluer, ce qui permettrait de réduire le temps passé à analyser les cibles détectées.

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1 Introduction

Monitoring of vessels on a sea, ocean or other navigable waterway is an important part of the Maritime Domain Awareness activity. Monitoring vessels can be done with various sensors such as Synthetic Aperture Radars (SAR), Automatic Identification System (AIS) and Electro-Optical/Infrared (EO/IR) Sensors. The focus of this report is SAR. A SAR system for detecting vessel targets can be used in any weather condition and at any time of day (i.e., day or night). Also, the mapping area of a SAR can be large. The technique of extracting vessel information from SAR images is called ship detection. Current ship detection techniques are quite mature and are used operationally [1]. However, the ship detection algorithm that is used has limitations when it comes to correctly identifying ship targets for ocean regions in the vicinity of sea ice.

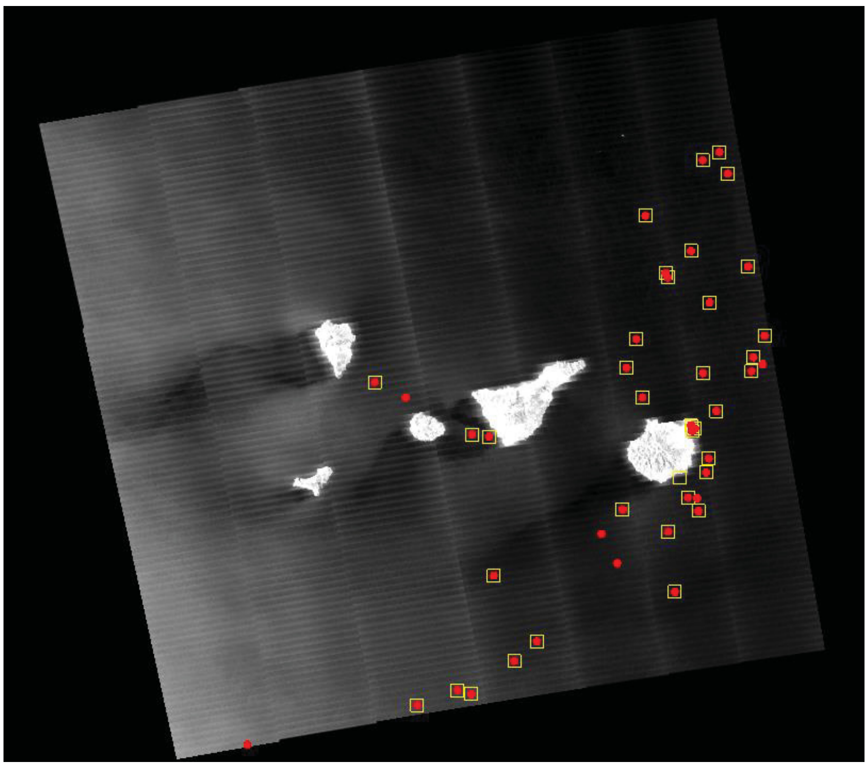

Figure 1: *DVWF image of the Canary Islands. The yellow squares are the detected ship locations using the ship detection algorithm in IA Pro and the solid red circles are the AIS-reported ship locations. RADARSAT-2 Data and Products © MacDonald Dettwiler and Associates Ltd (2013)—All Rights Reserved. RADARSAT is an official mark of the Canadian Space Agency.*

Image Analyst Pro (IA Pro) is a software developed by Defence Research and Development Canada (DRDC). It is a testbed and demonstration software used to test various image analysis algorithms. The ship detection algorithm in IA Pro is based on a Constant False Alarm Rate (CFAR) method. The ship detection algorithm performs well for open ocean regions. Figure 1 shows the ship detection results for a RADARSAT-2 Detection of Vessels Wide Far (DVWF) mode Canary Islands image that was collected on 17 January 2013. The yellow squares show the ship detection results and the solid red circles show the

AIS-reported ship locations. In this case only one target detected by the ship detection algorithm was not supported by the available AIS data. In this case, the AIS data provide a pre-screening of the data and an analyst could very quickly analyse the sole anomaly (i.e., the AIS-dark target for which there was a SAR-based ship detection but no supporting AIS data).

However, ship detection algorithms may not perform as well in areas with sea ice. Figure 2 shows a DVWF image of the Ross Sea that was acquired on 1 February 2015. The ship detection algorithm detected many targets (yellow squares), only two of which had corresponding AIS data (solid red circles). It would be a very difficult and time consuming process for an image analyst to go through and inspect the AIS-dark targets one-by-one. Two of the targets that were detected by the ship detection algorithm, but not declared by AIS, are displayed in Figure 3. These two targets do not look like a ship and may be sea ice. These targets can be readily removed from the detection list by an analyst. This is also often the case for Ocean Surveillance Very-wide Near (OSVN) mode images. Therefore, this report focuses on several different approaches to automatically discriminating ships and sea ice for DVWF and OSVN mode images.

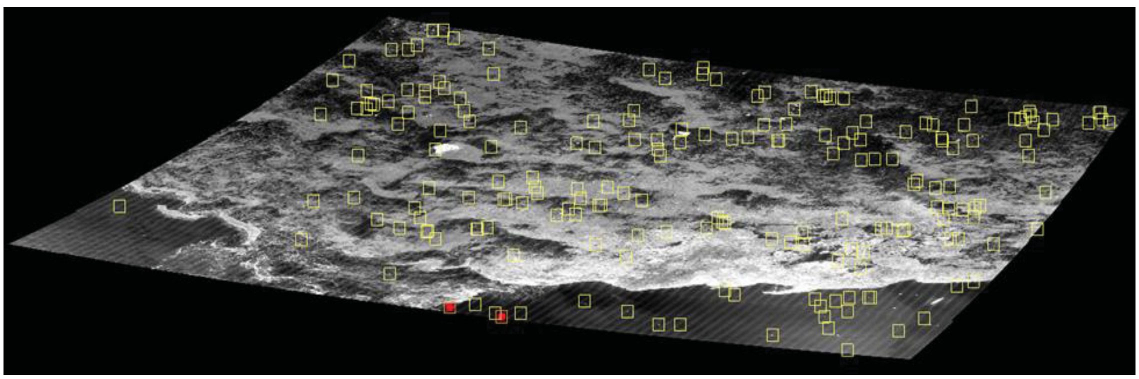

Figure 2: *DVWF image of the Ross Sea. The yellow squares are the detected ship locations using the algorithm in IA Pro and the solid red circles are the AIS-reported ship locations. RADARSAT-2 Data and Products © MacDonald Dettwiler and Associates Ltd (2015)—All Rights Reserved. RADARSAT is an official mark of the Canadian Space Agency.*

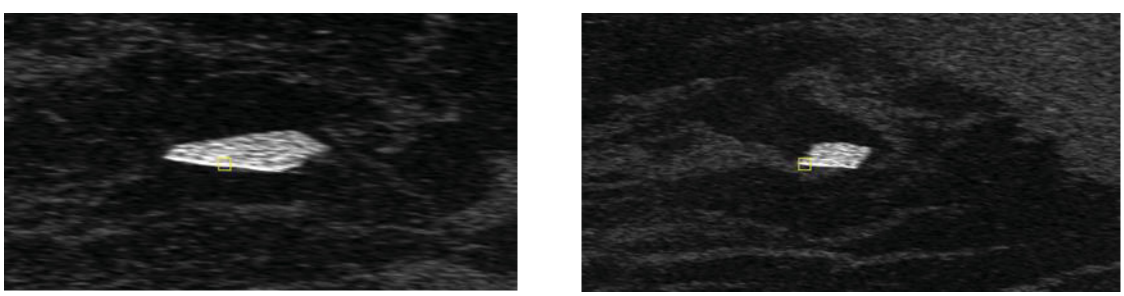

Figure 3: *Two examples of detected ship targets from the image of Figure 2 that were not reported by AIS and are likely sea ice. RADARSAT-2 Data and Products © MacDonald Dettwiler and Associates Ltd (2015)—All Rights Reserved. RADARSAT is an official mark of the Canadian Space Agency.*

The aim of this report is to demonstrate how false alarms can be reduced by applying Automatic Target Recognition (ATR) algorithms. This study focussed on false alarm reduction in sea ice conditions in Synthetic Aperture Radar (SAR) images. Sea ice targets are considered false targets in this report. ATR methods are applied on the ship detection results to remove false targets. This report is organized as follows:

- Chapter 2 describes the data that are used in this report;
- Chapter 3 goes through various methods of discriminating ships from sea ice;
- Chapter 4 discusses the results derived using the various discrimination methods; and
- Chapter 5 provides the conclusions of this work and provides recommendations for future work.

2 RADARSAT-2 Data

RADARSAT-2 Maritime Satellite Surveillance Radar (MSSR) mode data were used for this study. There are two MSSR modes: DVWF and OSVN. DVWF is imaged in a single polarization (HH) and is optimized for ship detection. The incidence angle varies from 35 to 56 degrees across a ground swath of approximately 450 km [2]. OSVN mode may be imaged in dual polarization (VV and VH or HH and HV). For ship detection, usually HH and HV polarizations are used. The incidence angle varies from 20 to 50 degrees across a ground swath of approximately 500 km. For ship detection, co-polarization (i.e., HH) is used for higher incidence angles and cross-polarization (i.e., HV) is used for lower incidence angles.

The OSVN and DVWF mode data were acquired over the Ross Sea area for this study. The data collections occurred between December and February from 2014 to 2017. Ship targets were identified based on AIS-reported ship locations (based on the predicted ship signature location at the SAR imaging time) and were visually evaluated to ensure that the AIS-reported target was visible. Sea ice targets were identified from all potential targets detected by the ship detection algorithm. Of course, sea ice targets do not provide any AIS reports and do not look like ship targets (that is, they may be visually analyzed and removed). We selected the 1 February 2015 and the 21 December 2015 DVWF images for testing the DVWF mode discrimination algorithms. Similarly, we selected the 26 January 2015 and the 23 December 2015 OSVN images for testing the OSVN mode algorithms. These test images are different from the training images. Table 1 shows the selected number of targets for the training and testing algorithms for both modes. Training ship targets were extracted from 18 DVWF mode images and training ice targets were extracted from 17 DVWF mode images. Similarly training ship and ice targets were extracted from 16 OSVN images. Extracted target chip's width and height were 1500 meters in both directions and each chip contained a single ship or sea ice target. All algorithms were exposed to all the training data for tuning their variables and were then validated using the complete test data. Unfortunately, the number of ship samples is much fewer than the number of ice samples for training the algorithms. This allows the training algorithms to learn more about the ice targets than ship targets.

Table 1: *Number of extracted OSVN and DVWF targets for the training and testing algorithms.*

Mode	Training Data		Testing Data	
	Ships	Ice	Ships	Ice
DVWF	77	1817	19	1575
OSVN	64	1955	21	533

3 Target Discrimination Algorithms

In this section, the algorithms for discrimination of ship and sea ice are described. Support Vector Machine (SVM), Autoencoder Neural Network (AENN), and Convolutional Neural Network (CNN) are investigated in this report. The input image chips to these algorithms contained sigma calibrated value.

3.1 Support Vector Machine

Binary SVM was used to discriminate ships and sea ice. Segmentation and feature extraction algorithms were applied before feeding the data into the SVM classifier. As indicated in Figure 4, a segmentation algorithm was applied to the extracted image chip (each chip contains only one candidate target). The main purpose of the segmentation is to preserve most of the target signature and to remove most of the background signature. Segmentation is done based on a threshold value. A median filter was applied to the chip first and then the mean was calculated. The threshold was calculated by multiplying the mean with a constant.

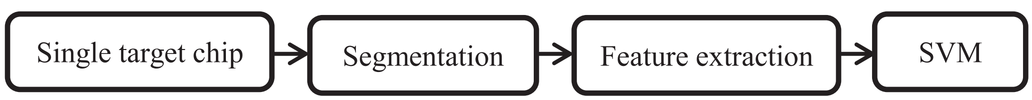

Figure 4: *SVM processing chain.*

The feature extraction algorithm was applied to the segmented targets. Segmented target chip contained a single ship or sea ice target. Five features were extracted including area, length, width, mean, standard deviation and number of segmented blocks in the chip. These features, with the exception of the number of segmented blocks, were evaluated previously for recognizing ship and iceberg targets [3][4].

The MATLAB® Statistics and Machine Learning Toolbox contains a built-in SVM classifier [5]. All five features were used in the SVM classifier to discriminate between ship and sea ice targets. A polynomial kernel function was used for training the SVM. The rest of the parameters were left at their default values. The function MATLAB® "fitcsvm" was used to train the binary SVM classifier.

3.2 Autoencoder Neural Network

AENN is a type of Neural Network [6]. AENN encodes the input data and then decodes the compressed data back into the original data. When AENN encodes and decodes the data, less important parts of the image information are removed and only important information is kept in the recovered data. AENN uses unsupervised and supervised training methods to train the weights. Auto encoder uses an unsupervised method and output layers (softmax classifier) use supervised method to train the weights.

The AENN classifier is shown in Figure 5. The first layer is the input layer which contains all of the input image pixels. The image is normalized before being fed in to the input layer. No other preprocessing method is applied to the image. The input image size was chosen to be 40 by 40 pixels, so there are 1600 nodes in the input layer. The second and third layers are the AENN. Here, only the encoder part of the AENN is used. Therefore, two encoders are placed back-to-back in the middle layers (i.e., the second and third layers). There were 711 nodes in the second hidden layer and 911 nodes in the third hidden layer. The first hidden layer is trained using the input layer data and an unsupervised method. After completing training of the first hidden layer, the second hidden layer is trained using the output of the first hidden layer using an unsupervised method. After training of the second hidden layer, the output layer is trained using a supervised training method. For this, the output of the second layer is used as the input. A softmax classifier is placed in the output layer. This allows mapping of the ship and sea ice labels to the input data. The output value of the softmax classifier is the normalized probability. The node with highest probability is assigned to the target class.

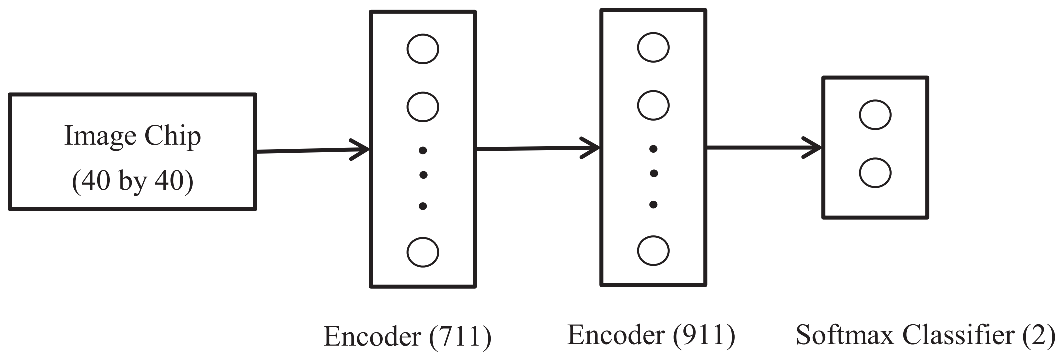

Figure 5: *AENN processing chain.*

3.3 Convolutional Neural Network

CNN is a well-known approach to image classification [7]. There are three main types of layers in a CNN: the convolutional layer, the pooling layer, and the softmax classifier layer.

The convolutional layer contains many filters with an activation function. Many activation functions can be used but for purpose of this study Rectified Linear Unit (ReLU) was selected. A ReLU function regulates the filter output value from zero to plus infinity. That is, a ReLU compares the filter output with zero and takes the maximum value. The filter dimension depends on the input image dimension. The size of the filter cannot be larger than the input image size. The window size varies from small to large, but the number of filters can vary depending on the complexity of the targets, number of classes, etc. Usually the initial weights (filter coefficients) contain random values, which are modified during the training process.

The pooling layer (sometimes called the down-sampling layer) reduces the size of the nodes in a layer. The window size of the pooling layer is usually rather small, such as 2 by 2. There are two types of pooling that are used in CNNs: max pooling and average pooling. Max pooling takes the maximum value and average pooling takes the average value within the window. The window slides over all of the input images.

The softmax layer is the last layer in the CNN architecture. This is similar to the AENN, which classifies input values to one of the known target classes.

Figure 6 shows the CNN architecture that was used in this work. Convolutional layer, ReLU and pooling layers were repeated three times (the pooling layer was not used in the third stack) in this structure. The filter size remains the same, which is 3 by 3, for all stacks. However, the number of filters is different for each stack: twenty filters in the first, twenty-five in the second, and thirty for the third. The max pooling method was selected for both stacks. The size of the window is the same in each case and was set to 2 by 2. There are two nodes for each of the classes (ship and ice). The first layer receives images of size of 40 by 40, that is, 1600 nodes in the first layer.

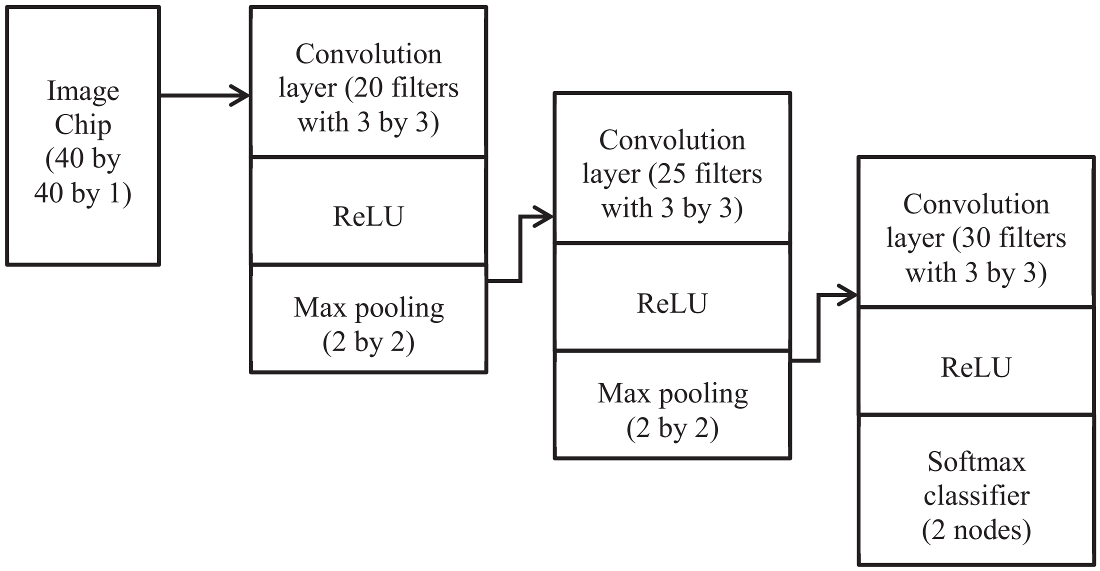

Figure 6: *CNN architecture used for this problem.*

4 Results and Discussion

Results of SVM, AENN and CNN ship and sea ice discrimination are provided in this chapter. The HH and HV channels of the OSVN data were combined into one two-dimensional image as follows: (|HH|.*|HV|)/mean(|HH|.*|HV|), where .* is a point-by-point matrix multiplication operation.

4.1 Training and Testing time

The time taken by any training system is dependent on the speed of the computer and the random selection of initial parameters. The computer used for this task was an Intel® Xeon® CPU E5430 @ 2.66 GHz (2 processors). The training and testing times were calculated for each of the methods (see Table 2 and Table 3). Each method was run three times and then the average was taken. The following tables show the training and testing times for the DVWF (Table 2) and OSVN (Table 3) data.

Table 2: *Average training and testing times for the DVWF data.*

Method	Training Time (Milliseconds)	Testing time/Target (Milliseconds)
SVM	42000	22.1
AENN	3120000	2.3
CNN	558000	6.0

The total training time for the DVWF mode is 0.7, 52.0, and 9.3 minutes for the SVM, AENN and CNN, respectively. Similarly for the OSVN mode the total trainting time is .0.6, 34.8, and 7.8 minutes for the SVM, AENN and CNN, respectively. The SVM required less time and AENN need more time to learn the samples in both beam modes. Testing time per target was very short for all the methods. This varied from 2.3 to 22.1 milliseconds for DVWF and from 3.2 to 10.8 milliseconds for OSVN. The fastest method is AENN for both modes. The testing time differences between these algorithms were very small (in milliseconds). But the training speed varied in minutes. If the time is very short (in seconds) between data collection for training and applying the trained model for the user application then SVM is the best choice (assume the classification accuracy is almost same). Our application is reduction of false alarm rate in sea ice condition after ship detection was applied on the SAR imagery. Therefore, a few hours of training is not going to affect the application. Accuracy is more important than training time for this case because the training time was less than an hour for all the algorithms.

Table 3: *Average training and testing time for the OSVN data.*

Method	Training Time (Milliseconds)	Testing time/Target (Milliseconds)
SVM	36000	10.8
AENN	2088000	3.2
CNN	468000	6.1

4.2 SVM, AENN and CNN methods

All algorithms were trained and tested with the same training and testing data. Table 1 shows the number of ships and sea ice used for training and testing. Results for the DVWF mode are tabulated in Table 4. The table shows the number of ship and ice targets that were correctly classified and misclassified.

A total of 19 ship targets were tested, 18 (94.7%), 19 (100%), and 18 (94.7%) of them were correctly recognized by the SVM, AENN and CNN respectively. The rest of the ships were misclassified as sea ice. The misclassification rate for SVM and CNN were 5.3% (one ship). There were no misclassified ships in AENN. A total of 1575 sea ice targets were tested and correctly identified. The number of sea ice targets that were recognised were 1528 (97.0%), 1546 (98.1%), 1541 (97.8%) for the SVM, AENN and CNN respectively. But 47 (3.0%), 29 (1.8%), and 34 (2.2%) sea ice targets were misclassified as ships in SVM, AENN and CNN. The balanced correct classification and misclassification rate were calculated [8] for all these methods. The correct classification rates were found to be 95.9%, 99.1% and 96.3% for the SVM, AENN and CNN, respectively. The balanced misclassification rates for the SVM, AENN, and CNN were 4.1%, 0.9%, and 3.8%, respectively.

Table 4: *SVM, AENN and CNN results for the DVWF mode.*

a) SVM					b) AENN				c) CNN			
Target class	**True ship**	**True sea ice**	**Misclassification (%)**	**Correct classification (%)**	**True ship**	**True sea ice**	**Misclassification (%)**	**Correct classification (%)**	**True ship**	**True sea ice**	**Misclassification (%)**	**Correct classification (%)**
Ship	18	1	5.3	94.7	19	0	0.0	100.0	18	1	5.3	94.7
Sea ice	47	1528	3.0	97.0	29	1546	1.8	98.1	34	1541	2.2	97.8
Balanced			4.1	95.9			0.9	99.1			3.8	96.3

There were limited number of ship targets (19) and more than a thousand (1575) sea ice targets available for testing the trained models. Therefore the results were more accurate with respect to sea ice target class than ship target class. Based on the balanced accuracy, all models correctly discriminated more than 95.9% and misclassified less than 4.1% of ship and sea ice targets. As a result, all three methods performed well in DVWF mode in discriminating ships and sea ice. These ATR models are useful in reducing false targets (sea ice) in DVWF modes.

Similar tests were conducted for the OSVN mode data. The training and testing data for OSVN mode was shown in Table 1. A total of 64 ships and 1955 sea ice were used for training all three methods. Test results for the OSVN mode are listed in Table 5.

Twenty one targets were tested and out of which 19 (90.5%) for SVM and AENN, and 20 (95.2%) for the CNN were correctly identified. Rest of the ships were misclassified as sea ice. A total of 2 (9.5%) ships for SVM and AENN, and one (4.8%) ship for CNN were misclassified as sea ice. A total of 533 sea ice were tested, 500 (93.8%), 499 (93.6%), and 512 (96.1%) of them were correctly recognized by SVM, AENN and CNN methods, respectively. Some of the sea ice targets were also misclassified as ships. The number of misclassified sea ice by SVM, AENN, and CNN were 33 (6.2%), 34 (6.4%), and 21 (3.9%), respectively. Total balanced correct classification and misclassification were calculated [8] for the OSVN mode. The best balanced correct classification rate was 95.6% by CNN method, which was the highest rate compared to other methods tested as part of this report. Still the balanced misclassification rate was 4.4% for this CNN method. The balanced correct classification rate for the SVM and AENN were 92.1% (7.9% balanced misclassification rate) and 92% (8% balanced misclassification rate), respectively.

Table 5: *SVM, AENN and CNN results for the OSVN mode.*

	a) SVM				b) AENN				c) CNN			
Target class	**True ship**	**True sea ice**	**Misclassification (%)**	**Correct classification (%)**	**True ship**	**True sea ice**	**Misclassification (%)**	**Correct classification (%)**	**True ship**	**True sea ice**	**Misclassification (%)**	**Correct classification (%)**
Ship	19	2	9.5	90.5	19	2	9.5	90.5	20	1	4.8	95.2
Sea ice	33	500	6.2	93.8	34	499	6.4	93.6	21	512	3.9	96.1
Balanced			8.4	92.1			8.0	92.0			4.4	95.6

Similar to DVWF mode, fewer number of ships (21) compared to sea ice (500) were available for testing. Therefore the confidence in the test results was higher in sea ice targets than ship targets. The balanced correct classification is greater than 92% and balanced misclassification rate is less than 8% for all ATR methods. It shows that these methods were able to discriminate 92% of the detected ships and sea ice and about 8% of these targets may be misclassified as sea ice or ship. Hundreds of false targets (sea ice) detected by ship detections can be reduced by these ATR methods.

The SVM, AENN, and CNN performed better for DVWF mode than for OSVN mode data. However, OSVN includes additional information in the HV channel. It is possible that different ways of combining both channels (HH and HV) or exploring different features for the OSVN mode can improve the OSVN performance. There is a need for additional study to confirm this finding. In all methods, the correct classification rate is higher for the sea ice target class than for the ship target class (except AENN in DVWF mode). One of the possible reasons for this is the training sample size for the sea ice target class was much larger than the training sample size for the ship target class.

5 Conclusions and Recommendations

RADARSAT-2 MSSR mode data was used for this study. A SAR ship detection algorithm was applied and the predicted ship location was calculated using available AIS messages. The SAR detections were associated with the AIS-predicted ship signature locations. As a next step, AIS reported ship targets were analyzed and visible signatures were extracted as ships for training and testing the algorithms. Sea ice targets were extracted by visually analysing detected targets that did not look like ship targets and for which there was no AIS-reported message close to the target. Training and testing data were selected from these extracted targets. Testing data were kept independent of the training data. It is important to note that extracted ship and sea ice targets were actual targets that were causing problems for ship detection algorithms in discriminating sea ice from ship targets and vice versa.

SVM, AENN, and CNN based discriminators were evaluated in this report to reduce the false rate due to targets such as sea ice. Parameter selection for SVM, AENN and CNN methods were not optimized. Also, the combined information from HH and HV channels for OSVN mode data were not optimized. Even then, the result show that the correct classification rate for the ship target class is more than 94.7% for the DVWF mode and more than 90.5% for the OSVN mode. The accuracy of removing sea ice targets from the detection report is more than 97% for DVWF and 93.6% for OSVN.

These ship and sea ice discrimination algorithms were applied after applying standard ship detection algorithms. These methods reduce false targets (i.e., sea ice) significantly, but there is a chance that a few ships can be mistakenly removed as false targets. Therefore it is recommended to apply these methods only to those images acquired in sea ice areas. These methods have not yet been tested on images with icebergs in open water. This study shows that applying ship and sea ice discrimination methods is an important step in ship detection in a sea ice environment to minimize the occurrence of false targets.

Based on this study, the following is recommended to improve ship detection methods:

1. Optimize the algorithms for ship and sea ice discrimination. For example, selecting a different number of layers and filters, filter sizes, and pooling methods might increase the performance of the CNN method;

2. Apply these algorithms to a large number of ship and sea ice targets and verify the performance of these methods;

3. Conduct a study to determine where and when to automatically apply false alarm reduction algorithms;

4. Extend the analysis to include the case of false alarms caused by icebergs.

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List of Symbols/Abbreviations/Acronyms/Initialisms

AENN	Autoencoder Neural Network
AIS	Automatic Identification System
CNN	Convolutional Neural Network
DRDC	Defence Research and Development Canada
DVWF	Detection of Vessels Wide Far
EO/IR	Electro-Optical/Infrared
HH	Horizontal transmit, Horizontally Receive
HV	Horizontal transmit, Vertical Receive
MSSR	Maritime Satellite Surveillance Radar
OSVN	Ocean Surveillance Very-Wide Near
ReLU	Rectified Linear Units
SAR	Synthetic Aperture Radar
SVM	Support Vector Machine

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Deep learning; Machine Learning; Support Vector Machine; Ship and Ice discrimination; Synthetic Aperture Radar (SAR); Automatic Identification System (AIS)

13. ABSTRACT (When available in the document, the French version of the abstract must be included here.)

Current ship detection algorithms for Synthetic Aperture Radar (SAR) imagery experience limitations due to false alarms that arise in sea ice conditions. The aim of this Scientific Report is to demonstrate how false alarms can be reduced by applying target discrimination algorithms. In this report, RADARSAT-2 Maritime Satellite Surveillance Radar (MSSR) images acquired in both Detection of Vessels Wide Far (DVWF) and Ocean Surveillance Very-wide Near (OSVN) modes are considered, because these are the operational modes used for ship detection. Training and testing data samples were collected in regions that include sea ice. Ship targets were identified using visual analysis and Automatic Identification System (AIS) data reported by ships. Sea ice targets were identified by removing detected ship targets, and ship-like targets were excluded via visual inspection. Testing data were kept independent from training data. Support Vector Machine (SVM), Autoencoder Neural Network (AENN), and Convolutional Neural Network (CNN) were applied to discriminate the false targets (i.e., sea ice) from ship targets. Preprocessing and feature extraction steps were applied to the SVM method but not to the AENN nor the CNN methods. AENN and CNN are deep learning neural networks. The results show that these methods can remove more than 93% of the false targets detected in DVWF and OSVN modes. However, a few of the ship targets were misclassified as sea ice targets in both the DVWF and OSVN modes. These methods should only be used in ocean regions in which sea ice is present.

Les algorithmes actuels de détection des navires dans les images par radar à synthès d’ouverture (RSO) sont confrontés à des limites à cause de fausses alertes qui surviennent e présence de glace de mer. Le but de ce rapport scientifique est de démontrer comment on peu réduire les fausses alertes en appliquant des algorithmes de différentiation des cibles. Dans c rapport, on utilise des images de Radar de surveillance maritime par satellite (MSSR RADARSAT-2 réalisées en mode DVWF et en mode OSVN, car il s’agit là des mode opérationnels utilisés pour la détection des navires. Les échantillons de données de formation e de mise à l’essai ont été prélevés dans des régions où il y a présence de glace de mer. Le navires cibles ont été identifiés par analyse visuelle et grâce aux données du Systèm d’identification automatique (SIA) transmises par les navires. Les cibles de glace de mer ont ét trouvées en retirant les cibles de navire détectées, et on a retiré par inspection visuelle les cible ressemblant à des navires. Les données de mise à l’essai ont été isolées des données d formation. On a appliqué une machine à vecteurs de support (SVM), un mécanisme d’encodag automatique à réseaux neuronaux (AENN) et des réseaux neuronaux convolutionnels (CNN pour différencier les fausses cibles (p. ex., la glace de mer) des navires. Des étapes d prétraitement et d’extraction des caractéristiques ont été appliquées à la méthode SVM, mai pas à celles de l’AENN et des CNN, qui sont des réseaux neuronaux d’apprentissage profonc Les résultats obtenus démontrent que ces méthodes arrivent à retirer plus de 93 % des fausse cibles détectées dans les modes DVWF et OSVN. Cependant, quelques navires ont été ma classés en tant que glace de mer à la fois en mode DVWF et en mode OSVN. Ces méthode doivent être réservées aux régions océaniques où il a présence de glace de mer.