DEEP LEARNING FOR ICEBERG DETECTION IN SATELLITE IMAGES

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***Abstract**:* Iceberg can cause a dangerous threat to shipping, offshore oil and gas production facilities, and subsea pipelines. Data on Iceberg and Island is significant for atmosphere science and for different marine activities in the sea. The detection and monitoring of the icy objects in the often dark and cloud covered polar region are done with the well-established tool know as synthetic aperture radar (SAR). In this paper, the deep learning-based CNN approach has been utilized for distinguishing the iceberg from high-resolution satellite images. This paper presents a robust and efficient method of extraction of features for SAR target classification using deep features. This approach is based on the adaptability principle and focuses on improving the efficiency of iceberg detection in uncertain environmental conditions with broad variation in textural, scale, and shape. The method used for iceberg classification includes SAR images, deep features extracted based on ROI, Sift, Surf, Threshold, Transfer Learning and CNN classifier for classification of the iceberg and other objects. The CNN method is applied to a dataset containing high-resolution SAR images acquired from satellites Landsat 8 and Sentinel 1 (Southern Ocean).

Keywords: Iceberg detection, CNNs, SAR images

1.INTRODUCTION

Icebergs provide a threat to navigation and marine activities in areas like offshore and deep ocean. Synthetic aperture radar (SAR) data is an important iceberg identification part of offering an operational iceberg surveillance program on drifting icebergs. It provides continuous monitoring with high-resolution two-dimensional satellite images that are independent of daylight, cloud coverage, fog, rain, and various weather conditions. Because coarser resolution satellite SAR data is sometimes not as intuitive as optical satellite data for classification of targets interpreted manually by humans. Therefore, an automated iceberg detection system is required to be implemented. Generally, accurate identification of icebergs relies on the performance of identifying icebergs from open water or sea ice under different climatological, sea or iceberg conditions. These situations result in variations in the extracted images, from highly bright to dark objects. Along with changing textural and patterns, this varying spectral behaviour makes it difficult to establish a general predictive model to distinguish icebergs from coexisting features in SAR images, thus supporting the need for adaptive approaches.

More than 15 spaceborne SAR satellites are currently operating for numerous applications, including sea ice and land surface surveillance. In the proposed system, we proposed an algorithm that automatically determines whether or not a remotely sensed target is an iceberg. When the radar detects an object, specific characteristics-shape, size and light intensity-need to be analyzed to classify it as an iceberg. With remote sensing systems over 600 km above Earth, the Sentinel-1 satellite constellation transmits and receives energy in the horizontal and vertical plane, producing a double polarization image. We use these raw images in this project to try to output. The training data given include the images of 75 x 75 pixels with corresponding features: HV, HH, and goal performance of whether or not the image is an iceberg. There are various situations where the icebergs can be detected.

Iceberg in open water: The icebergs show bright spots in optical images against a dark background, the higher the wind reduces the contrast between open water and icebergs. Iceberg in drifting ice: When larger floes of frozen ice occur, icebergs can create tracks in the drifting ice. Difficult to distinguish icebergs from a background in optical images when there is the only information available on backscatter. Some images are simpler to categorize while others are not easier to categorize. We use several techniques to reach this goal: CNN, feature extraction techniques. The method used for iceberg classification includes SAR images, deep features extracted based on VGG-S1 net and CNN classifier for classification. VGG-S1 net is used to derive profound characteristics from SAR images. The network is trained to classify an image into several categories. This determines all of CNN's parameters, such as the weights of the convolution filters. The trained network is used to produce discriminative features from the architecture layer response with the SAR image input. Then a conventional fusion based on a simple concatenation is introduced to combine the characteristics of the discriminative layer. The aim of this study is to derive or generate valuable features to further improve the efficiency of the algorithm.

2. RELATED WORK

Deep iceberg detection study provides, not only confined to, the shape predictor, contours and previous data model and the algorithms used in satellite images. R.Ninis, W.Emery suggested receiving and processing AVHRR images used in this study at the Satellite Oceanography Laboratory at the University of British Columbia's Department of Oceanography. The pictures were projected to a conical map with the U.S. This technique of navigation as defined by Emery and Ikeda [1984] produces images that are accurate to one pixel. The data is used to correct timing errors for the receiving system [1]. V.Y. Alexandrov, S. Sandven, K. Kloster S. Sandven, K. Monastery, S. Sandven. claims Icebergs are significantly smaller in the Eurasian Arctic than in the Antarctic and in Greenland and, consequently, the high resolution of satellite images using ERS SAR and RADARSAT ScarSAR is required to detect them. In SAR images icebergs, which had higher signatures and smaller dimensions compared to the darker signature of the surrounding drift and fast ice, were detected from the visual inspection. Therefore, expert knowledge on iceberg distribution in the northern part of Novaya Zemlya and in Severnaya Zemlya was further trained for the SAR image interpretation process. Iceberg images recognized glacier boundaries and areas of iceberg calving [2]. The iceberg signature is almostdeterministic for iceberg detection and can easily be set up with an automated detection method, which is always characterized by the parabolic shape. The selected method is based on the test of convolution productC between the thermal noise sections of the waveforms and filter, F, iceberg trademark character trait [3].

There has been a range of SAR image target classification algorithms, such as the SVM Support Vector Machine, Adaboost, Neural Network (NN), Gaussian Mixture Models (GMM), etc. [4]. AIS is a mandated safety system of the International Maritime Organization (IMO) that is designed as a low power, high- frequency (VHF) transponder (LOS) collision preventance system. AIS (SAIS) systems with satellite-based systems suffer from AIS messages collision when many vessels in the field of view of the satellite (FOV) [5]. Ordinary iceberg detection approach considers the use of algorithms for ship detection previously developed. Many of these methods are particularly aimed at differentiating the targets from the background noise by performing a statistical test of image brightness. A Neyman – Pearson lemma on the probability of detection (Pd) or false alarms (Pf) can solve the threshold problem [6].

The Sentinel1 satellite constellation is transmitted and received by a remote sensing system 600 km above the ground, generating a dual-polarization picture in both the horizontal and vertical levels. In this project, the useoff raw images with two channels (horizontally transmitted, received) and HV (horizontally transmitted and received vertically) [7]. The first step takes the sample SAR imagery of pixel sizes from 0 to 255. Amrani, Moussa Jiang, Feng stated that all training SAR target images were first processed in two steps. In the second pre-processing step, the integer mean value is subtracted from each of the features in the SAR images, and the VGG-S1 network is used to extract the deep features from the SAR images. The network is trained to classification an image in a C category, where C is the number of classes the MSTAR database [8]. In its paper, T.Hollands stated that according to its scale, sea ice changes its motion characteristics: sea ice is traditionally regarded as a non-rigid continuum at the large (basin) scale. However, it has a discontinuous behavior within the spatial dimension of the individual floes or nearby cracks, leads and deformation areas within the sea ice cover. The error is composed of a systematic component that corresponds to the mean measurement variation from the undisturbed "real" signal and a random measurement component. The random mistake is also known as noise. The interpretation of information in the signal is disturbed [9]. Modava, Mohammad Akbarizadeh, Gholamreza in his paper states that the FCM clustering algorithm was developed by J.C. Dunn and improved by J.C. Bezdek. It is an iterative algorithm that divides the image into cfuzzy clusters by grouping similar data points. The conventional FCM does not use the spatial image information that makes it susceptible to noise and imagery. This sensitivity is reduced if spatial information is imported into the conventional FCM.[10]. Muckenhuber, Stefan Sandven, Stein, states that GPS booys and meters currently measure ice drift at certain locations are important instruments. However, satellite remote sensing is today the most important data source to monitor sea ice drift on medium to large scales. We also use the Nansat toolbox Python to process

Sentinel-1 images within Python, which builds on the Abstract Data Library. We also change the projection of the ground control points provided into stereographical and use splints to calculate geographical coordinates, as in Muckenhuber et al [11].

3. DATA AND DATA EXTRACTION

This work consists of SAR images captured by satellite Sentinel-1 located 600 km over the surface of the Earth. The data set contains a total of 10,028 (test + train) satellite pictures. Each picture is 75 to 75 pixels in size and has two bands. Every band has associated 5625 meaningful floating values. There are 1604 pictures on the training package with the target component (is iceberg), the leftover 8424 are unmarked. Among 1604 samples of training, 753 are marked iceberg. Each training data set has an attribute that gives us details regarding the current angle at which the radar signals occurred on the subject. The massive difference in train and test datasets, as well as a wider unlabeled portion of the data, presents a challenge in the effective classification process. This has prompted us to adopt the semi-supervised approach. The code was fully implemented using Jupyter, a powerful Python language development system with efficient editing, numericalcomputing, and testing environment.

a. Extraction on Single Image Dataset

The image is preprocessed before segmentation with two main purposes. The first objective is to filter image noise and spindles in order in the following image segmentation to minimize isolation and noise. The secondis to improve the iceberg rims and suppress other unimportant rims inland or in the ocean.

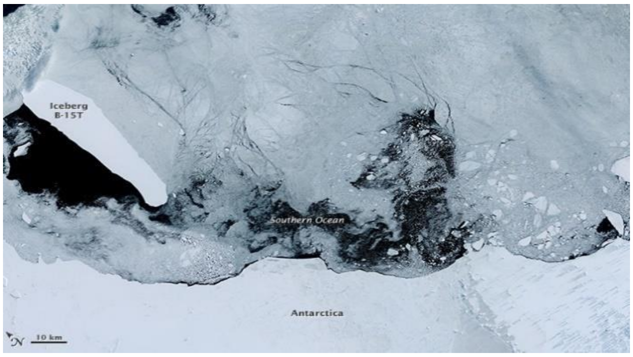

Fig. 3.1 Input Image - Iceberg B-15T Still Adrift

i. Noise Removal

A rim-preserving operator is required to remove the image noise to maintain the exact position of the iceberg. An optical filter from Gaussian can filter images with the most important rims without blur. The Lee filter reduces radar noise and range, without decreasing the edges sharpness.

ii. Corner Detection

Harris is the most famous corner detector among gradient-based methods that identify corners in the image through the use of a small Gaussian smooth window that changes vertically and horizontally with pixel ordinates. The central pixel of a window is described as the corner once the brightness distribution varies considerablemente.

iii. Edge Detection

The picture edge for machine learning algorithms is an important aspect. Canny border detection can offer much better and more consistent border detection results compared to other border detection algorithms and isnow the criterion for the evaluation of many other methods.

Canny Edge algorithm's fundamental characteristics are

1) Gaussian filter to smooth the picture.

2) Computing gradient orientation and magnitude for the partial derivatives using a finite differential approximation.

3) To use no maximum removal to the magnitude of the gradient.

4) To identify and link edge, use the dual-threshold algorithm.

iv. Surf Method

The SURF process is a quick and robust image description and a comparison algorithm for local, unchanging similitude. The SURF approach's primary interest resides in its fast computing by box filters, which enables applications in real-time such as tracking and object detection. In this paper, the SURF mechanism described is based on H's doctoral thesis.

v. Thresholding method

The aim of the division is to divide the image into its homogenous components. The border pixels can then be defined as the edge line between the divided iceberg/ water areas. A locally adaptive threshold methodology is used for picture segmentation to securely separate iceberg objects from the ocean background. If the whole image uses a single global threshold. Every pixel in the image is replaced by the easiest threshold techniques by a black pixel if the intensity of the image is less than some permanent T or a white pixel if the image intensity is more important than that constant.

Fig.3.1.5 a) Corner Detection

Fig.3.1.5 b) Grey Scale

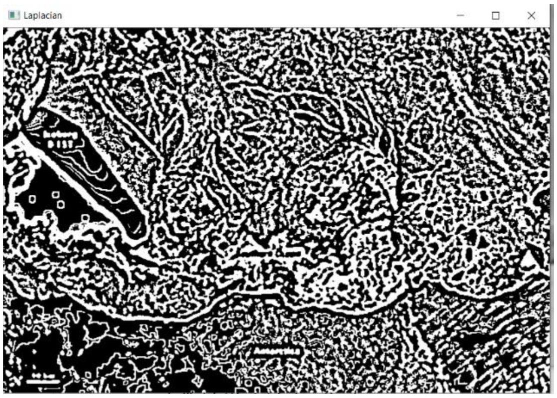

Fig.3.1.5 c) Edge Detection Laplacian

Fig.3.1.5 d) Edge Detection Canny

Fig.3.1.5 e) Finding ROI

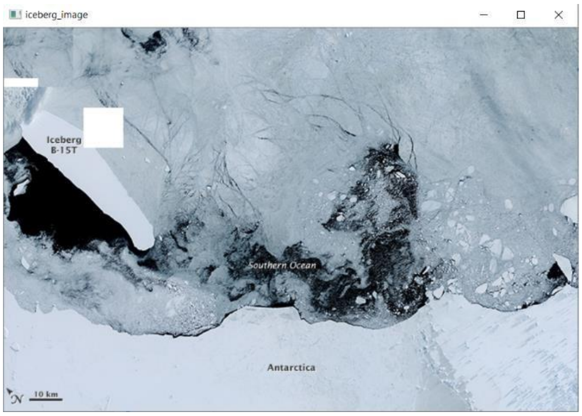

Fig.3.1.5 f) Finding Similar Region

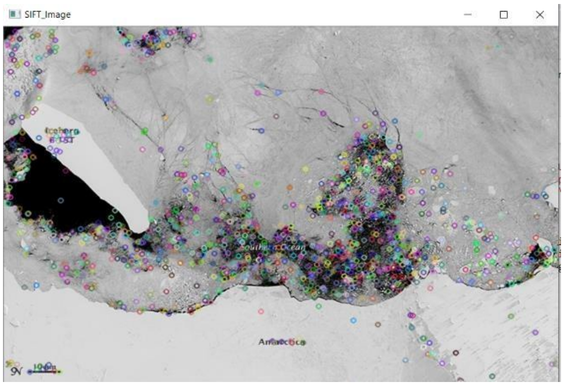

Fig.3.1.5 g) Sift

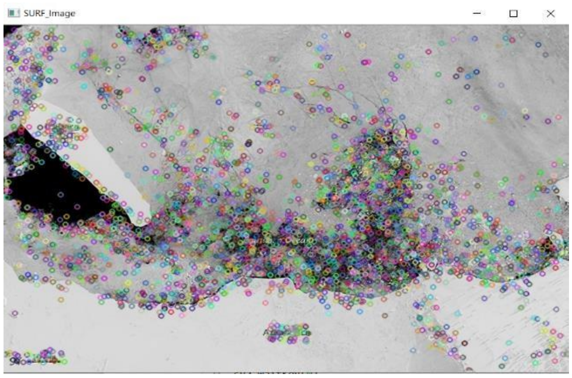

Fig.3.1.5 h) Surf

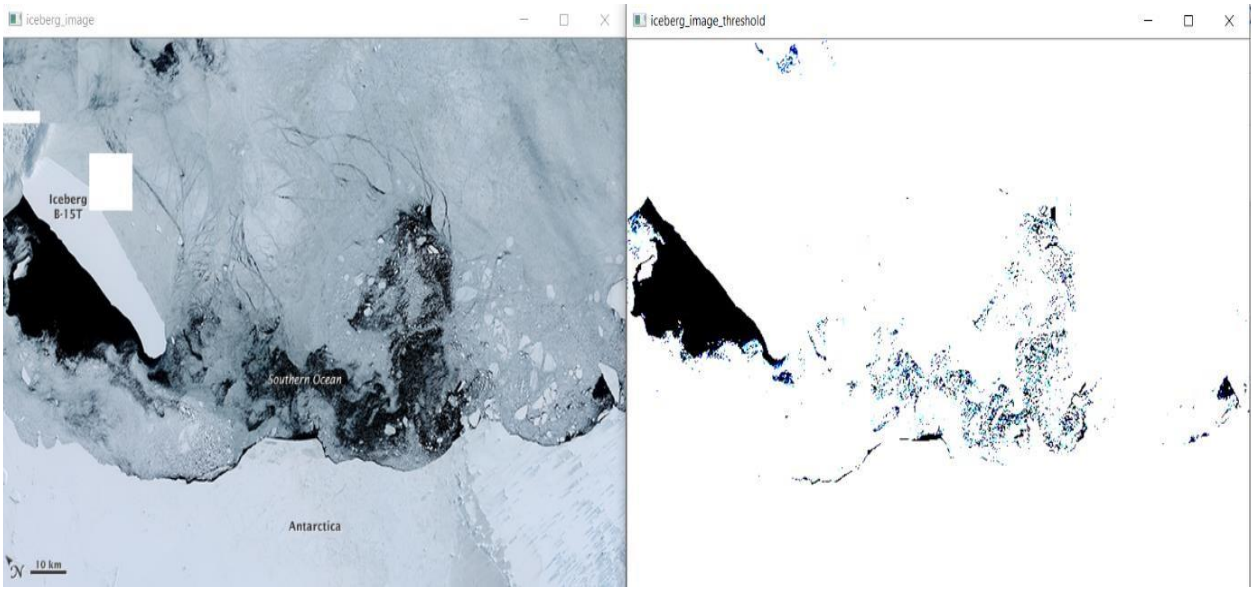

Fig.3.1.5 i) Thresholding Method

4. METHODOLOGY

The iceberg extraction procedure comprises three groups of algorithms for image processing: segmentation, pre-segmentation, and post-segmentation. The pre segmentation algorithms are intended to suppress the noise of the image and improve the edge of the images. The segmentation algorithms divide the image into homogeneous ice and water areas with an adaptive threshold. The processing algorithms for post-segmentation are intended to distinguish the iceberg from other object borders and to trace the iceberg pixels into a form of vector representation. Our goal is to obtain an exact location and an accurate geometric form for an iceberg. As derived iceberg geographical cohesion is inherited from satellite imagery, that input pictures must also be geocoded to allocate specific geographical co-ordinates to pixels and rectified before using our iceberg extraction method, to remove geometry and distortions in the picture. The geocoding of the original images and their orthorectification is beyond this paper. We presume that the input data imageis geo-corrected and terrain-corrected in our analysis. The input picture is also assumed to be panchromatic or a single-band gray-scaled picture with an intensity of 0 to 255.

a. Data Pre-processing

At around 680 Km above Earth, Sentinel-1 is the satellite that transmits pulses of signals and recalls them at a particular incidence point. Those signals reflected are known as backscattering. The data that we were given is the coefficient of backscatter which is the traditional form of the coefficient of backscatter given by the equation:

$$\boxed{\sigma_\circ(dB) = \beta_\circ(dB) + 10\log_{10}[\sin(ip)/\sin(ic)]}$$

If ip is the pixel incidence angle, ic is the center of the image's incidence angle, and k is constant. The satelliteof the Sentinel is very identical to the RISTSAT satellite, as it sends pings in H polarization rather than V polarization. H pings scatter and come back as a combination of H and V polarizations when an object occurs.As Sentinel has only an H-sender, only HH and HV are the return signals.

We first preprocess the data to eliminate irrelevant information present in it before we use the data for analyticpurposes. We substitute the lines with an angle of inclination as "na" with zero. There are two bands linked with each training sample (HH and HV). By averaging the two, the two bands are combined and a third channel is established to achieve the equivalent RGB three channels. Figures show the 3D structure of icebergbased on their band values in the Plotly library.

In order to learn from the different aspects of water and icebergs, we use these structural differences in the training of CNNs.

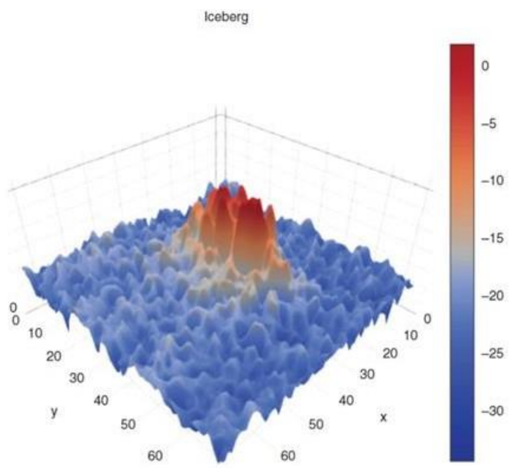

Fig. 4.1.1 3D Plot of Iceberg.

b. Data Augmentation

Data increase is a method to add value to the database data that is deprived of information by raising the quantity of training data samples. The more data connect the CNN model has, the more reliable its accuracy iscommon knowledge. By expanding the original data set, the data increase overturns the over-fitting of training datasets. We use conventional transformations in this project, which distort the training data. The original pictures are usually rotated, shifted, flipped, zoomed in, or blurred to obtain the enlarged pictures. In that case, the images are increased by reversing the image because this aids CNN in obtaining a different image orientation. While a copy of their original pictures, the flipping images significantly improve training accuracy. This is because the flipped image is intrinsically invariant on CNN and it may trigger the convolutional kernel matrix very differently from the initial. The neural network is fed with both image and replication. we are creating a 3N size set of data (vertical and horizontal flips) for a size N dataset by an increase in the data. The size of the training set rises to 4812 pictures after the data has been increased. Data enhancement not only serves to strengthen state-of-the-art classification algorithms in categorization tasks that lack sufficient data. Augmentation of the dataset risen the accuracy of CNN training by which is around 1.2 percent.

The global characteristics of the pictures were explored statistically -maximum, minimum, mean, third quartile, first quartile and standard deviation of the two HV and HH bands-and thus became new elements for the training data. The correlations are shown in Figure. With the Decision Tree, newly generated characteristics have been introduced with a decent result with a log loss of 0.21 value. Because of the limited data set, a deep learning training framework provided a challenge in its setup. Even if more data is beneficial, computational power and resource constraints this. A variation of image transitions, including smoothing, reflection, first and second derivatives, rotation, gradient, and Laplacian, accomplish the increase here. The very first pass test started by steadily increasing the data length while the underlying model was fixed and the test error and the training error reduced.

In addition to increasing data size, the divergence of the training failure and test failure contours are seenas driving – indicating that the model is less overfitting, allowing us to generalize wider test data.

Fig. 4.2.1

The curve of data increases showing loss of training (log) and loss of test (log)with increased data transformation with data size.

c. Building the CNN Model

CNN is an artificial neural deep feed network class that is widely used in computer vision. CNN is a notionthat is motivated by the hierarchy and connectivity of nerve cells in the human brain. CNN has confirmed to be very efficient in areas like image identification and classification with recent developments in neural networks. In addition to moving the view in robots and self-drive cars, ConvNet was effective in defining faces, objects, and road signs. In the project, we are developing a CNN consisting of four key aspects: A} Conv2D layer, B} non-linear activation function, C} pooling layer, and D} dropout layer The template was developed in a sample size of 32, defining the number of samples distributed by batch over the network. The model consists of four layers of Conv2D and 3 layers of dense. A 3x 3 convolutional filter was also used to implement CNN. After each convolutional layer, we use a 0.2 dropout and 2x 2 max pool layer. That dropout layer reduces excess to fit. Finally, we had a completely integrated layer of 256 neurons completely connected. The same padding method and 'relu' activation function were used for all convolutional layers. A number of 560,193 parameters were used in the model.

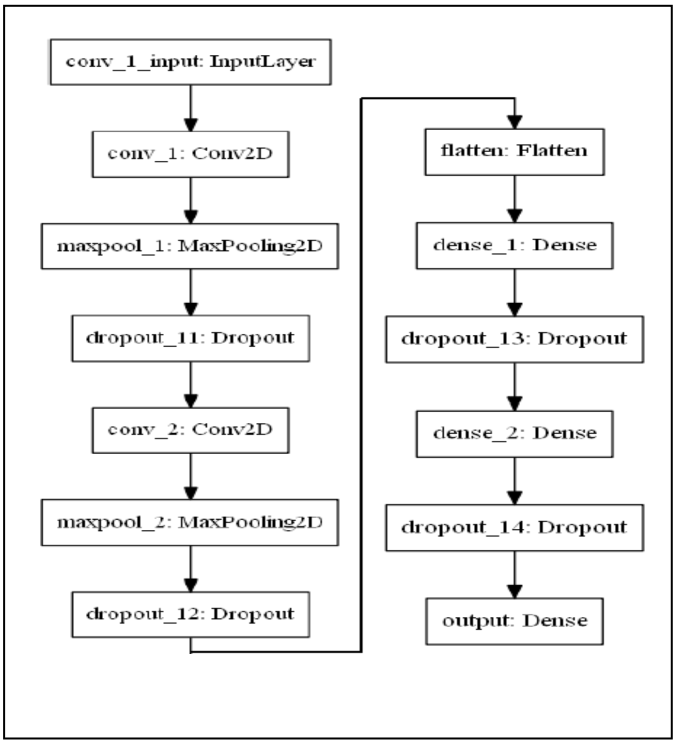

Fig.4.3.1 TensorFlow system visualization and analysis architecture

d. Deep Learning/Transfer Learning

The deep learning framework involves dividing the training data into 4:1 sets while using the train test splitfunction from python library sklearn. The model performance trained was analyzed using the accuracy metric, with the log loss of the loss function, which evaluates effectiveness by penalizing bogus classifications. For instance, if after a certain number of periods the managed output of the validation set does not increase, the learning rate is reduced by 90%. This is done to prevent the appropriate solution and jump back and forth when it comes to the optimal. Lowering the learning rate thus helps the model to get closer to the target. On the other hand, if the learning rate is decreased too rapidly, optimization can become highly inefficient.

Hyperparameters are a set of parameters in the machine learning context which are determined before the learning process begins. In short, other gaussian values are extracted by training. It is essential to improve hyperparameters for a learning algorithm. For deep learning, hyperparameter optimization includes optimization algorithms, learning rate, drop rate, number of hidden layers, number of units in each layer, etc. The best way to find a good model for this ' black box ' is to analyze the test collection. The number ofstructures and components in each hidden layer is difficult to adjust, which requires adaptation of the current and validated design, with further domain-based modifications. Thus, the evaluation of various optimization algorithms and different learning rate methods. Keras visualization shows the architect used for hyperparameterisation.

Some attractive benefits are: easy to use, computationally efficient, suitable for issues with very high noise or sparse gradients. The key element is ' transfer ' knowledge from enough unlabelled SAR transferable to labeled SAR target data. Several images were used to train a redevelopment path with piled auto-encoders andpretrained layers were subsequently reused for the classification task through ' transfer of expertise.

5. CONCLUSION

The deep learning algorithm was used to recognize instantly whether an image is a water or an Iceberg. Inspired by satellite data processing, standardization is one method for using the incident angle. The images are standardized to the same angle of incident, say 0 °, by the transformation. This can help the water and iceberg discrimination process. The other technique is to further increase the outcomes by stacking or designing, after developing several negatively correlated models. This paper describes the use of CNN's in high-resolution SAR pictures for water-iceberg segregation. In this phase, the main difficulty was that the measurements of the (unlabeled) test data were much bigger than the train (labeled). We have also compared the LB score of CNN model assumptions either with or without pseudo labeling, which represents a semisupervised ML approach to resolve this constraint. Our analysis can be further enhanced by investigatingthe pre-processing of the data. We disregard the angle of incidence which may have greatly influenced our result in our study. We recognize that the angle of incidence that influences satellite decibel measurement speed, and assumes that this parameter needs to be implemented to make detection more reliable. Using the log-loss performance system used in this contest, classification failure can influence submission scores exponentially. Through multiple alternative extraction methods and discovery of different CNN algorithms and hyperparameters, we are therefore hoping in our future work to minimize our classification mistakes.

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BIOGRAPHY

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