An Innovative Deep Learning Approach For Detecting Marine Oil Spills In Satellite Synthetic Aperture Radar Imagery

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Abstract- *Oil spill detection is essential for keeping the maritime ecology in good condition. The use of quad-polarimetric synthetic aperture radar (SAR) has demonstrated to be highly promising in this regard. It is advantageous to distinguish oil spill zones from other similar objects using various SAR polarimetric properties. For SAR pictures, we have also implemented masking to improve efficiency and lower noise. To draw attention to any correlations between the grounded truth and the expected outcome, we have used the dice coefficient and IoU coefficient. A fully convolution neural network-based technique for finding oil spills (F-CNN). All target types of categorization accuracy were increased, with the highest improvement in dice coefficient yielding an overall accuracy of 98% percentage.*

Keywords- oil-spill, quad-polarimetric synthetic aperture radar (SAR), polarimetric decomposition, pixel normalization, fully convolution neural network, dice coefficient, intersection over union

I. INTRODUCTION

Ocean and sea pollution brought on by oil spills has been a serious and inescapable issue. A planned or unintentional discharge of liquid petroleum hydrocarbons into the ocean can result in an oil spill, which can cause global ecological disasters that harm the marine environment's quality and productivity as well as the marine life cycle. Protecting marine habitats is crucial for both shortterm and longterm sustainability. Seas also contribute to human well-being and economic livelihood internationally.

Oil spills on rocky terrain are less dangerous and destructive than those in the marine environment. They have the potential to quickly cover hundreds of kilometers and generate a thin oil crust that might cover beaches. Such pollution requires time-consuming and expensive monitoring and detection. To prevent catastrophic impacts, it is imperative to create an emergency response program. The systematic monitoring of the maritime environment is necessary for a workable operation to reduce the pollution in oil. This process makes it possible to calculate oil distribution zones precisely, facilitating swift response and recovery. Oil spills in oceans have got a lot of attention recently due to the risks they pose to human health as well as the harm they bring to the environment.

The growth of maritime petroleum platforms and expanding marine transport traffic over the past few decades have both greatly raised the potential of environmental damage brought on by oil spills. Globally, there is an urgent need for public, political, and scientific concern about the marine environment due to the increased production, distribution, storage, consumption and refining of oil and petroleum products. Since oil spills commonly happen in the marine water bodies around the world, there is a higher chance of the detrimental and catastrophic effects of oil pollution.

According to worldwide literature, emissions from ships are the main causes of oil slicks. Although though there are many natural and man-made factors that contribute to oil slicks in the water, previous studies have revealed that marine tankers are the main offenders.

Contingency planning for oil spills is essential for protecting marine ecosystems and species. This involves monitoring, detecting, and predicting the trajectory of oil slicks. Effective monitoring and intervention tools are needed to respond to environmental emergencies appropriately. Hence, satellite data have been an appropriate and effective option that gives a cost-efficient way to perform such a task. The use of multi-sensor and multi-temporal data by satellite RS systems has allowed for the monitoring of the surface of the earth to be extended over a large geographic area.

Due to noise, space borne polarimetric SARs have limitations in their ability to detect oil spills. Thick oil coatings and emulsions can be observed by radars . We do not believe that fully-polar metric or quad-polar metric space-borne synthetic aperture radars (SARs) have the potential to considerably enhance oil spill detection, specifically in terms of distinguishing between mineral oil and naturally occurring biogenic films, in our view. This conclusion is drawn from the arguments made in this paper. [6].

In oil spill detection systems, five feature selection techniques were used. The accuracy of the classifier was increased through feature selection, which eliminated unnecessary characteristics. The method of SVM-RFE feature selection [7] produced the highest levels of accuracy. The results show that the SVM classifier, using six inputs, achieved an accuracy of 88.61% and a Kappa statistic of 79.06%. Additionally, 73.0% of the selected distinctive traits fall under the geometrical category.

Simple Linear Iterative Clustering (SLIC) is used to create super pixels. Despite its simplicity, this method, which is based on a k-means clustering methodology, generates super pixels that conform to boundaries as well as or better than earlier approaches. Moreover, SLIC enhances the performance of segmentation, is quicker and more memory-efficient, and can easily expanded to produce super pixels.2

In order to optimize the polar metric feature sets and reduce the feature dimension, layer wise unsupervised pre-training [9] and deep learning techniques such as the stacked auto encoder (SAE) and deep belief network (DBN) were employed. The experiment involved the examination of verified mineral, emulsion, and biogenic slicks using RADARSAT-2 quad-polar metric synthetic aperture radar (SAR) images taken during the Norwegian oil-on-water exercise in 2011.The results show that the deepneural networks perform better than traditional artificial neural networks (ANN) and support vector machines (SVM) when parameter values are similar, especially when there are few training data samples available.

Ocean remote sensing is an ideal application for synthetic aperture radar which track surface backscatter radiation and display the roughness of the ground. As a result of oil slicks dampening the sea waves, dark blotches may be seen. Methodology [10] consists of 3 steps: visual interpretation, picture filtering, and object-based oil spill identification. Visual interpretation: This method involves visually examining images or data to identify oil spills. Trained analysts analyze satellite imagery or aerial photographs and manually identify potential oil spill areas based on distinct visual characteristics.

Picture filtering: Picture filtering techniques involve applying various filters or image processing algorithms to enhance the visibility of oil spills in images. These filters can help to reduce noise, improve contrast, and highlight specific features associated with oil spills, making them easier to identify.

Object-based oil spill identification: Object-based analysis is a technique where individual objects or regions in an image are identified and analyzed based on specific criteria. In the case of oil spill identification, the analysis focuses on detecting and classifying oil spill regions as distinct objects based on their size, shape, color, texture, and contextual information. The retrieved properties of the ASAR subsets/scenes are used to construct fuzzy membership functions for object-based classification are accurately tuned for each case group.

TERMA SLAR [7] radar is used to collect a dataset on the Spanish coasts that included 28 different flight patterns in total. For the identification of oil spills, deep sectional auto encoders are employed. Various network configurations were evaluated, and it was determined that the topology that performed the best significantly outperformed earlier approaches.

By segmenting photos of oil spills [8], a two-stage methodology is created. In the first step, the backscattering from an oil spill image must be suppressed in order to produce the improved image. A variational segmentation model is introduced in the second step to cope with the augmented image. Alternating minimization is used to numerically solve the variational model. They conclude that calculations on 65 ENVISAT oil spill pictures demonstrate that the proposed method may achieve a 94% overall accuracy for dark spot segmentation.

Out of 225 oil spills and 26 look-alikes, a total of 35 feature parameters were retrieved and split into training and validation datasets. They conclude that extracted feature parameters have been evaluated and graded based on how well they can distinguish between oil spill and look-alikes.

II. METHODOLOGY

To maintain maritime ecosystem, oil spill detection is crucial. Passive monitoring of the sea surface is the method used to find and map oil spills most commonly. Many methods can be used to capture images in the visible and infrared spectrums. Indeed, different SAR polar metric features offer advantages in distinguishing oil spill regions from other similar-looking phenomena. Quad-polar metric Synthetic Aperture Radar in particular has shown great potential for this purpose. SAR works by emitting microwave radar signals towards the Earth's surface and recording the signals that bounce back. This allows SAR to capture valuable information about the physical characteristics of the surface, including oil spills. By analyzing the polarimetric properties of the returned signals, SAR can differentiate between oil spills and other substances or natural features, enabling effective identification and mapping of oil spill regions.

Fig 1.Oil Spill Regions

In addition, we use the masked image of the SAR images, in order to avoid noise. Image masking increases product production and gets imagery ready for processing. Alkanes (also known as "paraffins"), cycloalkanes, and aromatic compounds are just a few of the many chemicals that make up mineral oil films. Within oil patches, the oil layer's thickness might range from less than one millimeter to more than one millimeter.

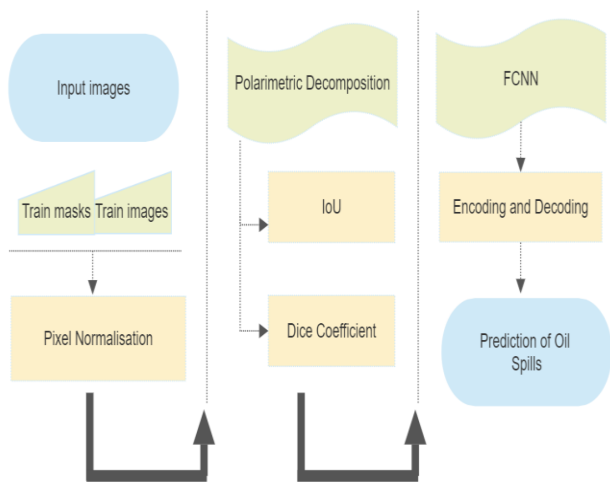


Fig 2.Work Flow

When there is an oil spill, a small amount of oil will be broken down and fall to the bottom. When oil spills and sinks into the ocean as it spreads, the health of the marine life suffers. The oil film is continuous after spilling or discharge, although it frequently fragments fast as a result of waves, currents, and turbulence, especially at high wind speeds. We masked the photographs since mineral oil coatings float on water's surface at a time, degrading and changing their chemical composition. We have suggested a convolutional neural network-based technique for finding oil spills. First the image is subjected to pixel value 0 to 1 (Pixel Normalization). The pixel normalisation method is frequently employed to quicken model learning. An image is normalised by dividing each pixel's value by the highest possible value for a pixel. The term "Normalization" refers to the 0–1 scaling range. To normalize image pixels, execute the following actions. By dividing the maximum value of a pixel by its minimum value, the rescale parameter can be adjusted to scale pixels in the 0–1 range: 1/255 = 0.0039.

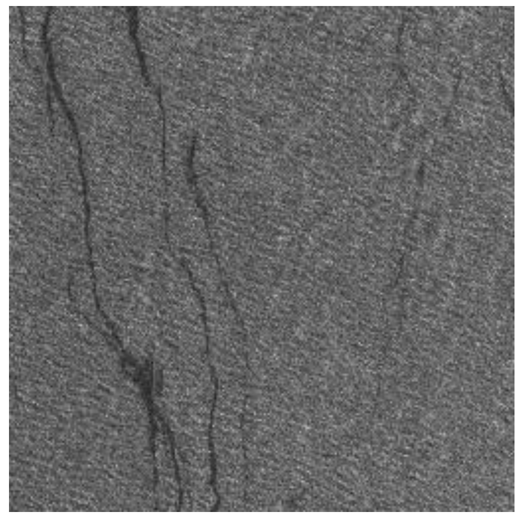


Fig 3.Detection of oil spill Regions

In Polarimetric Decomposition, the dice coefficient, and Intersection over Union (IoU) of the image is found. A measurement of the relative contributions of backscatter from various scattering mechanisms is provided by polarimetric decomposition methods. The foundation for oil spill differentiation, categorization, and monitoring is provided by the differential response of oil spill locations to polarimetric radar signals. The choice of the appropriate decomposition method is crucial in the classification of naturally distributed targets since polarimetric decomposition approaches quantify the relative contributions of backscatter from various scattering mechanisms. In fully CNN, the final segmented result is obtained using Up sampling method. The fundamental concept behind the conversion of a CNN to an FCN is that the fully connected layers can be interpreted as convolutions with kernels that encompass the entirety of the input regions.

Instead of relying solely on the exact spatial positions of features produced by the convolutional layer, subsequent actions leverage aggregated features. This makes the model more resilient to variations in feature locations within the input image. To encode the images in our model, we use the Max pooling approach. After the encoding is complete, the samples are un-pooled to produce the results, and this process is known as up-sampling. The Up-sampling network up-samples the abstract picture representations in a variety of ways to match the spatial dimensions of the input image.

III. ANALYSIS OF OIL SPILL REGION

To predict the region of oil spill, first we need to convert the training images and training masks to NumPy array format. NumPy library is used in Python to work on multi-dimensional arrays, linear algebra, Fourier transform, matrices etc. It enables the computation on high-level mathematical computations. Next, normalize the pixels in image array by dividing by 255 so that the pixel values range from 0 – 1, this process is called Pixel Normalization. Matplotlib pyplot is used for plotting the image.

Python's plotting tool, Matplotlib, creates publication-quality graphics for interactive and hardcopy contexts on a variety of platforms. Python scripts, Python shells, Jupiter notebook, internet application servers, and graphical programming toolkits. Matplotlib strives to simplify complex tasks while also enabling the accomplishment of challenging objectives. Pyplot is a collection of command functions that aims to provide a similar experience to using MATLAB with matplotlib. Each pyplot function performs specific actions that modify a figure, such as creating a figure, setting up a plotting space, plotting lines or data in the space, adding labels and decorations to the plot, and so on.

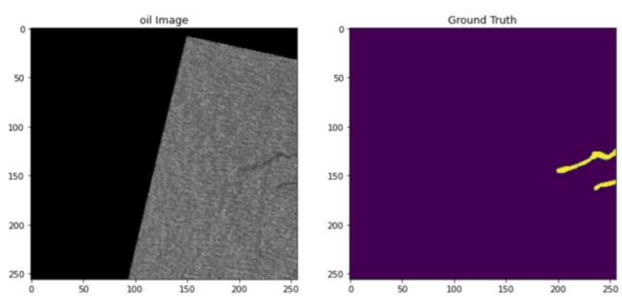
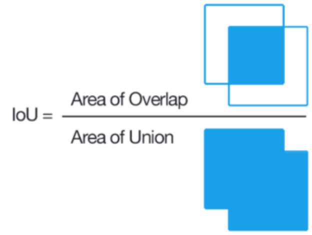


Fig 4. Train image and Train mask

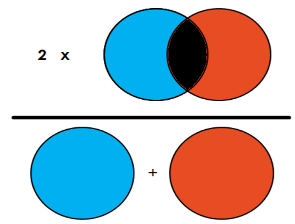
Polarimetric Decomposition

The dataset is divided into three sets: the training set, the test set, and the validation set, with a ratio of 7:2:1, respectively. In polarimetric decomposition, IoU coefficient and Dice coefficient is found and Dice loss is calculated.

- IoU is calculated to divide the overlap between the predicted result and the grounded truth by creating the union of both.



- The Dice Coefficient is utilized to evaluate the pixels of the inferred segmentation with the ground truth and quantify the similarity between them.



A. Fullly Convolutional Neural Network

- The images are then passed over the FCNN. Since there are no fully connected layers in FCNNs, the number of network parameters is drastically reduced, allowing for faster learning and inference of the networks as well as the solution of much simpler learning problems.
- With the (2,2) kernel, max pooling is done after up sampling, which includes zero-valued samples to speed up sampling.

IV. MODEL EVALUATION

In machine learning, it's usual practice to divide a data set into three parts before evaluating an algorithm. The training set is one of those sets, where we learn some characteristics, and the testing set is the other, where we test the learned qualities. The validation set is the other set, where we use it to confirm the accuracy of the training set.

The model is trained in Fully CNN, followed by MaxPooling and Up Sampling.

Layer (type)	Output Shape	Param #
input_1 (Input Layer)	[(None, 256, 256, 3)]	0
conv2d (Conv2D)	(None, 256, 256, 16)	448

conv2d_1 (Conv2D)	(None, 256, 256, 32)	4640
max_pooling2d (MaxPooling2D (None, 128, 128, 32))		0
conv2d_2 (Conv2D)	(None, 128, 128, 16)	4624
up_sampling2d (UpSampling2D (None, 256, 256, 16))		0
conv2d_3 (Conv2D)	(None, 256, 256, 2)	802
conv2d_4 (Conv2D)	(None, 256, 256, 1)	3

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Total params: 10,517
Trainable params: 10,517
Non-trainable params: 0

Early stopping is used, which is a method used to avoid overfitting while training the images. Model Check Point is used to save the snapshot of the model which contributes in resilience, generalization and tuneability. The model undergoes training for 100 epochs. The training and validation loss values serve as diagnostic tools to identify potential learning problems that can lead to an under fit or over fit model. They provide crucial information about how the learning performance evolves as the number of epoch's progresses. Additionally, these loss values inform us about the epoch at which the learned model weights can be used for inference purposes.

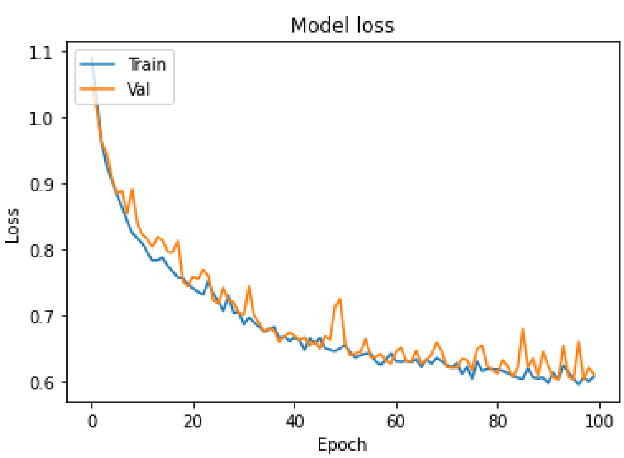

Fig 5. Model Performance

V. CONCLUSION

One of the primary hazards to the marine natural environment is sea surface oil spill, hence effective monitoring and early warning are required. Yet, due to the complexity of the surrounding ecosystem, finding oil spills can be difficult. In order to detect oil spills, we have focused on integrating multilayer characteristics with an FCN model using quad-polarimetric Synthetic Aperture Radar (SAR) as a data source. The model is built and tested with the test data set. We can learn about the loss, dice coefficient, IoU coefficient and accuracy of the model.

```
10/10 [==============================] - 0s 18ms/step - loss: 0.5489 - iou_coef: 0.2967 - dice_coef: 0.5259 - acc: 0.9840
[0.5489335060119629,
 0.29667243361473083,
 0.5259178876876831,
 0.9839887022972107]
```

The output is then plotted to display the Oil Image, Grounded Truth and Predicted mask.

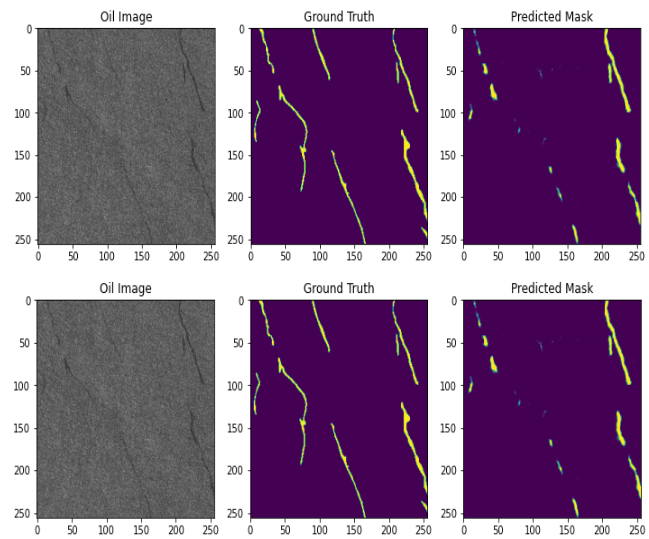

Fig 6. Model Performance

In our future work, we will concentrate on investigating the oil spill detecting abilities of the model developed under difficult circumstances in our upcoming study. We'll also try to make the network better in order to increase the model's effectiveness in detecting oil spills.

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