Study on Oil Spill Detection Over Ocean Surface Using Deep Learning

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Abstract - *Oil spills over ocean surfaces are mainly caused by release or leakage from the carriers while transportation through water, spill of any fuel or oil refuses used in ships, or even dumping oil remains from the land. Such left-overs on the sea surface may have disastrous consequences, especially because of the fact that they take more time to be accessed and cleaned up. The tides make it easier for the oil to break and spread over long distances. The major consequence is that, oil spills left on the ocean surface affect the marine wildlife and may have adverse effects related to climate and weather conditions. One of the most effective ways to deal with this issue is using remote detection and monitoring of the oil spills. The Synthetic Aperture Radar (SAR) is an instrument that can be used to detect oil spills on sea surface. SAR images show oil spills as dark patches which enables their detection. SAR can operate unaffected by weather conditions and even during night time. SAR observations are taken as input to detect oil spills with deep learning model. The segmented images from the model are trained and tested with different learning rates and varied input feed. The total number of epoches and the number of steps per epoch are changed and the resulting segmented images are studied with respect to loss and accuracy. This work is aimed to contribute to future work on oil spill detection based on effective segmentation.*

Key Words: **Oil Spill, SAR, Deep Learning**

1. INTRODUCTION

Marine environment is being polluted by human beings either knowingly or unknowingly. The oil spilled in the sea are discharged from ships, intentionally or unintentionally and oil spills across the sea surface can cause very serious problems, and it has to be cleaned up as soon as possible before it causes any adverse effects. Thus the early detection of oil slicks is vital in order to save the marine environment from further damage. Illicit oil discharges should also be tracked through surveillance systems which ensure safety and security. If untraced these oil spills create major threats to bio environment. The satellite or aircraft based technologies such as remote sensing has been helpful in monitoring and detecting oil spills .The most predominantly used technology is the Synthetic Aperture Radar (SAR) . The Synthetic Aperture Radar captures the images of ocean which represents the objects such as landscapes and ocean surfaces. Remote sensing of objects can be enabled by mounting SAR over aircrafts and satellites. This mechanism is used to acquire images of oil spills over the ocean surface using a sensor which emits the radio waves and their reception is monitored so as to produce SAR images. The sensor has a wide range of coverage which helps in capturing oil spills of huge area(in kilometers). The oil over the sea surface suppresses the radio waves. This results in the depiction of oil spills as dark patches in the generated SAR image. The sensors can possibly capture other objects such as ocean vessels, algae, weeds, etc. These are look-alikes depicted as dark instances in the generated image which has to be distinguished from the oil spills. Thus processing of the SAR images helps to classify whether the observed dark spot is oil or look alikes. Therefore firstly the dark spots has to be segmented using deep convolutional neural network (DCNN) segmentation models. This paper focuses on the U-Net segmentation model and how the losses and accuracy can be improved. The analysis is being carried out for increasing number of epochs, steps per epoch and by altering the learning rate.

2. LITERATURE SURVEY

In the earlier studies the various segmentation models for oil spill detection have been discussed. Marios Krestenitis et al.[1] proposed a method to discriminate oil spills from look-alikes over SAR images using three main steps. Initially dark spots are detected in the processed SAR image and then feature extraction from the initially identified regions. Last step is classification as oil slick or regions including look-alikes. The positive perspectives of this proposed method include that the remote sensing via SAR sensors can provide high resolution images where possible oil spills might be captured and semantic segmentation by deploying DCNNs can provide useful information regarding the depicted pollution scene. Suman Singha et al. [2] proposed a similar three stepped process including image segmentation, feature extraction and classification. The segmentation stage identifies candidate features. The features are broadly grouped into types based on the geometry and shape of the segmented region, or based on the backscatter values of the spot and its surroundings. The classification stage uses the feature vector information to segregate oil spills from look-alikes. This oil spill classification system uses two neural networks in sequence for image segmentation and feature classification respectively. K Topouzelis et al. [3] investigates two different NN architectures and compare their performances. Multilayer Perceptron (MLP) and Radial Basis Function (RBF) neural networks are used to detect oil spill and evaluated their performance. It derives to the fact that RBF networks work faster than MLP while MLP has smaller memory requirements for the classification and has better generalization than the RBF. Parth Praveen Deokar et al. [4] states the implementation of the steps as preprocessing the SAR image, Sobel Edge Detection, Canny Edge Detection, Morphology, Dilation, Erosion, Opening and Closing. In [5] it is determined that the following steps are sufficient to identify spilled oil on sea surface. Selection of an area in the image containing a dark object; computation of physical and geometrical features characterizing the object; classification of the object into oil spill or look-alike, based on the calculated features. An automatic detection method called thresholding-guided maximally stable extremal regions (TGMSERs) algorithm is proposed in [6]. The mRMR_SVM algorithm [7] is applied to choose the optimal eigenvector set and this eigenvector set is applied for training to efficiently classify oil spills and look-alikes. The convolutional neural network in [8] automatically extracts all category features thus eliminating the non-standardity of manual extraction methods and the extracted features are classified by Soft-max. All the discussed works holds back in certain points as that the false positives are not completely diminished, the reliability of the SAR data can be questionable since it can show dark patches for other matters like algae, the oil spills can be detected only when they are significantly large enough for detection.

3. PROPOSED WORK

SAR remote sensing of ocean and coastal monitoring supports a variety of marine applications and ocean researches these includes study of ocean surface, terrain surface etc. Synthetic aperture radar (SAR) is an instrument capable of producing high-resolution day or night imagery in all weather conditions. In the proposed work SAR images are taken as input and then it is fed to U-net architecture to extract the feature from the images.

3.1. DATASET

Oil spill detection dataset has jpg images extracted from satellite Synthetic Aperture Radar (SAR) data collected from European Space Agency (ESA) databases, the Copernicus Open Access Hub. The Sentinel-1 European Satellite is used to acquire the images. The European Maritime Safety Agency (EMSA) provided the geographic coordinates and time of the confirmed oil spills. The web site[9] provides a common oil spill dataset for academicians and researchers and the dataset comprises of annotated images so that the experimental results could be compared for accuracy. For segmentation purposes the dataset has a distinct RGB color for each of the 5 classes (Sea surface, Oil spills, Look-alike, Ship and Land). Likewise for the training and evaluation, one dimensional labels are used. Thus, one dimensional label masks are defined by an integer value from 0 to 4 for each color class. SAR image with its ground truth mask is shown in figure 1.

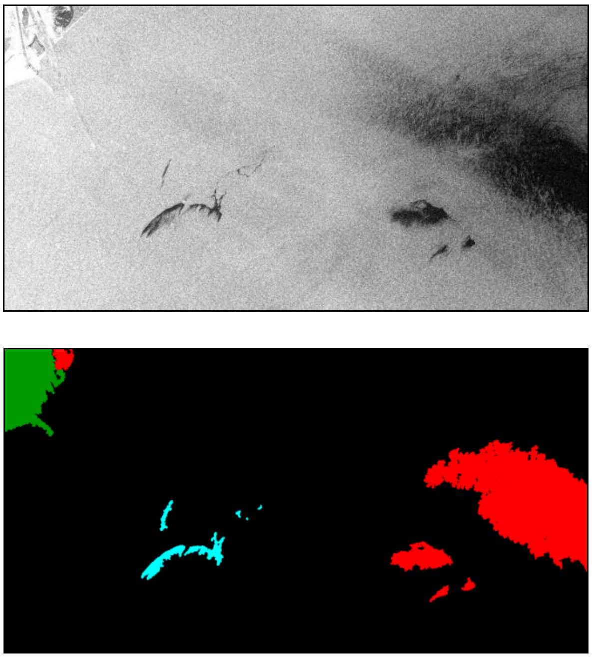

Figure 1: Sample SAR image with ground truth mask

3.2 SEGMENTATION

Image segmentation: The process of dividing the image into several segments or objects, making it easier to analyze the image. The aim of this process is to identify and locate objects and locate its boundaries in an image. The resultant image will have pixels grouped to be labelled as distinguished objects present in the original image.

Clustering algorithms: Identifying subgroups (clusters) in data, such that similar data points are clustered in the same subgroup. K-means clustering algorithm divides the datapoints into 'k' non-overlapping clusters where each data point belongs only to one cluster. The pre-processed oil spill dataset is subjected to K-means algorithm. The results are observed to be with minimal accuracy in identifying objects.

Semantic segmentation: The process of assigning a class label to every pixel of an image. Most of the semantic segmentation models consists of two implementation components, encoder and decoder blocks. The encoder block encodes the image into a compressed feature vector where the spatial dimensions of the image objects are diminished with the help of DCNNs. The consequent process includes decoding the extracted representation to produce a resultant that meets the dimensions of the original image. To achieve this, the decoder progressively reconstructs the encoder's outputs.

U-net: U-net segmentation was initially developed to semantically segment biomedical images. It is considered as an extension of the fully convoluted neural network (FCN). This segmentation uses feature mapping to convert an image into its corresponding vector and vice versa. This contributes to the up-sampling and down-sampling components of the architecture. The architecture also includes a bottleneck component in between encoder and decoder. The name "U-net" is derived from the U-shaped architecture. The encoder uses FCN based architecture to capture the objects of an image. The expansive decoder path up-samples the feature vector resulting similar to the original image form. The oil spill data is subjected to U-net segmentation on varied number of epochs and iterations to break the image. The results at various attempts are observed, studied and noted.

3.3. EXPERMINENTAL RESULTS

The grey-scale images of 1250 X 650 dimensions, are reshaped to 512 X 512. The preprocessed images are sent to U-net algorithm to detect dark patches in the input data. The detected patches can further be classified into oil spills and look alikes. As the proposed work is focused on studying loss and accuracy by increasing epochs and steps per epoch the input image is trained with varying epochs and steps per epoch. From the experiment it is found that if the number of epochs is 25, the number of steps per epoch are 50 and the number of test images is 10. The execution time observed is 2 hours. If the number of epochs is 25, the number of steps per epoch is 50 and the number of test images is 75. The execution time observed is 4 hours. If the number of epochs is 50, the number of steps per epoch is 25 and the number of test images is 200. The execution time observed is 6 hours. The loss for the above setup has improved from 0.02964 to 0.02670 and the observed image is shown in figure 2.

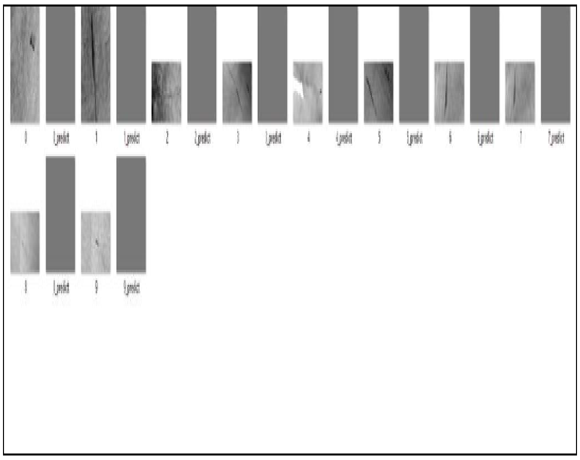

Figure 2: Output of 50 epochs

It is evident from the results that if number of epochs and step size is increased it greatly improves the performance.

4. CONCLUSIONS

Oil spills, when left unidentified or unattended over ocean surfaces, can become a serious threat. To minimize the possible environmental damage, specific monitoring and detection of harmful suspensions becomes necessary. This is achieved by the remote sensing mechanism using the SAR sensors. This paper aims to segment satellite images to identify oil spills and look-alikes. As it is a part of undergraduate studies with limited time we focused on study of accuracy and loss when deep learning is implemented for SAR images. With sample size of 10, 75, 200 it is found that increasing epochs and step size has greater impact on performance. Though there are methods proposed to directly process SAR data to detect spills, using DCNN to classify provides an advantage of resulting in comparable outcomes (in terms of accuracy and loss). The method proposed in this paper can be developed with advanced semantic segmentation model with greater efficiency like Deep lab segmentation models.

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