Look-Alike Detection using Deep Convolutional Neural Networks for Ocean Oil Spills

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\textbf{Abstract:} The marine and coastal ecosystems are placed in grave danger whenever there is a spill of oil. For the sake of protecting future generations, the authorities need a dependable mechanism that allows them to respond quickly and effectively to oil spills. As a result of their consistency also effectiveness in a wide series of weather and light situations, synthetic aperture radar (SAR) sensors are frequently utilized for this determination. The dark spots that are typically associated with oil spills remain easy for SAR sensors to spot, but it may be difficult to differentiate them from other objects or phenomena. A great number of methods have been outlined in order to automatically differentiate and categories these dark spots. The results are frequently unable to be compared with one another because of the heterogeneous nature of the data collected. It is often difficult to fine-tune settings or extract meaningful information because SAR images remain often classified through a solo label that is applicable to the entire picture. Because of this, the process of dealing with the images is made more difficult. The Random Forest Classifier and deep convolutional neural networks (also known as DCNNs) are examples of approaches that have been suggested as potential workarounds for

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these constraints. In addition, we make available to the public a search-and-rescue photo library that might
serve as a standard for the growth of upcoming oil spill recognition tools. On the dataset that was provided, a
number of well-known DCNN segmentation models as well as the Random Forest technique are evaluated and
compared with one another. When compared to other approaches, it was discovered that Random Forest had
the best test correctness and the quickest implication time. Additionally, the dataset is used to explore and
explain the challenges of the provided issue, which in this case is identifying between genuine and fabricated
oil spills. These investigations and demonstrations are carried out with the help of the dataset. According to
their training and evaluation on the dataset that was provided to them, DCNN segmentation models, when
paired with a Random Forest classifier, did quite well when attempting to detect oil spills. The novel method
is anticipated to be of significant use in subsequent research pertaining to the identification of oil spills and
the dispensation of SAR images.

Key words: SAR imagery, Oil spill recognition, Random Forest Classifier, Deep Convolutional Neural
Networks, Remote sensing.

1. INTRODUCTION

The "look-alike" phenomenon, in which the oil slick is mistaken for another feature, makes the synthetic
aperture radar pictures that are used to detect marine oil spills less trustworthy than they might be.
This is one of the reasons why these images are employed. At this time, the only choices available for
the accurate identification and differentiation of oil spills and other events with a similar appearance are
semantic segmentation machine learning models and basic machine learning approaches [1, 2]. When
developing a cutting-edge deep learning oil spill detection model, the authors of this study took this
into consideration. The model that they created used a Face Convolutional Neural Networks model as
the basis for feature extraction in computer vision. Finding any unseen oil leaks was the objective of
this mission. A Convolutional Neural Network (FPN) architecture was used to extract the features,
and the models were trained using transfer learning with ResNet 101 on COCO. The training of the
model was carried out over the period of 30 iterations at a learning rate of 0.001 [3], respectively. The
process of training also started from the very beginning. It is very necessary to identify the source of
an oil spill in order to calculate the extent of the pollution and the resulting damage to the coastline.
As a result of this, there has been a lot of recent interest in utilising data from synthetic aperture radar
(SAR) to verify and locate oil spills [4, 5]. This is so due to the fact that the information may be used
whenever it is necessary, irrespective of the time of year or the weather conditions. An inquiry has been
opened into the circumstances surrounding an oil spill that occurred in the Al Khafji district. Images
acquired by Sentinel 1 SAR-C are being used here as part of the investigation. Due to its position on
the international boundary between Saudi Arabia and Kuwait, the enclave of Al Khafji in the part
of the Persian Gulf known as the Gulf of Oman does not belong to either Saudi Arabia or Kuwait.
Instead, it maintains its independence. There is a possibility that the Al Khafji area might generate
more than 7472.403 m3 barrels of oil per day (m3/d). Finding the sources of oil leaks is very necessary
in order to save marine life [6]. In this application, SAR equipped with four polarimetric channels has
shown a lot of promise and may be able to help distinguish oil spill locations from background clutter by employing distinct polarimetric properties. We developed a superpixel-based convolutional neural network (CNN) for oil spill detection by using the simple linear iterative clustering (SLIC) approach [7–9]. The studies made use of three SAR pictures, each of which was acquired with quad polarisation from a Single Look Complex (SLC). The data gathered by Radarsat-2 and the Synthetic Aperture Radar for C and X-Band Imaging (SIR-C/X-AR) allowed for the creation of images such as this one. In order to recover the polarisation parameters, Yamaguchi and Freeman decompositions, each with three and four components respectively, were used as feature sets.

We present a technique based on deep learning that can automatically recognise and categorise large oil spills in synthetic aperture radar (SAR) images. The state-of-the-art performance in oil spill detection [10] is obtained by developing a neural network model for picture segmentation and then training it on a huge dataset. This allows for the identification of oil spills with unprecedented accuracy. Because it delivered results that were equivalent to those attained by human operators, our model made it possible to reach this state-of-the-art level of performance. In addition to this, we provide a novel system for categorising oil spills that may be used during search and rescue efforts. When an oil spill is discovered, the slick is categorised according to its size, shape, and consistency so that it can be cleaned up properly. It is possible that oil spill monitoring service providers may use the results of the classification as a basis to improve the services they provide. Our functioning pipeline and a tool for visualising huge datasets are presented as the last phase of this process [11, 12]. Large oil tankers and ships, as well as breaks in pipelines that dump oil onto sea surfaces, have a catastrophic influence on the ecology of the ocean. Images obtained by synthetic aperture radar (SAR) provide a reasonably accurate representation of the circumstances at the target. This category includes a wide variety of different things, including surfaces on land and water, boats, oil spills, and even duplicates. It is essential for both the preservation of the environment and the repair of leaks that oil spills be located and highlighted in SAR photographs. In order to detect oil spills in a dataset with a large number of inconsistencies, we develop a deep learning architecture with two stages. Finding strategies to improve the effectiveness of oil leak detection systems is the primary objective of this research. A one-of-a-kind 23-layer Convolutional Neural Network is used in the first stage, which is the categorization of patches according to the fraction of pixels inside the patch that are suggestive of an oil spill. Semantic segmentation, on the other hand, is carried out by using a U-Net structure that is comprised of five steps.

2. PROPOSED METHOD

In order to mitigate any further losses, it is imperative that the relevant scientific community solve the lack of a uniform dataset for oil spill detection as soon as possible. Previous research [11, 12] only tested their hypotheses on data sets that were engineered to match their needs. Because each method uses a different collection of information, it is hard to compare their final outputs fairly. To remedy
this, we analysed SAR images with the intention of providing the concerned community with a reliable dataset that can be castoff towards pinpoint oil spills. This set includes semantically labelled masks, which will allow researchers to gauge the impact of their work. Here, we'll take a closer look at the information we've been discussing thus far and explain what it all means. In short, the European Space Agency used the Copernicus Open Access Hub database to compile satellite SAR images of oil-affected coastlines. The EMSA helped get the word out to the public about when and where the pollution incident took place. SAR images have dark dots that, according to EMSA’s data, are oil spills. The high-accuracy subset has been confirmed by this finding. Sentinel-1 satellites use a method called SAR for delivering data over the C-band. The SAR sensor’s pixel spacing can be as small as 10 metres, allowing it to simultaneously scan a ground range of about 250 miles. These results suggest that the SAR sensor can keep tabs on large areas of interest and, in some cases, spot ships. We get the radar picture by fusing two polarisations, one in which the signal is sent and received in the same direction (VH) and another in which the signal is sent and received in the opposite direction (HV). The VV band raw data was processed to produce the SAR image library. This was accomplished by subjecting the data to a battery of pre-processing techniques meant to strip it of its typical representations. In order to prepare ready, I went through the following steps: All reported oil leaks have been addressed, as documented by EMSA’s records. Second, the initial SAR picture was cleaned up by erasing oil spills and possibly other irrelevant background data. The original 1250650 image was reduced in size and cropped prior to uploading. All 1,250,650 photos were finally aligned hooked on the similar plane using radiometric standardization. It was decided to utilise a speckle filter to mitigate the wide-area sensor’s noise contribution. A 7 7 median filter was working to remove the roughness introduced by the fleck noise. Fifth, after converting dB values, absolute luminance values were computed using a linear transformation.

Using this technique, we were able to pull 1112 pictures, or the vast bulk of the mining target, from the raw SAR data. This information made up the bulk of the mining objective. This is how we came to learn this. The study includes images of oil spills, lookalikes, ships, scenery, also the sea surface; the sea superficial is the only image not considered background. (Remote Sensing, Vol. 11 (1762), 2019) Only five percent of a class of twenty-two students. Human IDs and EMSA data are used together for accurate image classification. Each of the five classes has been assigned a distinct colour drawn from the RGB colour space. The photographs included in the file contain the ground truth masks themselves. These masks are the result of assigning colours to each feature based on the category information that was provided. While the masks shine when used to the visualization of semantic data, the training and evaluation methods now in use require 1D target labels rather than RGB values. This holds true despite the fact that such data is best visualized with the aid of masks. Label masks for a single channel are generated by assigning integer values between 0 and 4 to the various colour categories. Given the rarity of perfect classifiers in practice, many approaches have been developed to efficiently partition data into distinct classes with a minimum of processing. However, many classifiers’ goal is to improve accuracy rates in classification. In most cases, this is
achieved by merging the results of multiple, sometimes low-quality, classifiers or training sets. An actual collaborative knowledge system requires a library of various classifiers. However, it is not always easy to get both good performance and a large number of classifier options. Solutions to this problem have been developed using a variety of collaborative learning strategies. Ensemble learning techniques based on decision trees (DT), such as Random Forest, have been proven to be highly effective in recent years. Random Forest, an ensemble methodology, is founded on result trees. This document provides an overview of Random Forest as well as introductory instructions for its use. The attributes are randomly sampled during the development of the decision trees that make up this set of prediction trees, and the inducers then select the best split among the sampled attributes. Both of these processes occur as the prediction trees are being built.

**Random Forest’s algorithmic procedures:**

**Input:** Sum of Characteristics Used in Each Tree (N), Iterations (I), Sampling Ratio (r), and Decision Tree Inducer (DTI).

**Train:** For all i from 1 - T Get a replacement model St as of S using r/Construct a classifier Mt using inducer data that casually selects N features.

**Classification:** The majority vote is used to determine the classification of a new instance by a set of classifiers Mt (t=1,...;T).

### 3. RESULT & DISCUSSION

Radarsat-2 was the first commercially available SAR satellite to provide quadrature polarization (quad-pol), and it was used to test three fully polarized SAR images. The photos were evaluated using a C-band frequency and a spatial resolution of 1-100 meters. MDA Geospatial Services Inc. contributed, without charge to the researchers, the following data sets that were incorporated into the studies throughout the research (http://gs.mdacorporation.com, Grant of Licence). The ultimate spatial resolution of each dataset was 8 by 8 meters, and it was achieved by recording in the fine quad polarized mode. Reference maps for future research were created using the high-resolution optical images accessible on Google Earth. The published results of previous studies based on the same data set were used to create these maps.

Main component analysis led us to conclude that a target retention rate of 92% was most desirable. Average accuracy, total accuracy, and the kappa statistic were used to assess the methods’ capacity for categorization. The characteristics of polarimetry are categorized as follows: F1: T3-db; F2: stacked T3-db, span, and TFs; F3: stacked T3-db, span, and MPs; F4: [T3-db, span, TFs, and MPs]. The table below compares the accuracy of several classifier features using Random Forest and provides measures of both average and total accuracy. For your convenience, included the following Table 1.
Table 1. Accuracy of classification produced by Random Forest for a given dataset, expressed as a percentage

<table>
<thead>
<tr>
<th>Classifier Feature</th>
<th>F1</th>
<th>F2</th>
<th>F3</th>
<th>F4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>99.43</td>
<td>98.54</td>
<td>99.21</td>
<td>98.97</td>
</tr>
<tr>
<td>Built-up1</td>
<td>88.47</td>
<td>88.7</td>
<td>88.37</td>
<td>81.45</td>
</tr>
<tr>
<td>Vegetation</td>
<td>91.04</td>
<td>91.13</td>
<td>89.41</td>
<td>92.37</td>
</tr>
<tr>
<td>Built-up3</td>
<td>91.23</td>
<td>91.43</td>
<td>92.27</td>
<td>94.62</td>
</tr>
<tr>
<td>Built-up2</td>
<td>88.56</td>
<td>89.47</td>
<td>89.34</td>
<td>88.5</td>
</tr>
<tr>
<td>OA(%)</td>
<td>90.93</td>
<td>90.24</td>
<td>90.41</td>
<td>91.97</td>
</tr>
<tr>
<td>AA(%)</td>
<td>93.12</td>
<td>91.79</td>
<td>91.72</td>
<td>90.90</td>
</tr>
<tr>
<td>Kappa</td>
<td>0.78</td>
<td>0.88</td>
<td>0.83</td>
<td>0.85</td>
</tr>
</tbody>
</table>
4. CONCLUSION

Oil spills represent a significant danger to marine life and the ecosystems that live along the coast; therefore, it is critical to be on the lookout for them and to respond expeditiously in the event that one occurs. Because of the high-resolution images they provide, SAR sensors are an essential component of remote sensing systems. There is a possibility that some of these photographs will show evidence of oil spills. In an effort to differentiate oil spills from other occurrences that may appear visually comparable, a number of strategies have been developed for automatically evaluating SAR pictures. Because it has the ability to offer helpful insights into the contaminated environment that is being displayed, the Random Forest classifier that is based on DCNN is showing promise as a possible method for identifying oil spills. Another problem is that it is impossible to compare the results because the various approaches all utilise their own unique datasets, hence it is impossible to do so. The analysis of the Random Forest method and the creation of a centralised repository for SAR images are the two most important things that can be learned from this research.

References


