A Study on Oil Spill Detection in Ocean with Look a likes

Dr. J. Senthil Murugan[1], Dr. S. Durga Devi[1], M. Sakthivel[2], Dr. W. T. Chembian[1],G. Anushiya[3], S. Kavi priya[3], Infanta Mendez[3]

[1]Associate Professor Department of Computer Science Engineering, Vel Tech High Tech Dr. Rangarajan Dr. Sakunthala Engineering College,
[2]Assistant Professor Department of Computer Science Engineering, Vel Tech High Tech Dr. Rangarajan Dr. Sakunthala Engineering College, Email id: jsenthilmuruganmtech@gmail.com
[3]Students Department of Computer Science and Engineering, Vel Tech High Tech Dr. Rangarajan Dr. Sakunthala Engineering College, India
Email id: jsenthilmuruganmtech@gmail.com

Article Info
Page Number: 90 - 97
Publication Issue:
Vol 72 No. 1 (2023)

Abstract

One of the biggest dangers to marine and coastal areas is oil spill. Effective oil slick monitoring and early detection are essential for the relevant authorities to respond quickly, control environmental pollution, and prevent additional harm. Because of their reliability and efficiency across a wide range of environmental and illuminative conditions, synthetic aperture radar (SAR) sensors are commonly used for this purpose. SAR sensors can clearly detect black patches that are likely connected to oil spills, but differentiating them from other objects that seem similar is a difficult task. Many alternative approaches have been put forth to automatically find and categorise these dark patches. The vast majority of them offer incomparable results due to the usage of different datasets. As an added complication, SAR images are generally labeled with a single label that applies to the whole picture, making it difficult to adjust nuanced parameters or extract relevant data. Deep convolutional neural networks (DCNNs) and the Random Forest Classifier are suggested as an effective method to get over these restrictions. A publicly accessible SAR picture collection is also introduced with the intention of serving as a standard for future oil spill detection technologies. The performance of well-known DCNN segmentation models and the Random Forest method in the given job is evaluated using the dataset that is being presented.Random Forest performed most efficiently in terms of test accuracy and inference time. Furthermore, using the provided dataset, it is explored and demonstrated how complex the given challenge is, particularly in light of the difficult task of differentiating actual oil spills and their imitations. Results suggest that effective oil spill detectors can be implemented using DCNN segmentation models with Random forest classifier, trained and assessed on the presented dataset. Future research on oil spill identification and SAR image processing is anticipated to benefit considerably from the current work.

Article History
Article Received*: 15 October 2022*
Revised*: 24 November 2022*
Accepted*: 18 December 2022*

Keywords: Deep convolutional neural networks, Remote sensing ,Oil spill detection, SAR imagery,Random Forest Classifier.

1. Introduction

Synthetic aperture radar (SAR) photographs used for marine oil spill detection are less reliable due to the visual similarity of the oil slick and other features, which is sometimes referred to as a "look-alike." Semantic segmentation machine learning models and classical machine learning algorithms are now the only solutions that are available for the successful detection and distinction of oil spills and similar-looking events [1-2]. In light of this, the authors of this study built a cutting-edge deep learning oil spill detection model by using a computer vision feature extraction Face Convolutional Neural Networks (Mask R-CNN) model. This was done in order to identify oil spills. The model was trained using transfer learning by employing ResNet 101 on COCO as the backbone, and the Convolutional Neural Network (FPN) architecture was used for feature extraction in the process. The training procedure included 30 iterations at a learning rate of 0.001 [3, and the model was trained throughout the duration of those iterations. The training method also included an initialization phase.

It is essential to locate an oil spill in order to conduct an analysis of the likely spread and float of the contaminant from the point of origin to the neighboring coastal terrains. Consequently, there has been a lot of recent interest in using Synthetic Aperture RADAR (SAR) data for the detection and verification of oil spills [4-5]. This is because the data may be used day and night, regardless of the season or the weather. At now, investigators are trying to figure out what caused an oil spill with in Al Khafji neighborhood. Sentinel 1 SAR-C images are being utilized in this probe. In the region of the Persian Gulf known as the Gulf of Oman, Al Khafji is considered to be a neutral zone due to its location on the boundary between Saudi Arabia and Kuwait. Over 7472.403 m3 barrels of oil have the potential to be provided per day (m3/d) from the Al Khafji area. Locating oil spills is very necessary for the conservation of the marine ecology [6].

Synthetic Aperture Radar (SAR) with four polarimetric channels has been shown to have great promise for this application, and different SAR polarimetric properties may help distinguish oil spill locations from environmental clutter. Based on a simple linear iterative clustering (SLIC) technique [7], we created a superpixel-based convolutional neural network (CNN) to detect oil spills. Three SAR images with a Single Look Complex (SLC) quad polarization were used for the experiments. These pictures were gathered by Radarsat-2 and the Spaceborne Imaging Radar-C/X-Band Synthetic Aperture Radar (SIR-C/X-AR). The Yamaguchi 4-component decomposition, the Freeman 3-component decomposition, the H/A/Alpha decomposition, the Single-Bounce Eigenvalue Relative Difference (SERD), correlation coefficients, and conformance coefficients were all retrieved as feature sets for the polarized parameters.

We provide a technique that makes use of deep learning to rapidly identify and classify massive oil spills in synthetic aperture radar (SAR) images. To attain state-of-the-art performance in oil spill detection [10], we create a neural network model for image segmentation and train it on a large dataset. This state-of-the-art performance was made possible by our model, which produces outcomes competitive with those obtained by human operators. In addition, we offer a classification assignment that has not been done before for the purpose of detecting oil spills in search and rescue operations. After an oil spill has been found, it is given a unique classification based on a variety of criteria, including the form and texture of the spill itself. Top-tier providers may use the findings of the categorization to better create oil spill monitoring services. Finally, we show both our working pipeline and a tool for visualizing massive amounts of data [11, 12].

Large oil tankers and ships, as well as pipeline leaks that release oil onto sea surfaces, wreak havoc on the ecosystem of the ocean. Synthetic aperture radar (SAR) images [13] depict target situations in a manner that is approximatively accurate. Surfaces at sea and on land, vessels, oil spills, and doppelgangers all fit within this category. For the sake of environmental protection and leak cleanup, it is important to be able to detect and isolate oil spills in SAR pictures. In this work, we build a two-stage deep-learning architecture for spotting oil spills from an extremely imbalanced data set. The study's focus is on enhancing oil leak detection efficiency. In the initial part of the process, a one-of-a-kind 23-layer Convolutional Neural Network is used in order to categorize patches according to the percentage of pixels that signify an oil spill. In contrast, the second phase makes use of a U-Net structure that is comprised of five stages in order to carry out semantic segmentation [14-15].

2. Proposed System

The lack of an uniform dataset for spilled oil detection is a significant issue that the research community that is relevant has to solve. Previous studies [13,14,15] on the topic only applied their methods to specialized datasets that were adjusted based on the method's evaluation. Each method relies on its own unique data set, making it impossible to directly compare the results obtained using different methods. As a result of this deficiency, we decided to analyse SAR photos with the objective of delivering to the appropriate community a well-established dataset that is appropriate for oil spill detection. Because semantically labeled masks are included in this collection, researchers will have the ability to assess the usefulness of the experiments they conduct owing to this feature. This section presents a comprehensive analysis and explanation of the dataset that was previously discussed.

In a nutshell, satellite SAR photographs of oil-polluted maritime areas were acquired using the database managed by the ESA called Copernicus Open Access Hub. EMSA, information on the specific location of the pollution event as well as the time it occurred was made accessible to the public. The high accuracy subset is validated in this manner by the EMSA data, which validate the fact that the black patches seen in the SAR photos are in fact oil spills. The SAR photos were obtained via the use of European satellites of the Sentinel-1 series, and the data on oil pollution covers the time period from September 28, 2015 to October 31, 2017. Data is sent on the C-band using a technique called SAR[16], which is carried by the Sentinel-1 satellites. With a pixel spacing of 10 10 meters, the SAR sensor can scan a ground range of around 250 kilometers at a time. These statistics indicate that the SAR sensor is capable of monitoring large areas of focus and may be able to detect objects, such as ships, depending on the circumstances[17].

The radar picture is a combination of two polarizations—one in which the signal is sent and received in the same orientation, and another in which the signal is sent and received in the opposite orientation (VH). After undergoing a variety of pre-processing techniques to remove common visualisations, just the obtained raw data from the VV band was processed to build the SAR picture collection. The preliminary procedure consisted of the following steps: If EMSA's data is to be believed, every single oil leak has been found since it was first reported. Second, an area of the original SAR picture that was thought to include oil spills and maybe other relevant background data was removed. In order to make the 1250650 picture fit, it was cropped and scaled. Third, all 1,250,650 images were projected onto the same plane using radiometric calibration. It was decided to use a speckle filter to cut down on the sensor noise that was present all over the picture. Using a 7 7 median filter, we were able to get rid of the grainy appearance of the speckle noise. Five, a linear transformation was employed to convert dB to absolute luminance values.

A total of 1112 pictures, representing the majority of the mining target, were retrieved from the raw SAR data using this approach; these values were obtained by extracting them from the raw SAR data. Data obtained using this approach[18]. The images represent five distinct types of interest; they include oil spills, lookalikes, ships, terrain, and sea surface; the last is always considered to be background Remote Sens. 2019, 11, 1762 5 out of 22 students. Human identity and EMSA data are used to label each picture for maximum efficiency. Due to the fact that the dataset that has been supplied is intended to be exploited with semantic segmentation methods, each of the five classes has been given a unique RGB color[19-20]. The ground truth masks that are produced as a consequence of coloring each object of interest in accordance with the category provided are included in the photographs that make up the dataset. Although the masks are best used for visualizing semantic information, training and assessment methods need 1D target labels rather than RGB values. The color categories are assigned integer values between 0 and 4 so that label masks may be generated for a single channel.

Because flawless classifiers are so uncommon in practice, several methods aim to separate classes as efficiently as possible in a single processing step. On the other hand hand, one of the primary objectives of a various classifiers is to enhance the performance of classification by combining many outputs from of the training sets or from other classifiers, which are often of low quality. A collection of several types of classifiers is required for an efficient ensemble learning system. However, achieving both a high degree of classifier variety and excellent performance at the same time is not always a straightforward task. Many different approaches to learning in groups have been proposed as potential solutions to this issue. During the course of the last ten years, ensemble learning algorithms that are based on decision trees (DT), including such Random Forest, have shown to be especially successful. Random Forest represents a broad category of ensemble techniques that use decision trees. The basic procedures of Random Forest are outlined here. The decision trees in this collection of prediction trees are constructed using a resampling approach with replacement; the attributes are sampled at random; and the optimal split among the sampled attributes is chosen by the inducers.

Algorithmic steps of Random Forest.

Input: Decision Tree Inducer(DTI), Train Sets(S), Sampling Ratio(r), and Number of Iterations (N) (number of attributes used in each tree)

Train: for i = 1 to T Get sample St from S with replacement using r/Build classifier Mt based on the inducer randomly samples N of the attributes and choose the best split.

Classification: new instance classified by classifiers Mt (t=1,...;T) then performed using majority vote.

3. Result & Discussion

On Radarsat-2, first commercially space based SAR satellite with quadrature polarization (quad-pol) capabilities and the capacity to create full polarization datasets (HH, HV, VV, and VH) at a C-band and 1-100 m spatial resolution; three totally polarized SAR photos were tested. The following data sets, which were generously supplied by MDA Geospatial Services Inc. and used into the studies over the duration of the research (http://gs.mdacorporation.com, Grant of License), were made available by MDA Geospatial Services Inc. The fine quad polarized mode was used to capture each dataset; as a consequence, the final spatial resolution was 8 meters by 8 meters. The image of high-resolution optical pictures on Google Earth was used to construct reference maps for the subsequent studies. These maps were produced using findings that had been previously published on the identical sets of data.

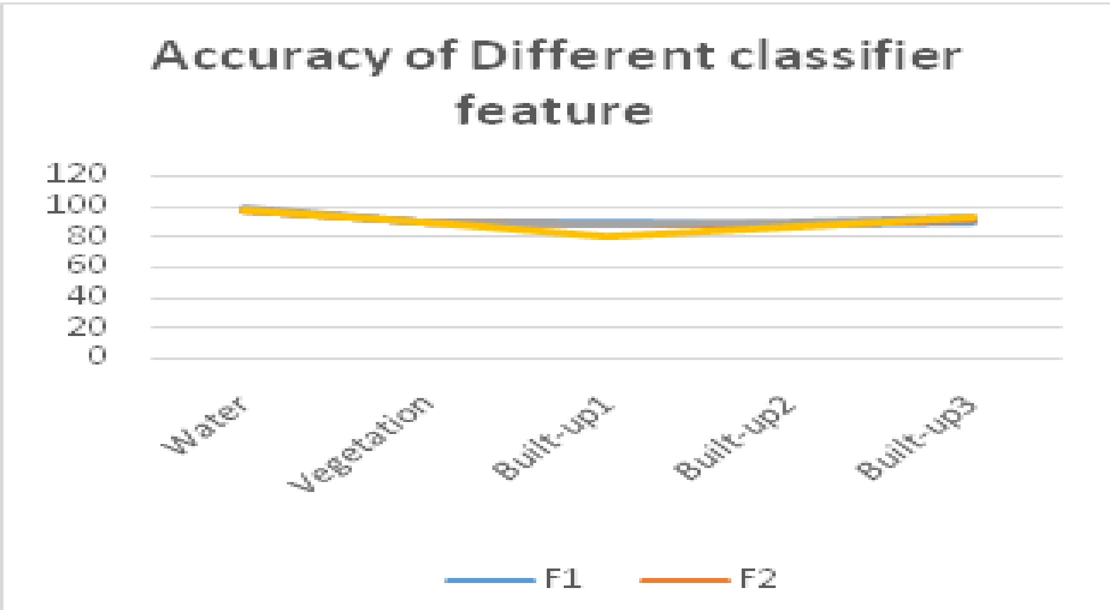

Figure 1 Accuracy of Different classifier feature using Random Forest

After doing PCA analysis, we decided that the goal percentage of retained data would be 90%. The classification performances of these approaches were evaluated using the average accuracy (AA), the overall accuracy (OA), and the kappa statistic. Polarimetric features (F1: T3-db), polarimetric-textural features (F2: stacking T3-db, span, and TFs), polarimetric-spatial features (F3: stacking T3-db, span, and MPs), and polarimetric-textural-spatial features (F4 (F4: [T3-db, span, TFs and MPs]). Table illustrating the accuracy, the average accuracy, and the overall accuracy of the performance of different classifier features while employing Random Forest.

Table 1 Random Forest's accuracy of classifications (in percentages; AA stands for average accuracy and OA for overall accuracy) on a given data set

Classifier Feature	Random Forest			
	F1	F2	F3	F4
Water	98.33	97.54	99.21	97.87
Vegetation	90.04	90.03	89.41	90.27
Built-up1	89.47	87.7	88.37	80.35
Built-up2	87.56	88.37	89.34	87.5
Built-up3	90.23	90.33	92.27	93.52
AA(%)	91.12	90.79	91.72	89.90
OA(%)	89.93	89.24	90.41	90.87
Kappa	0.75	0.77	0.8	0.81

(T3-db is represented by F1; T3-db, span, and MPs by F2; T3-db, span, and TFs by F3; and T3-db, span, TFs, and MPs by F4)

Conclusion

Because oil spills represent such a significant danger to marine life and the ecosystems of coastal areas, it is essential to be vigilant in the event that one occurs and to take corrective action without delay. When it comes to remote sensing, SAR sensors are essential because to the high-resolution photos that they are able to offer. Some of these photographs may reveal potential oil spills. Several different strategies have been presented for automatically evaluating SAR photos in order to recognize and differentiate oil spills from other situations that are visually similar. The Random Forest classifier that makes use of DCNNs has the potential to be used successfully in oil spill detection due to the fact that it has the potential to supply beneficial information about the polluted environment that is portrayed. Another problem is that different datasets are used by the majority of the approaches, which makes it impossible to compare the findings. The most important contribution of this study results from these two factors; it is an analysis of the Random Forest method as well as the creation of a centralized repository for SAR photos.

References

1. Yekeen ST, Balogun AL, Yusof KB. A novel deep learning instance segmentation model for automated marine oil spill detection. ISPRS Journal of Photogrammetry and Remote Sensing. 2020 Sep 1;167:190-200.
2. Zeng K, Wang Y. A deep convolutional neural network for oil spill detection from spaceborne SAR images. Remote Sensing. 2020 Mar 22;12(6):1015.
3. Chaturvedi SK, Banerjee S, Lele S. An assessment of oil spill detection using Sentinel 1 SAR-C images. Journal of Ocean Engineering and Science. 2020 Jun 1;5(2):116-35.

4. Zhang J, Feng H, Luo Q, Li Y, Wei J, Li J. Oil spill detection in quad-polarimetric SAR Images using an advanced convolutional neural network based on SuperPixel model. Remote Sensing. 2020 Mar 14;12(6):944.
5. Bianchi FM, Espeseth MM, Borch N. Large-scale detection and categorization of oil spills from SAR images with deep learning. Remote Sensing. 2020 Jul 14;12(14):2260.
6. Harikrishnan, G., & Rajaram, A. (2017). Improved throughput based recognition connection denies for aggressive node in wireless sensor network. Journal of Computational and Theoretical Nanoscience, 14(12), 5748-5755
7. TemitopeYekeen S, Balogun AL. Advances in remote sensing technology, machine learning and deep learning for marine oil spill detection, prediction and vulnerability assessment. Remote Sensing. 2020 Oct 18;12(20):3416.
8. Karthikeyan, T., & Rajaram, A. (2014). Efficient Multicast Data Replication Approach For Power Consumption In Manet. Journal of Theoretical & Applied Information Technology, 69(2).
9. Alexandrov C, Kolev N, Sivkov Y, Hristov A, Tsvetkov M. Oil spills detection on sea surface by using Sentinel–1 SAR images. In2020 21st International Symposium on Electrical Apparatus & Technologies (SIELA) 2020 Jun 3 (pp. 1-4). IEEE.
10. Carvalho GD, Minnett PJ, Ebecken NF, Landau L. Classification of oil slicks and look-alike slicks: A linear discriminant analysis of microwave, infrared, and optical satellite measurements. Remote Sensing. 2020 Jun 28;12(13):2078.
11. Lentini CA, MENDONÇA LF, Conceicao MR, Lima AT, VASCONCELOS RN, Porsani MJ. Comparison between oil spill images and look-alikes: an evaluation of SAR-derived observations of the 2019 oil spill incident along Brazilian waters. Anais da Academia Brasileira de Ciências. 2022 Jun 17;94.
12. Rathish, C. R., & Rajaram, A. (2017). Robust early detection and filtering scheme to locate vampire attack in wireless sensor networks. Journal of Computational and Theoretical Nanoscience, 14(6), 2937-2946.
13. Shaban M, Salim R, Abu Khalifeh H, Khelifi A, Shalaby A, El-Mashad S, Mahmoud A, Ghazal M, El-Baz A. A deep-learning framework for the detection of oil spills from SAR data. Sensors. 2021 Mar 28;21(7):2351.
14. De Laurentiis L, Jones CE, Holt B, Schiavon G, Del Frate F. Deep learning for mineral and biogenic oil slick classification with airborne synthetic aperture radar data. IEEE Transactions on Geoscience and Remote Sensing. 2020 Nov 17;59(10):8455-69.
15. Joseph, S., & Rajaram, A. (2017). Efficient secure and fair cluster routing protocol: An improved bee colony optimization cluster based efficient secure and fair routing protocol for mobile ad hoc network. Journal of Computational and Theoretical Nanoscience, 14(7), 3503-3509.
16. Abou El-Magd I, Zakzouk M, Abdulaziz AM, Ali EM. The potentiality of operational mapping of oil pollution in the mediterranean sea near the entrance of the suez canal using sentinel-1 SAR data. Remote Sensing. 2020 Apr 24;12(8):1352.

17. Ronci F, Avolio C, Di Donna M, Zavagli M, Piccialli V, Costantini M. An adversarial learning approach for oil spill detection from SAR images. In2020 IEEE Radar Conference (RadarConf20) 2020 Sep 21 (pp. 1-4). IEEE.
18. Baek WK, Jung HS, Kim D. Oil spill detection of Kerch strait in November 2007 from dual-polarized TerraSAR-X image using artificial and convolutional neural network regression models. Journal of Coastal Research. 2020;102(SI):137-44.
19. Sridevi, A. P., & Rajaram, A. (2014). Efficient Energy Based Multipath Cluster Routing Protocol For Wireless Sensor Networks. Journal of Theoretical & Applied Information Technology, 68(2).
20. Krestenitis M, Orfanidis G, Ioannidis K, Avgerinakis K, Vrochidis S, Kompatsiaris I. Early identification of oil spills in satellite images using deep CNNs. InInternational Conference on Multimedia Modeling 2019 Jan 8 (pp. 424-435). Springer, Cham.