Oil Spills Identification on Satellite Radar Data using Deep Learning

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ABSTRACT

Oil spills in oceans are a major pollutant endangering oceanic and coastal marine life, and their detection is of high environmental importance. Manually detection presents a challenging and lengthy task. We presented a deep learning model based on the U-Net structure to identify oil bodies in satellite radar images with promising results. Our model successfully classified larger oil bodies with moderate success on smaller ones. Image feature engineering, such as a four-directional cumulative sum, brought important information to the model and performed more accurate predictions. Limited by computer resources, our model was relatively simple. We used pre-trained weights from the MobileNetV2 model. Although initial results are unsatisfactory, we will continue to explore the transfer learning methodology to generate more accurate oil detection algorithms.

INTRODUCTION

Oil in seas and oceans is considered one of the significant pollution dangers to marine ecosystems. It can originate from accidents at pipelines or drilling platforms, as well as illegal spills from discharges of ballasts and tank cleaning from ships (Brekke & Solberg, 2005; Solberg, Brekke, & Husoy, 2007; Solberg A. H., 2012). These spills happen often but are hardly detected due to the size of the oceans.

Trying to detect those spills can be accomplished with the use of satellite images of different sources (Fingas & Brown, 2014), such as *infrared* (its temperatures are 3-8K larger than the water around), *laser fluorosensors* (it differs from the background), and *radar* (oil bodies contain fewer waves than the water around it). An interpreter can do oil spill detection manually or automatically using classification and regression methods (Topouzelis, 2008). *Deep Convolutional Neural Networks* (DCNN) can be the method of choice (Krestenitis, et al., 2019).

Deep learning methods can detect objects inside pictures by classifying each pixel as a specific class. *Geoscientists use u-Net models (Ronneberger, Fischer, & Brox, 2015)* for different goals, such as to identify salt bodies in seismic sessions (Guarido, Li, & Cova, 2018) and detect faults in seismic sessions (Fathalian, Guarido, Trad, & Innanen, 2020). Due to a large amount of data and complexity, training a deep learning model can be computationally costly, and transfer learning may facilitate and improve the training process (Lume, Guarido, Emery, & Innanen, 2021).

In this project, we implemented a U-Net model to identify oil spills in satellite radar data provided by [Xeek: Slick in a Haystack – a Localization Challenge] competition as a baseline model. In the future, we will use a more complex pre-trained model for transfer learning, aiming to get more accurate predictions.

THE DATA

In this project, we are using satellite radar data provided by the Xeek: Slick in a Haystack – a Localization Challenge competition to automatically identify oil spills in the ocean. FIG. 1 shows one of the provided images. It is a vast image covering a large area of the ocean. Manually finding an oil spill candidate (red marks in FIG. 1) can be an arduous job, as there are thousands of images like that. Those images are too large to feed to a deep learning model.

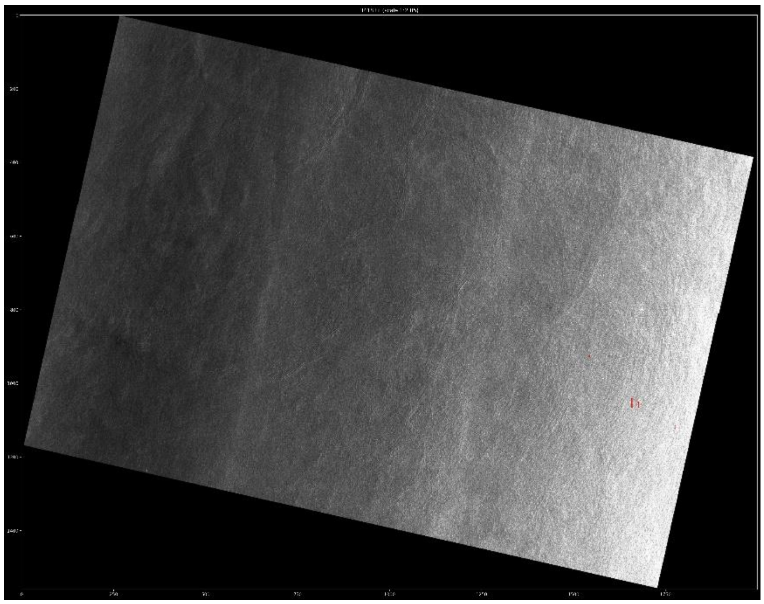

FIG. 1: One example of satellite radar images. The minor red marks are oil spill locations.

We are training a U-Net type model for image segmentation (pixel classification) by considering the model's size, the size of the input images, the number of images, and the available memory in the computer. Deep learning models work better when several images are fed at once, limiting their size. Our solution was to divide the large image into several patches of images and masks with 128x128 pixels (FIG. 2) and keep only the ones that contain our target.

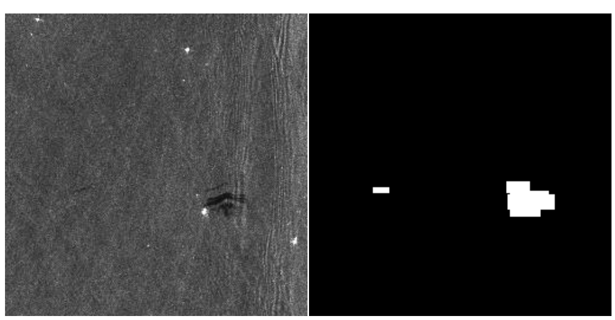

FIG. 2: Zoom of an oil spill on the left and its mask on the right.

Observing the oil tail in FIG. 2 makes clear that the mask marks the events rectangularly. So, it is not a mask but a border around the event. This can confuse the model in some cases, as several pixels inside the rectangle are not oil but water.

FEATURE ENGINEERING

Feature engineering means creating new features based on the ones we have. For image classification or segmentation, feature engineering is used to create more images for training (by rotating, zooming, flipping, and filtering) or making the target clearer (by filtering or manipulating the images). In this project, feature engineering was applied to highlight the target.

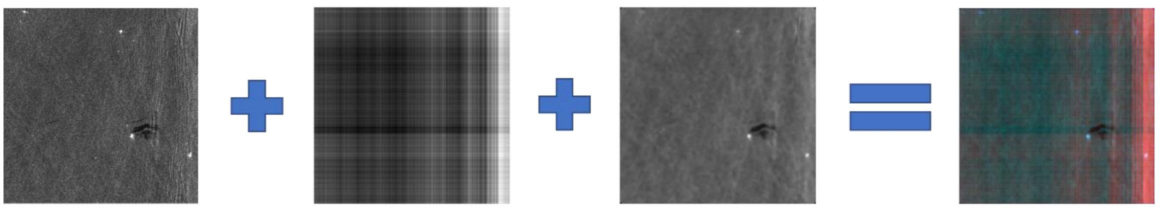

FIG. 3: Feature engineering.

FIG. 3 shows the feature engineering strategy. To generate the final RGB (red, green, and blue colour channels) image on the right, we started with the original grayscale image (one colour channel) as the first colour channel, a four-directional cumulative sum as the second channel, and a smooth version of the original one (from a 2D median filter) as the last channel. The goal is to keep the information of the original image where the black spots correspond to colour numbers close to zero and add scope aim with the cumulative sum. The median filter helps to regularize the colour values around the image. This process had a positive impact on the modelling part.

MODELLING AND RESULTS

The U-Net model (Ronneberger, Fischer, & Brox, 2015) is the structure of choice for this project (FIG. 4). It consists of a sequence of 2D convolutional (feature extraction, blue arrows) and pooling (size reduction, red arrows) layers in the encoder (first half) part extracting small parts of different figures and keeping them in the central part of the model. The decoder (second half) of 2D transpose convolution (increase image size, concatenate with previous layers, green arrows) and 2D convolutional layers to localize the small extracted features in the image. The output is a matrix of probabilities for each class in the classification. As we have only one class (oil, not oil), the output is a single matrix with the probabilities for each pixel being oil.

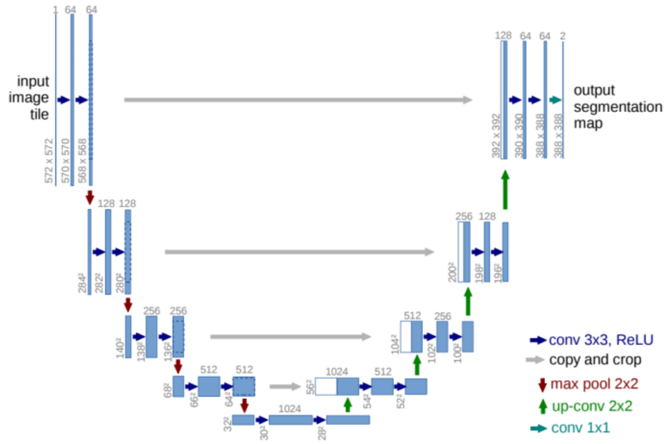

FIG. 4: U-Net model structure (Ronneberger, Fischer, & Brox, 2015).

The results using a U-Net model are presented in FIG. 5. The masks are in green, the predictions are in red, and the overlap presents a purplish colour. Although the masks are rectangular marks, predictions follow worm-shaped oil patterns. Another observation is that the predictions are more frequent on larger oil bodies. A few misclassifications are present in darker areas that are not related to spills but to some other event. Results so far are promising.

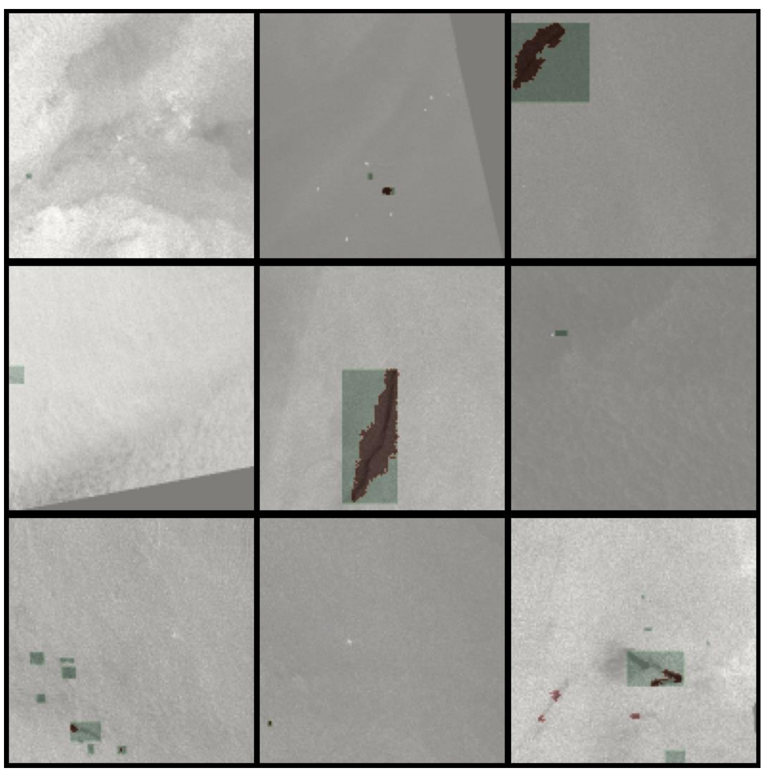

FIG. 5: True mask in green and predictions in red. The model seems to work better on significant events.

Improving predictions requires more image preprocessing, such as thresholding the image to separate black spots from the other ones and using a deeper and more complex model. However, computer limitation is a reality, and a larger model presents a challenging task. A solution is taking advantage of *transfer learning*, which consists of using a part of a model trained on different images and using the calculated weights on our data. We tried this method, but the results are still unsatisfactory, and more tests will be done in the future.

CONCLUSIONS

Oil spills in oceans are a major pollutant endangering oceanic and coastal marine life, and their detection is of high environmental importance. Manually detection presents a challenging and lengthy task.

We presented a deep learning model based on the U-Net structure to identify oil bodies in satellite radar images with promising results. Our model successfully classified larger oil bodies with moderate success on smaller ones. Image feature engineering, such as a four-directional cumulative, brought important information to the model and performed more accurate predictions.

Limited by computer resources, our model was relatively simple. We used pre-trained weights from the MobileNetV2 model. Although initial results are unsatisfactory, we will continue to explore the transfer learning methodology to generate more accurate oil detection algorithms.

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