Development of Oil Spill Detection Technology using Video Image Processing by Deep Neural Network

Motivation and Purpose

Oil spills cause massive damage on the marine ecosystem, effecting a wide array of species from phytoplankton to dolphins. Even worse, the as they travel through sea currents, it is almost impossible to mitigate damage after the oil sheen thins to a certain point. Once it spreads among species, it cannot be retracted. They cause mutations. The threat does not stop at marine animals; it also threatens us. When these marine animals are consumed, they can cause massive cumulative damage. Oil changes due to photo oxidation, causing air pollution. Not only are oil spills hazardous, they are also difficult to predict.
Hence, early detection is key to preventing future oil spills from damaging the ocean. Remote sensing in disasters has proven itself useful in multiple cases. Many oil spill detection methods are currently out in the market; however, many of them are expensive – which limits citizens from taking part in the voluntary recovery process. Human labor, an alternative, is very expensive and cannot be acquired by multiple developing countries.
This research aims to detect oil spills in regions where human supervision is difficult and to provide an alternative to human labor by developing a model optimizing Computer Vision.

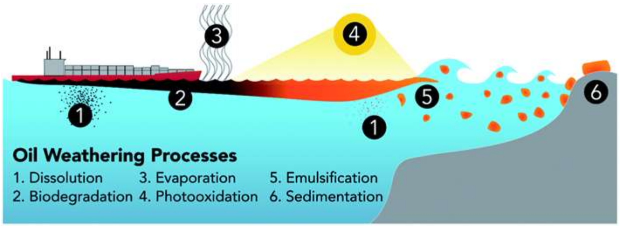
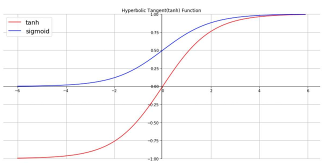


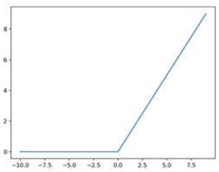
Image 1: Types of possible oil conversion, Collin P.Ward, "How the 2010 Deepwater Horizon spill reshaped our understanding of crude oil photochemical weathering at sea: a past, present, and future perspective", 2020

Materials and Methods

Hidden Relu activation function (graph 2) and output sigmoid activation function(graph 1) were used to normalize values and reduce scale of calculation in the model. Vanishing gradients were avoided by using the relu function as a hidden function (which is repeatedly used) and using the sigmoid activation function as an output function. The relu function does minimal calculation hence prevents vanishing gradients. An output function is used only before the result, so they have a less chance of causing vanishing gradients.



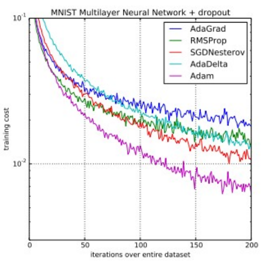
Graph 1: Tanh and the sigmoid function



Graph 2: Relu function

An Adam optimizer adjusts weight values based on the its contribution to the answer. The Adam optimizer was chosen as it was the most efficient among the list of potential optimizers (graph 3). The Adam optimizer combines both RMSprop and Adagrad optimizer. By a characteristic of those optimizers, the Adam optimizer alters the learning weight of each separate weight values. This leads the Adam optimizer to have an uncentered variance.

The feature is extracted through CNN in our case, GoogLeNet is fine tuned to extract features from image data. Dropout layers are then applied to prevent overfitting. Dropout layers randomly set input layers to 0 with a pre-set frequency. Avoiding overfitting is crucial as video footage may be unintentionally repetitive. This also helps remove any human bias of the perceptive of an oil spill/clear ocean.



Graph 3: performance of the Adam optimizer compared to other optimizers, such as AdaDelta, RMSProp, SGDNEsterov, etc.

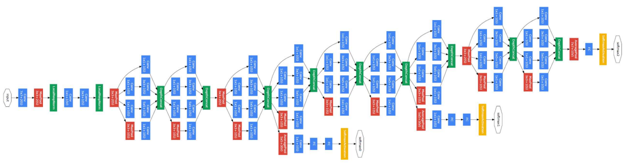


Diagram 1: Architecture of GoogLeNet

Data

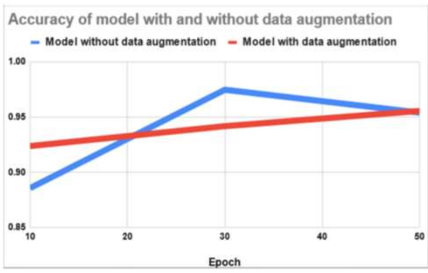
Data used to train the model was collected by a Crawling software called ImagerGeek and a Kaggle image dataset. There were 700 images collected in total, but data augmentation was used- increasing number of data to 1400 images.
Image sequences from a drone footage in a Santa Barbara oil spill were used as test data it is most similar to the image data that will be given in practical use.

Image 3, 4: Data collected from image sequence of drone video

Image 5. Data collected from Kaggle and Crawling software

Results

As the table suggests, contrary to expectation the model without data augmentation had a higher accuracy than the model with data augmentation. It also has a smaller loss value- a 1/10 of the other.
However it can be seen that the model with data augmentation shows a reliable, steady increase in accuracy, unlike the model without data augmentation.



Graph 4: Accuracy of model with and without data augmentation on epochs

Table 1: Accuracy and loss of model with and without data augmentation on epochs

	Model without Data Augmentation		Model with Data Augmentation	
epoch	Loss	Accuracy	Loss	Accuracy
1	0.299	0.8856	0.2437	0.9237
10	0.0897	0.9747	0.1549	0.9417
30	0.1375	0.9540	0.1226	0.9555
50	0.0126	0.9955	0.1028	0.9629

Conclusion

By the results presented, it is clear that the model is capable of detecting oil spills with a consistent accuracy higher than 96 %. The model was created with a basis of MLP with sigmoid and Relu activation functions, Adam optimizer, and pooling layers. GoogLeNet, as a CNN base model, was incorporated to improve filtering and modifying data. Data was collected from both Kaggle and by Crawling and was augmented in order to create a more diverse dataset.

Discussion and Application

Many developing nations are unable to cope with oil spills. It is not only just because of weak infrastructure- corporations knowingly deny to pay proper compensation as media coverage is very little.
Based on the results shown, we are able to expect a high success rate in practical use. For further research, a robot can be connected with the model so that the robot is able to remove detected oil without delay.