OIL SPILL DETECTION

Authors: Rahul Krishna Gunneri(2210264), Mohana Krishna Koripella(2252332), Nikitha Peddi (2252332), Surya Pavan Peruri(2247005)

University of Houston

Table of Contents

ABSTRACT

Oil spills occur due to human activities or natural disasters that damage oil storage facilities, pipelines, or oil-carrying vessels. When oil is spilled into water bodies, it spreads rapidly and can harm marine ecosystems, wildlife, and human health, and detecting them early is crucial to mitigate their impact. In recent years, segmentation-based approaches have emerged as a promising technique for oil spill detection which are collected using synthetic aperture radars (SAR). This report presents a novel approach that uses a combination of traditional image processing techniques and deep learning-based segmentation algorithms for detecting oil spills. The proposed approach first uses a Convolutional Neural Network consisting of 23 layers, which is utilized to categorize image patches based on the area containing oil spill pixels. Then to achieve semantic segmentation, a U-Net architecture with ten layers is employed. In proposed method initially we deployed Sequential CNN which is used to detect the class whether it belongs to Spill or No Spill. Later we deployed a Lime Model Inception binary segmentation algorithm and finally we deployed U-Net model on the segmentation of images.It has the potential to provide a reliable and accurate tool for oil spill detection, thus helping in the timely response and mitigation of environmental damage.

1. INTRODUCTION

Crude oil, a type of fossil fuel produced from the remains of prehistoric plants and animals, is utilized to create diverse fuels and products. It is discovered in underground or undersea reservoirs, where oil droplets are present in rock pores or cavities. Once extracted through drilling and pumping, crude oil is transported by oil companies to refineries via pipelines, ships, trucks, or trains. Accidents may occur during transportation.

Oil spills are more frequent than one might expect and can happen in various ways. Thousands of oil spills occur annually in the US seas, most of which are minor, such as those that occur during ship fuelling. Nevertheless, even minor spills can cause harm, particularly if they happen in sensitive areas like beaches, mangroves, and wetlands. Large-scale oil spills, such as those caused by pipeline breaks, sinking of large oil tanker ships, or failed drilling operations, are severe and life-threatening events. Following a significant oil spill, the impacts on ecosystems and economies can last for decades.

Oil spills can happen at any time, whether it be during drilling, transportation, or usage. Whenever an oil spill occurs in the ocean, the Great Lakes, on the shore, or in rivers that drain into these coastal waterways, the experts from NOAA are called in. The goal of the Office of Response and Restoration is to devise scientific methods to keep the coasts free of oil, chemicals, and marine debris. The amount of damage an oil spill causes is determined by the location of the spill, the type of plants, animals, and ecosystems that are present, as well as the amount and type of oil that is spilled. Marine life is severely impacted by oil spills, and the response to an oil spill often involves recovering, cleaning, and rehabilitating wildlife. However, rescuing all the species that are affected by oil spills is impractical because wildlife is difficult to locate and capture, and oil spills can cover large areas.

Synthetic Aperture Radar (SAR) is a radar technology that utilizes planes or satellites to acquire images of the earth's surface and sea. The sensors on the SAR emit radio waves, which bounce back from the surface and are processed to produce a visual representation of the target area. SAR images can capture various features, including sea and land surfaces, oil spills, ships, and objects that may resemble spills. Environmental conditions such as low-speed wind zones, sea wave shadows, and grease ice may cause similar features to appear in the SAR images. In the images, both oil spills and similar-looking features can appear as dark or black dots, making it challenging to differentiate between them.

i. Literature review

Paper 1: Oil Spill Detection Using Satellite Imagery
(Amber Bonnington, Meisam Amani, Hamid Ebrahimy), provides an overview of recent advances in remote sensing techniques for oil spill detection and monitoring, with a focus on optical and SAR sensors. The authors discuss the challenges of oil spill detection in different environmental conditions and the potential for using emerging technologies such as unmanned aerial vehicles (UAVs) and machine learning algorithms. These studies highlight the potential of remote sensing techniques for detecting and monitoring oil spills, and the importance of developing new approaches and technologies to improve the accuracy and timeliness of oil spill detection and response.

Paper 2: Oil Spill Detection Using LBP Feature and K-Means Clustering in Shipborne Radar Image.
(Jin Xu, Xinxiang Pan, Baozhu Jia,Xuerui Wu,Peng Liu,Bo Li), It compares the effectiveness of shipborne X-band radar and satellite synthetic aperture radar (SAR) for oil spill detection in the Aegean Sea. The authors use a feature extraction and classification approach based on gray-level co-occurrence matrix (GLCM) texture features and fuzzy c-means clustering algorithm to detect oil spill regions in the radar images. The results show that shipborne radar and SAR can complement each other in detecting different types of oil spills in different environmental conditions. These studies suggest that shipborne radar can be an effective tool for oil spill monitoring and detection, and that various image processing and feature extraction techniques can be used to improve the accuracy and reliability of oil spill detection in radar images.

Paper3:BO-DRNet: An Improved Deep Learning Model for Oil Spill Detection by Polarimetric Features from SAR Images
(Dawei Wang, Jianhua Wan, Shanwei Liu, Yanlong Chen ,Muhammad Yasir), Oil spill pollution in the marine environment has become a serious problem that can cause significant damage to the ecosystem. The use of Synthetic Aperture Radar (SAR) technology has become essential in detecting oil spills in the sea due to its ability to provide polarization features. Deep learning models based on polarimetric features have shown to be effective in detecting oil spills; however, these models suffer from insufficient feature extraction due to model depth and

loss of target information. Additionally, fixed hyperparameters may lead to incomplete or misclassified detection results. To address these issues, this paper proposes an improved deep learning model named BO-DRNet that uses ResNet-18 as the backbone in the encoder of DeepLabv3+ to obtain fuller and more sufficient features. Bayesian Optimization (BO) was used to optimize the model's hyperparameters. Experiments were conducted using ten prominent polarimetric features extracted from three quad-polarimetric SAR images obtained by RADARSAT-2. The results showed that BO-DRNet outperformed other deep learning models, achieving a mean accuracy of 74.69% and a mean dice of 0.8551. This study provides a valuable tool for effectively managing oil spill disasters in the future.

ii. Business/Analytics problem

The contamination of water by oil and its by-products is a global issue, and the detection of oil spills on the surface of the sea is crucial due to the potential ecological disasters that can arise from such accidents. The frequency of marine oil spills has risen in recent years, and the continuous increase in marine crude oil transportation accidents and oil exploitation has led to significant damage to the marine environment, making it one of the leading causes of water pollution. Synthetic Aperture Radar (SAR) images can be used to monitor marine oil spills, reducing the spread of oil spill pollution over time, and mitigating the economic losses and environmental pollution associated with such spills.

iii. Objective

The objective of this study is to explore the application of deep learning algorithms to distinguish and categorize oil spills. The researchers utilized UNet, a type of convolutional neural network that was initially developed for biomedical image analysis and adapted for the identification of oil spills and similar-looking features. The model was trained on a synthetic aperture radar (SAR) image dataset of oil spill detection, which is publicly available and widely used for benchmarking purposes.

iv. Impact and Value

The implementation of the aerial view segmentation system can accelerate the identification of oil spill areas and reduce the need for human involvement. It can also improve pipeline monitoring and cover a wider area, resulting in time and cost efficiency. Detecting oil spills promptly can help prevent short-term economic losses for organizations.

2. DATA

The images of oil spills in marine coastal areas and deep oceans were obtained through satellite imaging. The data was collected from various sources, including Statista and NASA satellite images. The images come in different sizes and pixel resolutions, and they are modified to meet specific needs.

i. Dataset background and quality

Initially, data was collected by means of Statista, consisting of a total of 412 pictures in JPEG format. The dataset was comprised of 238 images depicting oil spills and 174 images portraying non-oil spills. Following this, the 238 images representing oil spills were divided into two sets, with a 70:30 ratio assigned for training and testing purposes.

ii. **Data processing, wrangling band EDA**

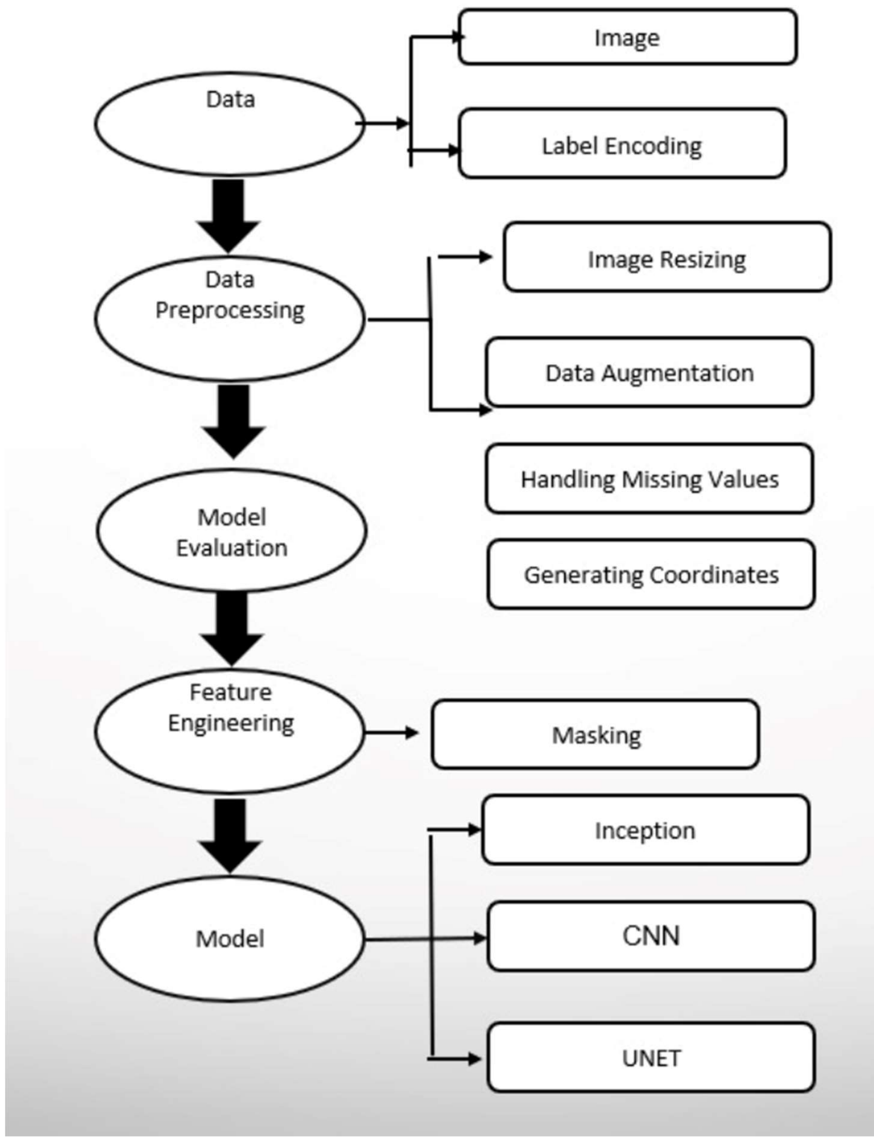
In the second step, the data is imported. To ensure consistency in the image data as it passes through machine or deep learning models, all images must be resized to a uniform size. Additionally, the image labels are modified after resizing. Specifically, in this project, grayscale images of dimensions 96x96x1 are transformed into RGB images of size 96x96x3.

In the subsequent phase, the data contained within the csv files is subjected to exploratory data analysis (EDA), with class labels of 1 assigned to images depicting oil spills and 0 assigned to those depicting non-oil spills. The dimensions of oil spill images are determined from top to bottom, while non-oil spill images have dimensions of 1x96. In the subsequent phase, any missing data is addressed using appropriate measures.

Keras operates with images in batches, where the first dimension of the batch represents the number of samples or images available. The shape of a single image is determined by its size and number of channels, and is expressed as (size1, size2, channels). In order to create a batch of images, an additional dimension must be added in the form of (samples, size1, size2, channels). To ensure that the image is in the correct format for the model, the pre-process input function is employed.

3. METHODOLOGY

i. Workflow



After the data preparation, there are more steps in the project's workflow. After the data has been processed, feature extraction, also known as masking, is used to improve the contours needed for the image. The models are run with the previously prepared data to get a variety of findings that are further discussed.

ii. Methods description

Object Segmentation

In order to distinguish and identify specific categories while also precisely marking their boundaries, semantic segmentation involves assigning a category label to each pixel in an image. Instance segmentation designates specific instances of the same object type in addition to identifying each category. In the project, the U-Net is trained for picture segmentation.

iii. Feature Engineering

A method of identifying all the objects associated with and visible in an image is image labelling. The photos may contain several things; nevertheless, we simply focus on the necessary label, and the background is eliminated. Masking is the

process of mapping the necessary area by moving a polygon over the contours and onto a plain background.
Data Set is taken into account for creating labels

iv. Modelling

Basic Sequential CNN:

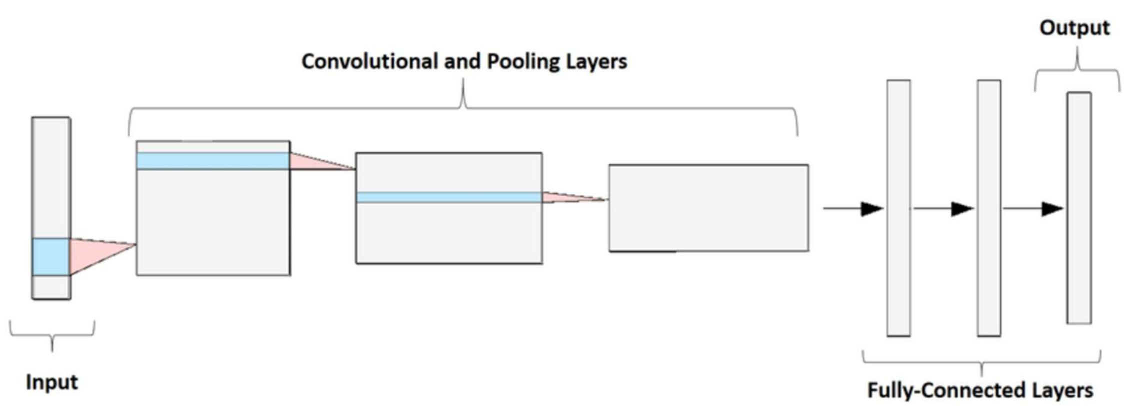
Image recognition of Oil Spill and No Oil Spill using sequential CNNs can be achieved by adapting the sequential CNN architecture to process image data. The goal of the model is to classify an input image as either a Spill or a Non Spill

To achieve this goal, the first step is to prepare the dataset. A dataset of images of Spills and Non Spills needs to be collected, and each image needs to be labelled with the corresponding Spill and Non Spill type. The images should also be resized to a consistent size, such as 224 x 224 pixels, to ensure that all images have the same dimensions.

Once the dataset is prepared, a sequential CNN architecture can be designed to process the image data. The architecture would typically consist of several convolutional layers followed by pooling layers, with each layer learning increasingly complex features of the input image. The final output layer would consist of a set of neurons corresponding to the possible Spill and Non Spill types in the dataset.

During the training process, the weights of the CNN are adjusted to minimize the difference between the predicted outputs and the actual labels of the training images. The model can be evaluated on a separate set of validation images to ensure that it is not overfitting to the training data.

Finally, the trained model can be used to predict the type of Spill and Non Spill in a new input image. The input image is passed through the model, and the output of the final layer is used to determine the predicted type of Spill and Non Spill

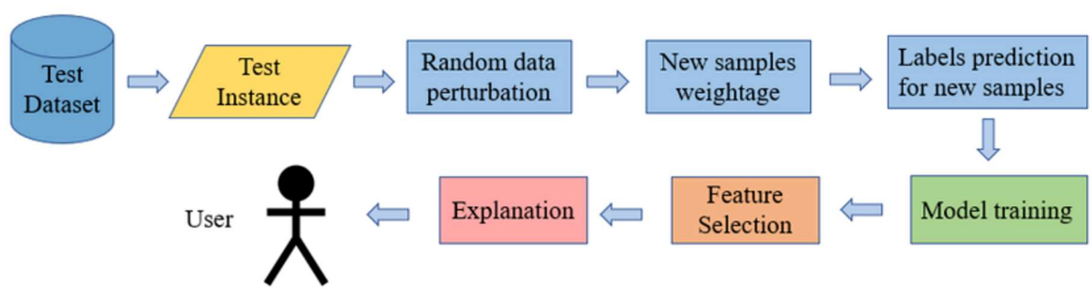


Lime Model Inception:

LIME (Local Interpretable Model-agnostic Explanations) is a popular method for explaining the predictions of machine learning models. It works by generating local explanations for individual predictions, which can help users understand why a particular model made a particular prediction.

In the context of binary image segmentation, LIME can be used to explain the predictions of a model that is trained to segment images into two classes (e.g., foreground and background). To do this, LIME generates a set of super pixels (i.e., small regions of the image) and trains a separate model on these super pixels to predict the segmentation mask. This model is then used to generate explanations for the original model's predictions by highlighting the super pixels that are most important for a given prediction.

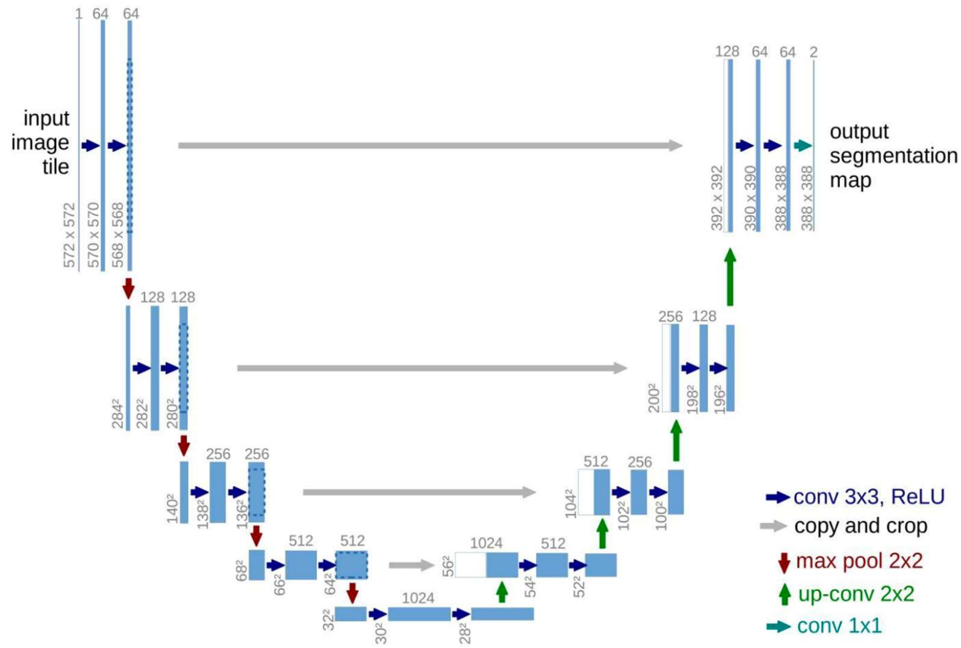
One potential benefit of using LIME for binary image segmentation is that it can help identify regions of an image that are most important for a given segmentation task. For example, if the goal is to segment an image of a person from the background, LIME might highlight the face and body as the most important regions for making the prediction.



The workflow of LIME method

U-Net Architecture:

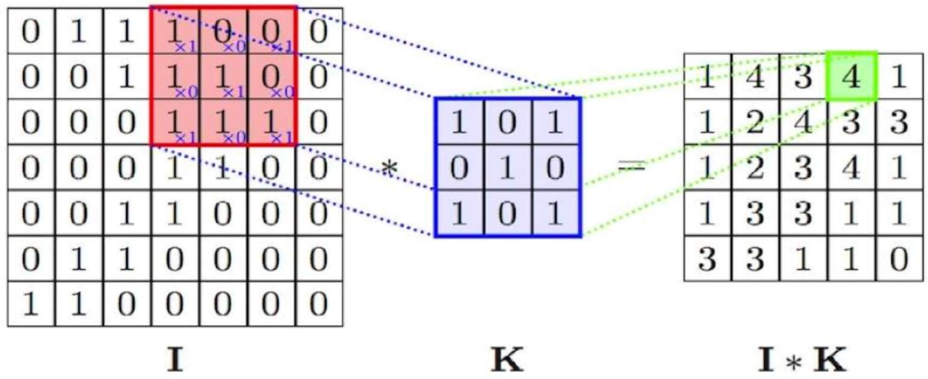
U-Net is a special type of architecture for image segmentation purposes, where the input is an image, and the output is a label. The architecture is an arrangement of deep learning tools which majorly contains convolutional layers, maximum pooling layers, activation layers. It was published by Ronneberger, Fischer, et al. 2015 for biomedical segmentation and quickly gained popularity in many other domains due to its ability to swiftly and accurately segment images, and it is currently one of the standard models for image segmentation. The architecture is named as U-Net because its shape is similar to the alphabet 'U'.



The first part of the architecture, on the left, is called the contraction path, where the input image is downscaled along the path and can also be called an encoder path. The second part of the architecture is called the expansive path where the input image is upscaled along the path and is also called as decoder path, on the bottom of the architecture is the bottleneck. The connections between both the paths in gray color in Figure 3.18 are called skip connections. This section provides a detailed description of the U-Net as the other models used in the project are also based on U-Net.

– Convolution

A convolutional layer is the building block of Convolutional Neural Networks. Convolution is a mathematical operation, in the case of CNN, it can be explained as an element-wise multiplication between two matrices. Matrix K is a kernel or also called a filter. A kernel is generally a 3x3 or a 5x5 matrix and is used to multiply image I. The resultant matrix I*K is a convoluted image or also called a feature map. During the convolution operation, different values for the kernel produce different feature maps on the same image. A convolutional layer typically consists of multiple kernels thereby extracting feature maps.

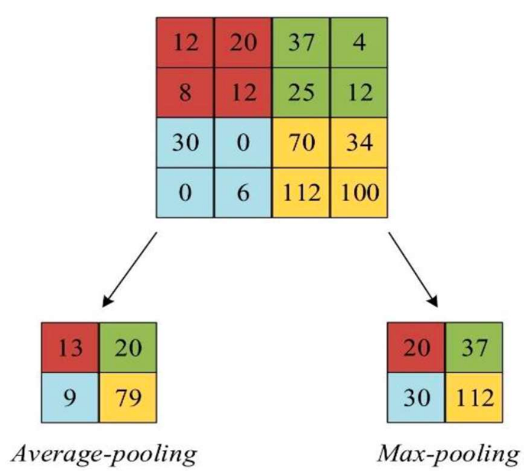


-Stride and padding

When a kernel is applied to the image, certain parameters need to be defined to monitor the sliding movement of the kernel over the image. Striding allows us to control the way the kernel convolves over an image. For example, a 3x3 kernel with a stride of 1, shifts the kernel by 1 unit. Padding refers to adding more rows and columns on the borders of the image. Zero padding refers to the case where the image is used as it is and it keeps on shrinking because the convolution operation produces an image that is smaller than the input image. Padding at size 2 refers to two additional columns and rows on the border of the image and thus the output image will have the same resolution as the output image.

-Pooling Layer

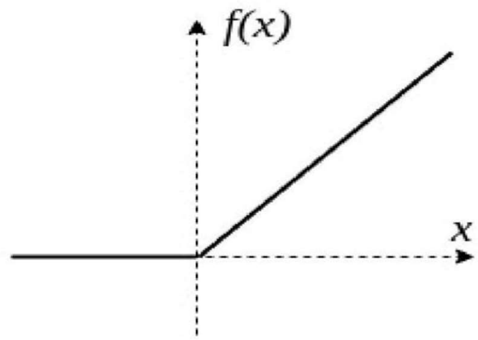
The basic property of CNN is to downscale the input image, this is achieved by using pooling layers. First, it divides the image into several non-overlapping subregions based on the specified size, generally into 2x2 square regions. Now it gives out maximum values from the subregion in the case of max-pooling or the average of the square region in the case of average pooling



ReLU stands for Rectified Linear Units and is one of the standard activation functions used in CNNs. Linear activation functions make the neural networks obsolete, ReLU is a non-linear activation and can be defined as equation below.

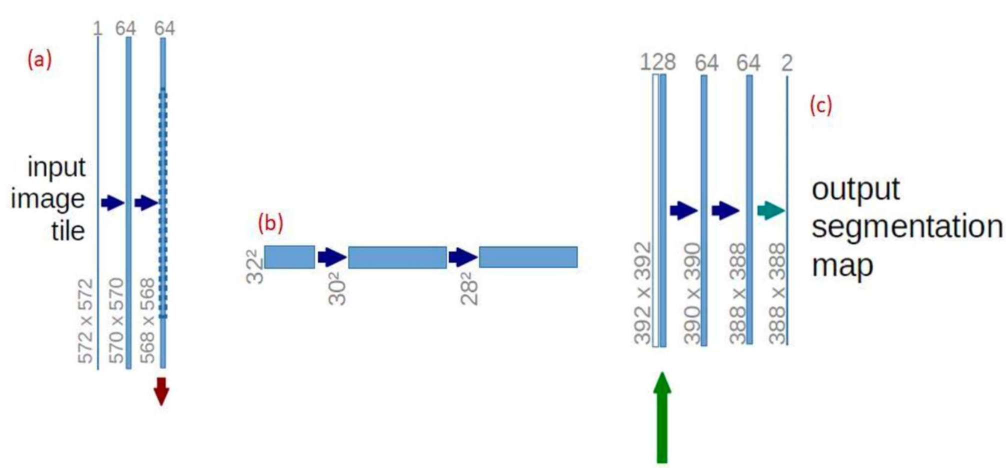
$$f(x) = max\ (0, x)$$

The activation function performs the pixel-wise operation, therefore the more complex it is the longer it takes to train the model. It is relatively easier to compute ReLU among other non-linear functions like the hyperbolic tangent function, or the sigmoid function and it increases the non- linearity properties of the whole network. It takes in each pixel value of an image and replaces them with 0 if they are negative or returns the same value if it was positive



Convolution block

Standard U-Net contains four convolution blocks for each path, i.e. for the contraction path and expansive path. Each convolution block contains two convolution layers with 64 filters which refers to 64 feature maps for each input. The same continues for all the convolution blocks but with an increasing number of filters as the network goes down and decreasing number of filters going up the expansive path. The red arrow indicates the max-pooling operation where the resolution of an image is halved which is from 568x568 to 284x284. The reduction of resolution from 572 to 570 is because of the padding in the convolution operation.



At the bottom of the architecture is the bottleneck where the image is in its lowest resolution representation shown in (b) The last block in the U-Net is a convolution block with a sigmoid activation function to predict the classes for each pixel. One of the most important parts of U-Net is the skip connections which can be seen as horizontal gray arrows connecting the expansive path and contraction path which helps in transferring the information from one convolution block to the other. This also helps in efficient learning of the model by comparing the data in the intermediate steps.

U-Net is known for extracting local features. The filters passed onto the image extract features, Convolution blocks in the beginning extract low-level features like a sharp edge and would go on to extract high-level features while the image goes towards the bottom of the architecture. Feature extraction is sensitive to a particular case, where the model tries to learn about features from the images and their corresponding labels. The model would update weights and filters to extract useful information for the efficient classification of the image.

The pictures are given for training after the model is finished. The learning rate is set to 0.00003, there are 100 iterations, and there are three batches. Use of the DICE loss function. Adams is the optimizer in use. Metrics like mIOU, accuracy, and precision are employed.

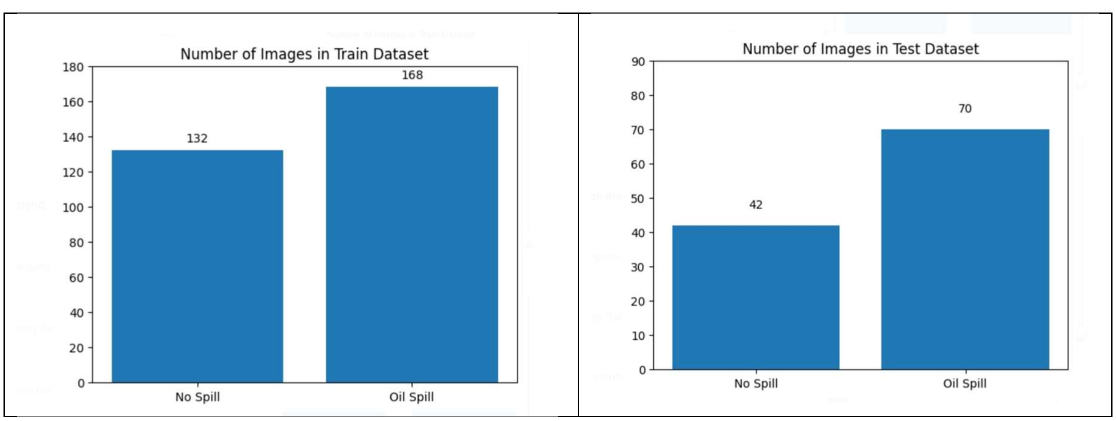
Jaccard's Co-efficient for image segmentation:

Jaccard's coefficient is used as an evaluation metric for image segmentation tasks. It is known as the Jaccard similarity index or Intersection over Union (IoU) metric

IoU = Area of Overlap / Area of Union

v. Training and Testing

Once the models have been developed to meet the requirements, 70% of the dataset is used for training and 30% for testing. This standard ratio of dataset division. Following training, images are sent for testing and the corresponding metrics are assessed.



4. RESULTS AND DISCUSSION

i. Model Evaluation

Sequential CNN:

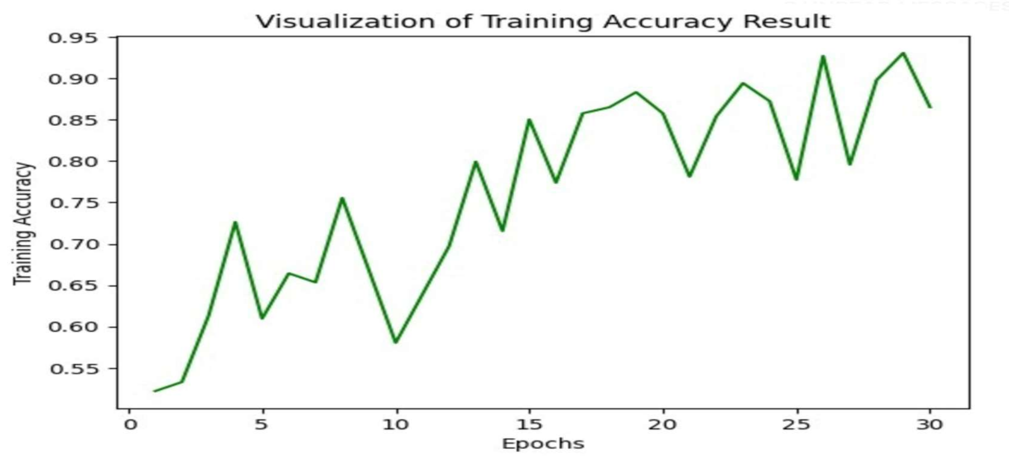


Fig 4.1 Visualization of Training Accuracy

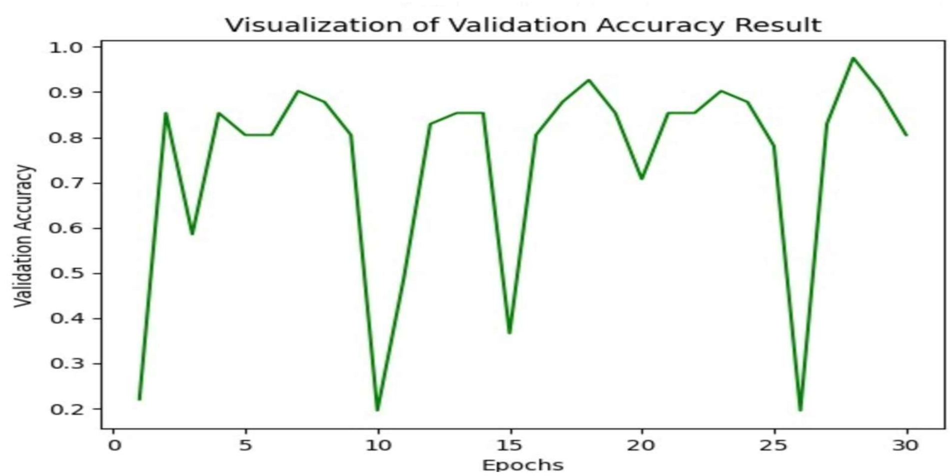


Fig 4.2 Visualization of Validation Accuracy

Accuracy:

```
print('Validation set Accuracy: {} %'.format(training_history.history['val_accuracy'][-1]*100))

Validation set Accuracy: 80.48780560493469 %
```

LIME Model inception:

The first model helps in recognizing oil spills with an accuracy of 96% and with a loss of 1.79 with 5 epochs. The model successfully predicted the classification by identifying regions around the oil spill.

	precision	recall	f1-score	support
Non Oil Spill(Class 0)	0.91	1.00	0.95	42
Oil Spill (Class 1)	1.00	0.94	0.97	70
accuracy			0.96	112
macro avg	0.96	0.97	0.96	112
weighted avg	0.97	0.96	0.96	112

Fig4.3 classification report for Lime model inception

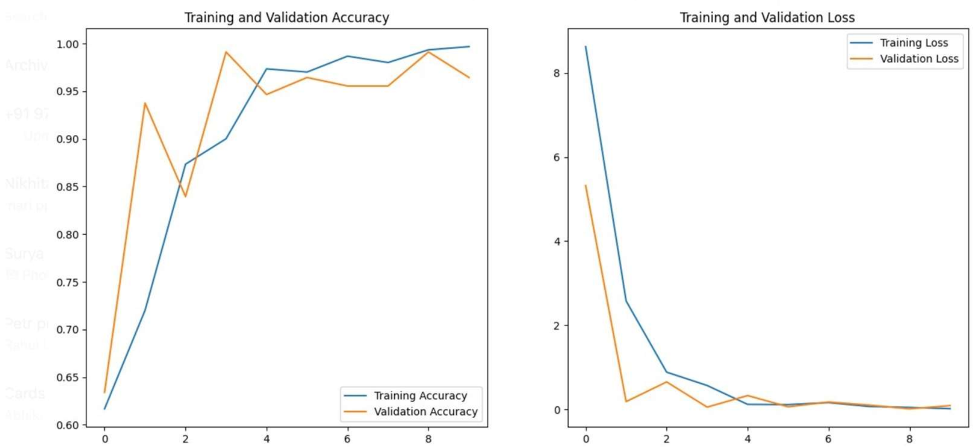
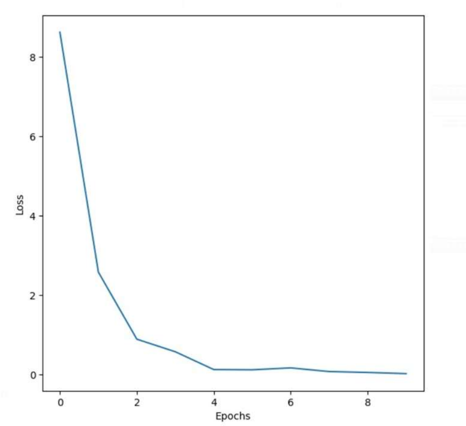


Fig 4.4Training and validation Accuracy and loss



The output of the segmentation is as follows:

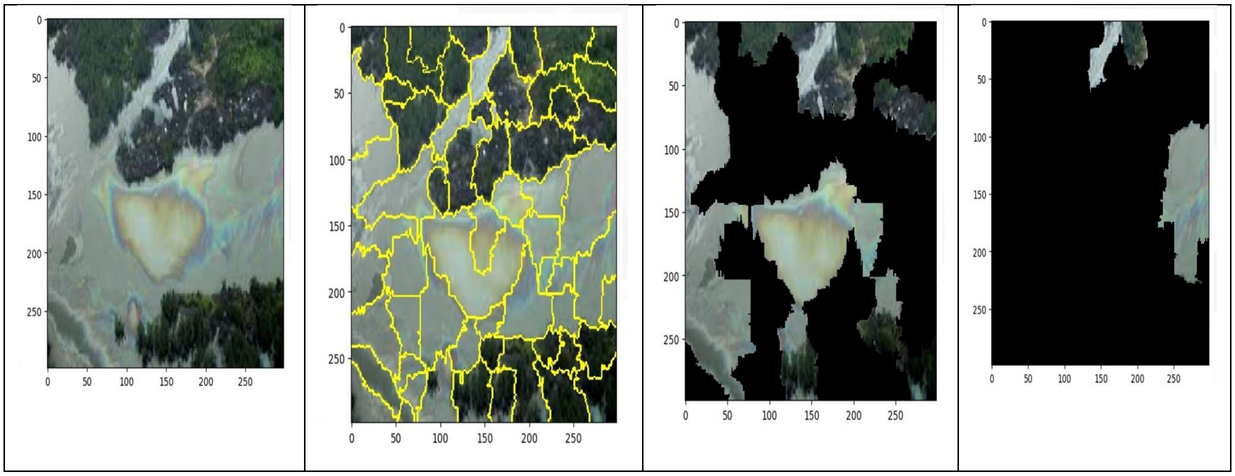


Fig 4.5 Segmentation of oil spill Images

U-Net Image SEGMENTATION:

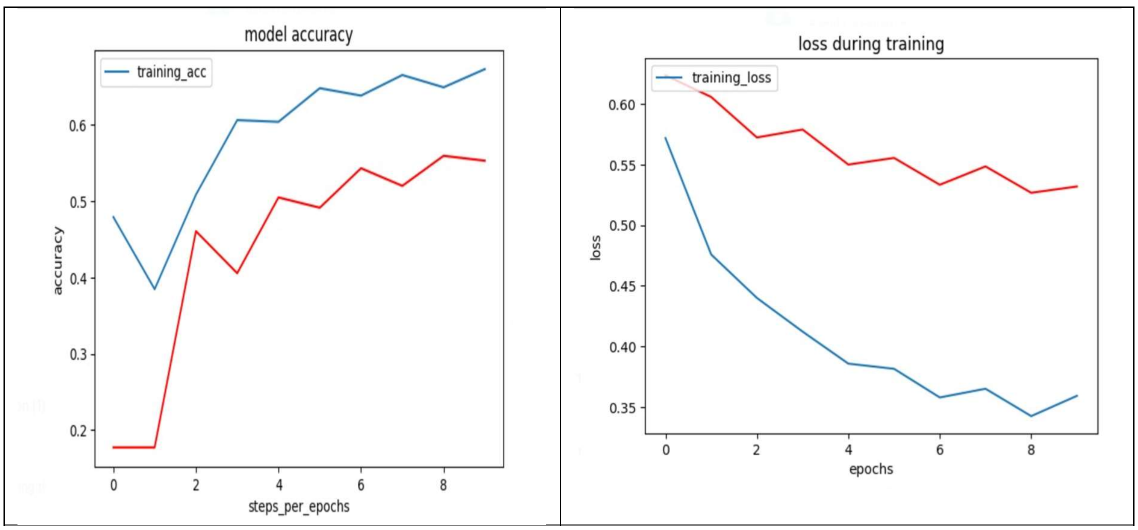


Fig 4.6 Model accuracy and Loss

5. CONCLUSION AND RECOMMENDATIONS

Oil spills significantly affect the economy, the economic climate, and transportation. Unsurprisingly, spills happen more frequently, and accidents do happen. Deep learning Accuracy:assists in the quicker detection of oil spills as well as the quicker location of their origin, assisting in the prevention of spill spread and expediting damage repair.

6. ACKNOWLEDGMENTS

This work and the research that underlies it would not have been feasible without the tremendous assistance of my professor, Dr. Mohamed Mohamed. His enthusiasm, skill, and painstaking attention to detail have been an inspiration and kept our work on track from our first meeting with the machine learning algorithm through the final draft of this report. The Big Data Analytics for Petroleum Engineering course has increased our interest in applying machine learning techniques to the petroleum sector. We also value the insightful criticism

provided by the peer reviewers from our class. Every one of you has contributed to this study in various ways and prevented us from making many mistakes; the ones that inevitably remain are only our responsibility.

7. REFERENCES

1. Amber Bonnington, Meisam Amani et al., Oil Spill Detection Using Satellite Imagery

2. Jin Xu, Xinxiang Pan et al., Oil Spill Detection Using LBP Feature and K-Means Clustering in Shipborne Radar Image.

3. Dawei Wang, Jianhua Wan et al., BO-DRNet: An Improved Deep Learning Model for Oil Spill Detection by Polarimetric Features from SAR Images

4. Olaf Ronneberger et al..., 2015 - U-Net: Convolutional Networks for Biomedical Image Segmentation

5. TY Shamsudeen et al.., 2020 - Advances in Remote Sensing Technology, Machine Learning and Deep Learning for Marine Oil Spill Detection, Prediction and Vulnerability Assessment

6. TY Shamsudeen et al.., 2020 - Advances in Remote Sensing Technology, Machine Learning and Deep Learning for Marine Oil Spill Detection, Prediction and Vulnerability Assessment