Department of Artificial Intelligence and Machine Learning

AI 19611- MINI PROJECT

Enhancing Marine Safety: U-Net Approach for Oil Spill Detection

Project Guide:
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OBJECTIVES

- To develop a robust U-Net model tailored for aerial SAR imagery to accurately detect and segment oil spill regions from complex backgrounds.

- To enhance the model's performance by optimizing hyperparameters to ensure high accuracy and efficiency.

- To validate the effectiveness of the U-Net approach through rigorous testing on diverse datasets, including different oil spill sizes, shapes, and noise conditions.

- To use the U-Net architecture's encoder to capture context and extract features from input images and its decoder to generate accurate segmentation masks for effective oil spill detection.

- To tackle the challenges associated with oil spill detection, such as variability in spill sizes, shapes, and environmental conditions.

ABSTRACT

- Oil spills pose significant environmental threats, impacting marine ecosystems, coastal communities, and economic activities.
- Detecting oil spills promptly is crucial for effective mitigation and response efforts.
- We leverage satellite or aerial imagery to identify areas affected by oil spills, enabling timely intervention and resource allocation.
- Our approach integrates image preprocessing, feature extraction, and deep learning-based image segmentation to accurately segment oil-contaminated regions.
- This work helps to find oil spills automatically, making it easier to protect the environment and handle disasters.

INTRODUCTION

- Protecting our oceans and coastlines from oil spills is crucial for ensuring marine safety. Rapid detection and response to such incidents are essential for minimizing environmental damage and safeguarding marine ecosystems.
- Leveraging the advanced capabilities of the U-Net architecture, our focus lies in enhancing marine safety through oil spill detection.
- Utilizing high-resolution satellite and aerial Synthetic Aperture Radar (SAR) imagery, coupled with the robust segmentation abilities of U-Net, we aim to develop a reliable and efficient methodology for early detection and monitoring of oil spills in marine environments.
- This approach holds promise for improving the effectiveness of oil spill management strategies, ultimately contributing to the preservation of our precious marine ecosystems.

PROBLEM STATEMENT

- The detection of oil spills in natural environments, particularly in marine and coastal regions, is a critical task due to the significant environmental and economic impacts they pose.

- Traditional methods of oil spill detection often rely on manual observation, which can be time-consuming, subjective, and limited in coverage.

- In recent years, advanced deep learning methods, such as CNNs and specialized architectures like U-Nets, have proven effective in enhancing the accuracy and speed of detecting oil spills from satellite or aerial images.

- Applying image segmentation techniques to segment satellite or aerial images into color regions corresponding to oil-contaminated and clean areas.

- We can enhance environmental monitoring efforts, improve response times, and mitigate the impact of oil spills on ecosystems.

LITERATURE SURVEY

Here's a structured literature survey outlining key papers and findings related to our project:

1.)Original U-Net Paper:

- Thomas Brox, Olaf Ronneberger, and Philipp Fischer. "U-Net: Convolutional Networks for Biomedical Image Segmentation." MICCAI 2015.

This seminal paper introduces the U-Net architecture, originally designed for biomedical image segmentation but applicable to various image segmentation tasks.

2.) Deep Learning for Oil Spill Detection:

- Bo Wang, Chen Yang, Xuebin Qin, and Licheng Jiao. "Optimizing U-Net by Fusion of Superpixel with Deep Learning for Oil Spill Detection." Remote Sensing 2019.

It Proposes optimizations for U-Net using superpixel fusion techniques for improved oil spill detection in remote sensing imagery.

3.)Adaptations for Remote Sensing and Environmental Monitoring:

- Ahmed Samy Nassar, Tarek M. Mahmoud, and A. E. Hassanien. "Remote Sensing Image Segmentation Based on U-Net Architecture for Environmental Monitoring." 2019 - International Conference on Innovative Trends in Computer Engineering (ITCE).

Investigates the use of U-Net for remote sensing image segmentation, which can include applications such as oil spill detection.

4.)Satellite Imagery and Oil Spill Detection:

- Changchang Liu, Linlin Zhang, and Jianping Li. "Satellite Image Multi-Scale Feature Fusion Oil Spill Detection Based on U-Net." Sensors 2020.

Explores the application of U-Net for oil spill detection using multi-scale feature fusion techniques applied to satellite imagery.

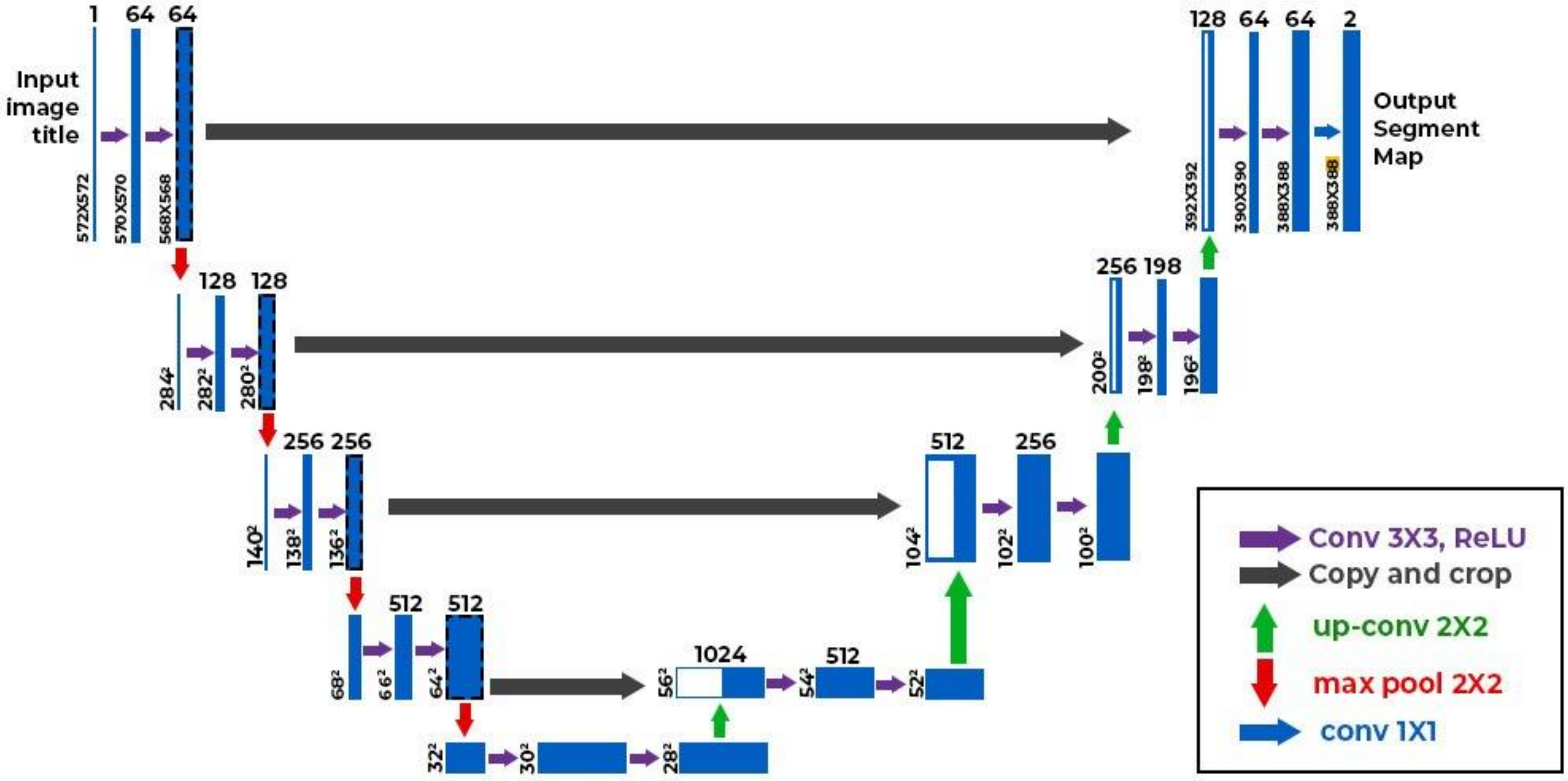
EXISTING SYSTEM

Sr. No	Author(s)	Year	Technique	Description	Outcome
1.	Pablo Gil, Damian Mira	2017	Detecting oil spills using RNN with SLAR data.	Oil Spill Detection in SLAR-Data : A RNN Approach	RNN approach in SLAR data enhances accuracy and responsiveness.
2.	Thomas De Kerf,Jona Gladines,Seppe Sels,Steve Van	2020	UAVs with infrared sensors and CNNs for oil spill detection.	Oil Spill Detection Using Machine Learning and Infrared Images.	It increase the detection rate and decrease the overall cleaning costs of an oil spill.
3..	Dawei Wang et al.	2022	BO-DRNet: An Improved Deep Learning Model for Oil Spill Detection	Using deep learning models based on polarimetric features, oil spill detection can be achieved	BO-DRNet have a better recognition ability for oil spill pixels than the other models.
4.	Andrew Coulson ,Caixia Wang et al.	2023	Fine Tuning MobileNet Neural-Networks for Oil Spill Detection	A deep learning model based on MobileNet neural networks to detect oil spills in remotely sensed images.	It improves oil spill detection, helping respond faster to protect the environment

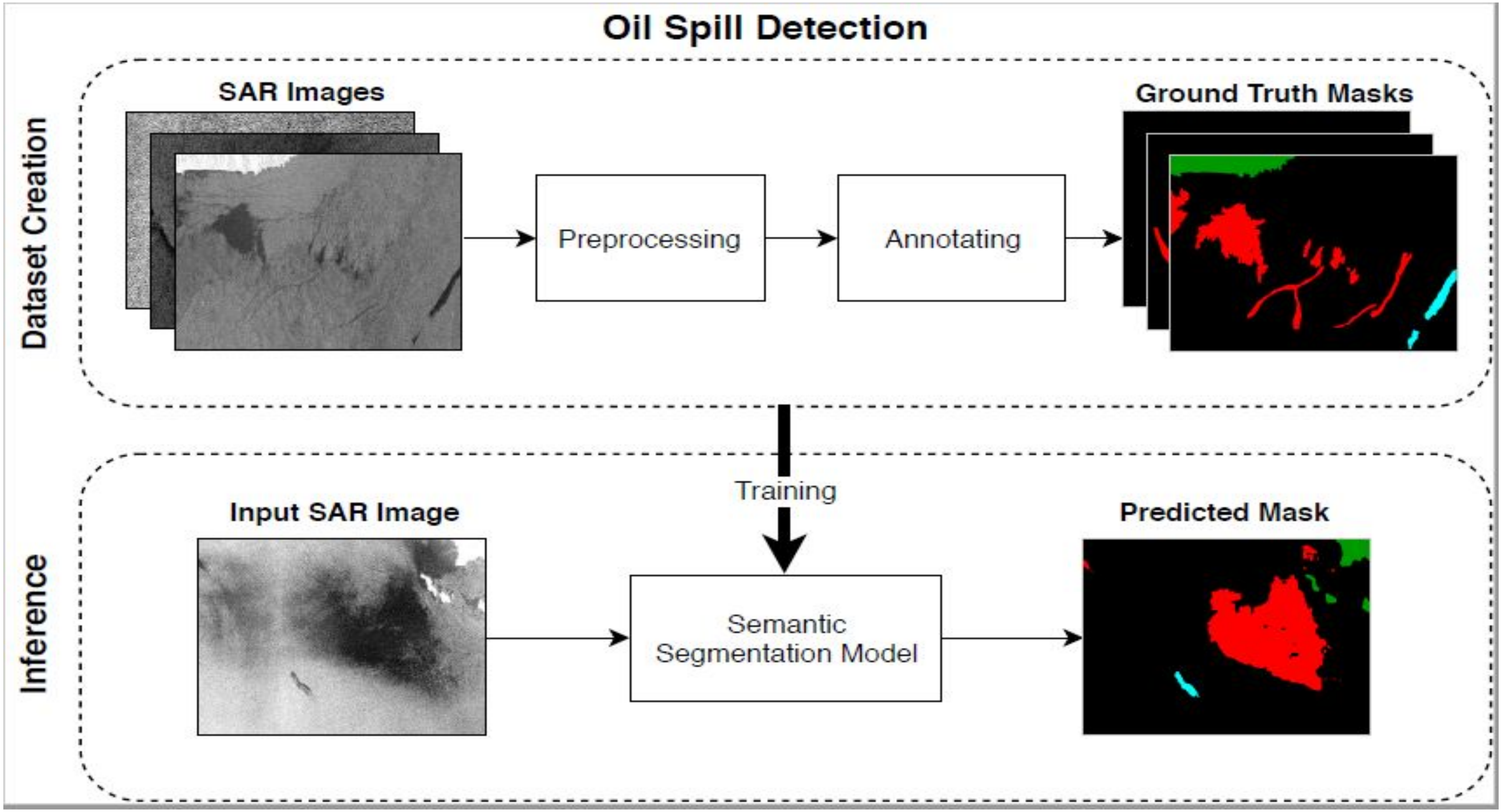
PROPOSED SYSTEM

- Our proposed system harnesses the power of U-Net, a cutting-edge convolutional neural network architecture, to revolutionize the detection of oil spills in natural environments, especially marine and coastal regions.
- U-Net's unique design, with its symmetric encoder-decoder structure and skip connections, enables highly accurate semantic segmentation of satellite or aerial images into distinct color regions corresponding to oil-contaminated and clean areas.
- The efficiency and scalability of U-Net allows for real-time processing of large volumes of satellite imagery, ensuring timely response and mitigation efforts to minimize environmental and economic consequences.
- Through the integration of U-Net into our data, we aim to provide a robust and efficient solution for early detection and monitoring of oil spill incidents, ultimately contributing to the preservation of our natural ecosystems.

ARCHITECTURE DIAGRAM



ARCHITECTURE DIAGRAM



Import Required Libraries:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.image as mpimg

import cv2
import PIL.Image as Image
from PIL import ImageOps
import os
import glob as glob
import seaborn as sns

import tensorflow as tf
from keras import layers, models, callbacks
from keras.models import Sequential, Model
from keras.utils import load_img, normalize
from keras.layers import Input, Conv2D, MaxPooling2D, UpSampling2D, Conv2DTranspose, AveragePooling2D
from keras.layers import Concatenate, concatenate, BatchNormalization, Dropout, Lambda, Activation
from keras.applications import ResNet50

from tqdm import tqdm
from skimage.io import imread, imshow
from skimage.transform import resize
import random
from IPython.display import Image, display

from sklearn.metrics import confusion_matrix
from sklearn.metrics import precision_score, recall_score, f1_score
from sklearn.metrics import precision_recall_fscore_support

from keras.models import Model
from keras import backend as K
```

IMPLEMENTATION MODULE-1

Prepare paths of input images and target segmentation masks for train and test set

```
IMG_HEIGHT = 256
IMG_WIDTH = 256
IMG_CLASSES = 5
IMG_CHANNELS = 3

IMG_PATH = '/kaggle/input/oil-spill/oil-spill/train/images'
LABELS_PATH = '/kaggle/input/oil-spill/oil-spill/train/labels'

IMG_PATH_TEST = '/kaggle/input/oil-spill/oil-spill/test/images'
LABELS_PATH_TEST = '/kaggle/input/oil-spill/oil-spill/test/labels'
```

```
# Get a list of all image filenames in the directory
IMG_IDS = sorted(os.listdir(IMG_PATH))
LABELS_IDS = sorted(os.listdir(LABELS_PATH))

IMG_IDS_TEST = sorted(os.listdir(IMG_PATH_TEST))
LABELS_IDS_TEST = sorted(os.listdir(LABELS_PATH_TEST))
```

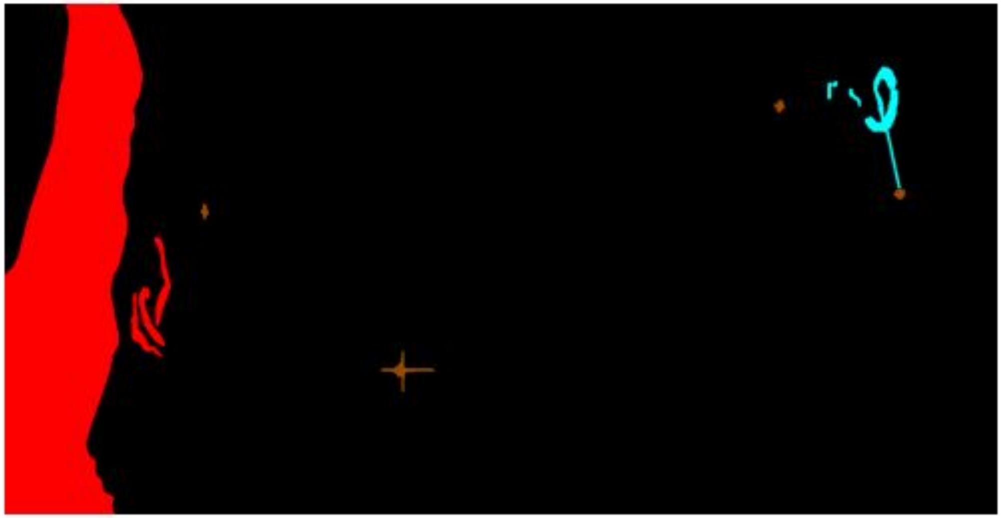
```python
# Get a list of all image filenames in the directory
IMG_IDS = sorted(os.listdir(IMG_PATH))
LABELS_IDS = sorted(os.listdir(LABELS_PATH))

IMG_IDS_TEST = sorted(os.listdir(IMG_PATH_TEST))
LABELS_IDS_TEST = sorted(os.listdir(LABELS_PATH_TEST))
```

+ Code + Markdown

```python
# Choose a random image and mask filename from the list
random_image_name = IMG_IDS[5]
random_mask_name = LABELS_IDS[5]

# Construct the full image path
image_path = os.path.join(IMG_PATH, random_image_name)
mask_path = os.path.join(LABELS_PATH, random_mask_name)

# Read and plot the image
img = mpimg.imread(image_path)
mask = mpimg.imread(mask_path)

plt.imshow(img)
plt.axis('off')
plt.show()

print("Randomly selected image:", random_image_name)

plt.imshow(mask)
plt.axis('off')
plt.show()

print("Randomly selected mask:", random_mask_name)
```

IMPLEMENTATION MODULE-1

Randomly selected image: img_0006.jpg



Randomly selected mask: img_0006.png

IMPLEMENTATION MODULE-2

ALGORITHM/ARCHITECTURE USED:

U-Net is a convolutional neural network architecture commonly used for image segmentation tasks, particularly in biomedical image analysis. It was introduced by Olaf Ronneberger, Philipp Fischer, and Thomas Brox in their 2015 paper titled "U-Net: Convolutional Networks for Biomedical Image Segmentation.

The U-Net architecture consists of two main parts: the contracting path (encoder) and the expansive path (decoder).

- The contracting path follows the typical architecture of a convolutional network with successive convolutional and pooling layers to capture the context of the input image.
- The expansive path involves upsampling the feature map and concatenating it with the corresponding feature map from the contracting path to localize and refine the segmentation.

IMPLEMENTATION MODULE-2

Key components and operations used in U-Net include:

- **Convolutional Layers:** Convolutions are used to extract features from the input image.
- **Pooling Layers:** Max pooling operations are used to downsample the feature maps, reducing spatial dimensions and extracting high-level features.
- **Upsampling Layers:** Transposed convolutions or upsampling operations are used to increase the spatial resolution of feature maps.
- **Skip Connections:** These connections allow information from the contracting path to be directly passed to the corresponding layers in the expansive path. They help preserve fine-grained details during upsampling.

IMPLEMENTATION MODULE-2

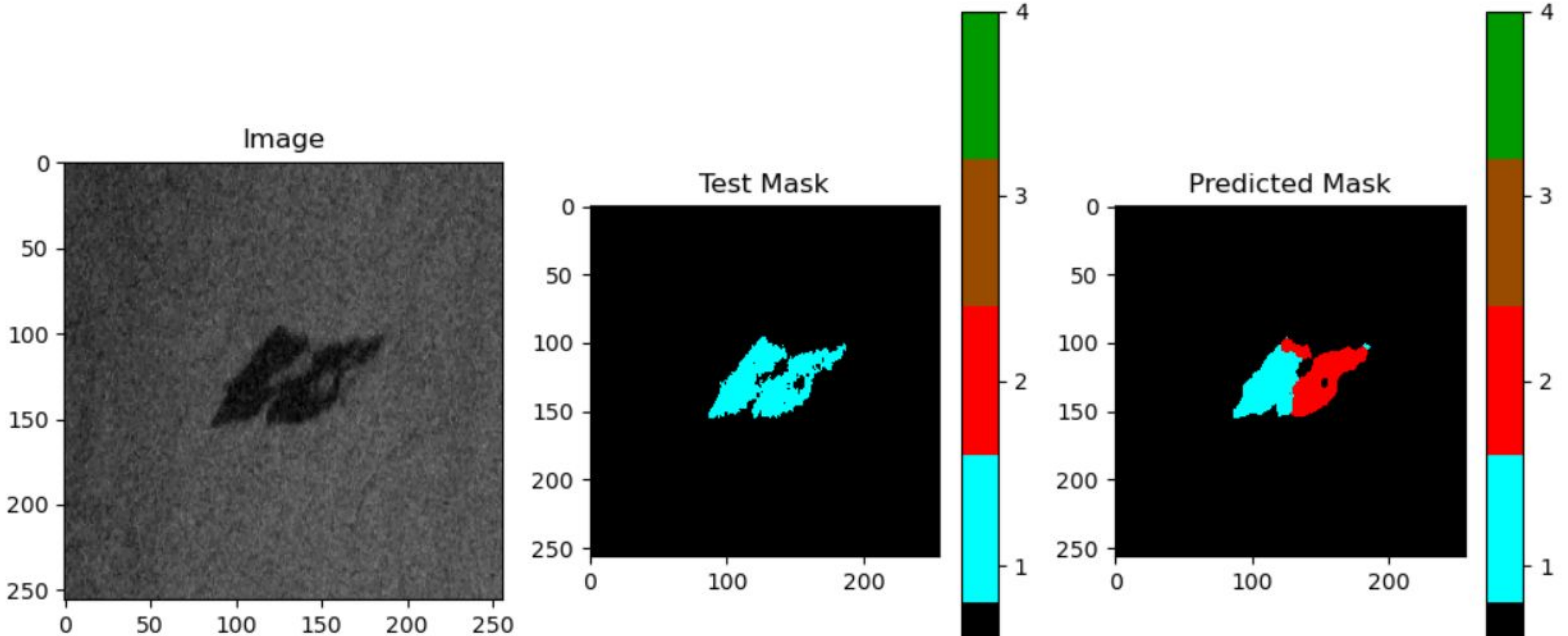
- **Concatenation:** Feature maps from the contracting path are concatenated with the upsampled feature maps in the expansive path to combine low-level and high-level features.

- **Activation Functions:** Common activation functions like ReLU (Rectified Linear Unit) are used to introduce non-linearity into the network.

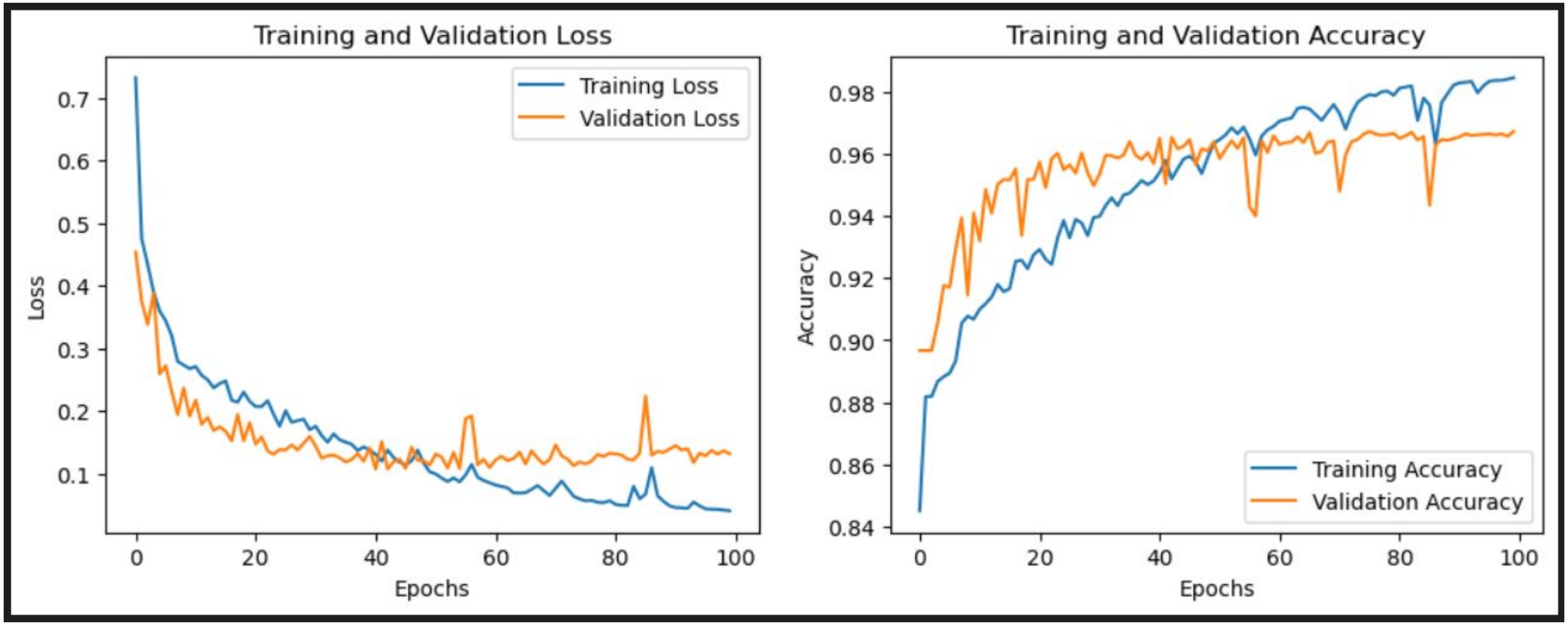
- **Final Layer:** A final layer typically employs a sigmoid activation function to produce pixel-wise segmentation masks, indicating the presence or absence of objects in the input image.

IMPLEMENTATION MODULE-4

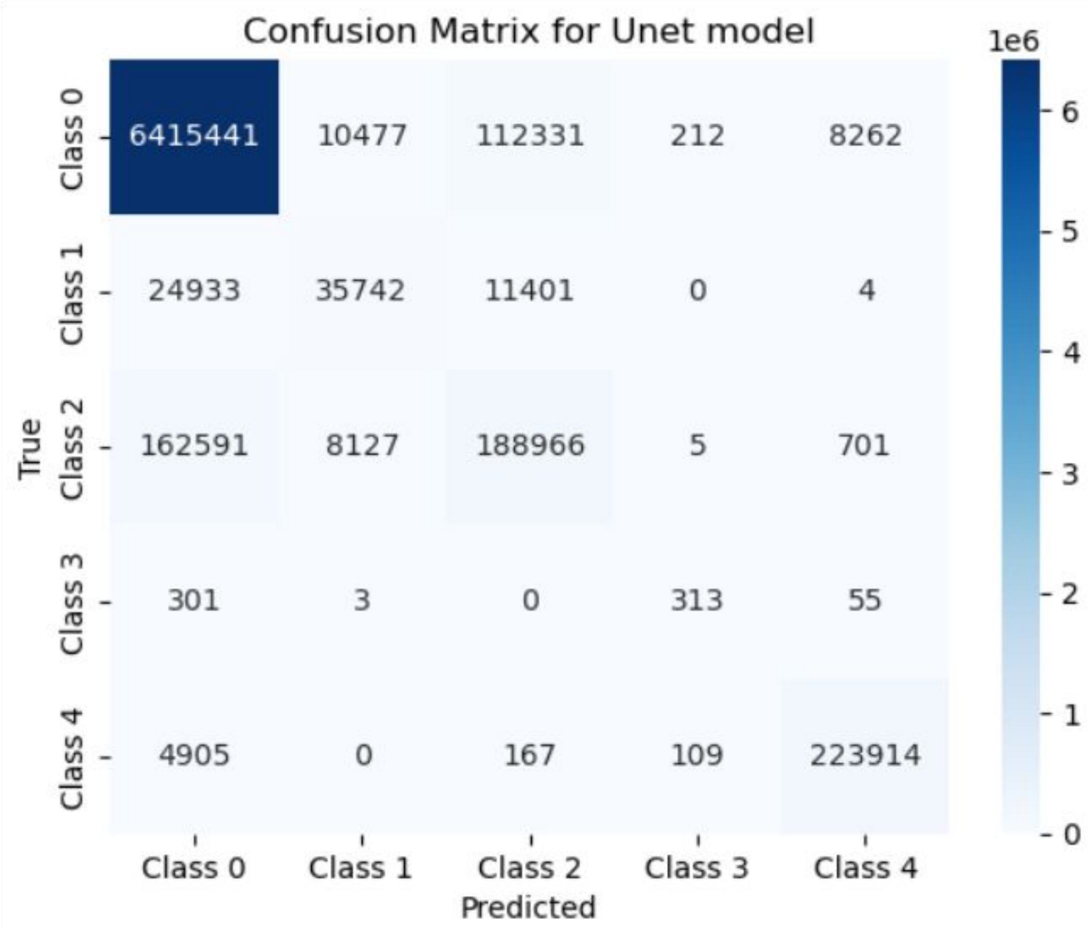
Prediction Visualisation:



IMPLEMENTATION MODULE-4



Confusion Matrix for Simple U-Net model:



CONCLUSION

- The U-Net architecture is well-suited for image segmentation tasks, allowing for precise identification of oil spill areas in satellite or aerial images.
- The U-Net model can be trained with relatively small datasets, making it suitable for scenarios where labeled data is limited or costly to obtain.
- Once trained, the U-Net model can quickly process new images and identify oil spill locations in near real-time, enabling timely response and mitigation efforts.
- The U-Net architecture can be adapted and fine-tuned to specific environmental conditions or types of oil spills, enhancing its versatility and performance in different contexts.
- The U-Net model hold the potential to enhance its capabilities and contribute to more effective and timely responses to oil spill incidents.

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THANK YOU