20CS713 PROJECT PHASE I

OIL SPILL DETECTION IN OCEAN

A PROJECT REPORT

Submitted by

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BONAFIDE CERTIFICATE

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INTERNAL EXAMINER

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ABSTRACT

Oil spills in marine environments pose a significant threat to ecosystems and coastal regions. Detecting these spills swiftly and accurately is imperative for effective mitigation. This project presents an innovative system designed to address the critical issue of oil spill detection with a focus on precision and efficiency. The system incorporates advanced machine learning techniques, including deep learning models, to enhance detection accuracy. It utilizes satellite imagery for data collection, covering diverse geographical locations associated with significant oil spill incidents. By fine-tuning models such as VGG16 for classification, PSPNet for semantic segmentation, and Mask R-CNN for instance segmentation, the system accurately identifies and delineates oil spills within images. Moreover, it leverages the YOLOv3 model for vessel and oil rig detection in maritime environments. The project's comprehensive approach to image preprocessing and deep learning models significantly enhances the accuracy and effectiveness of oil spill detection, even in challenging offshore conditions.

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CHAPTER 1
INTRODUCTION

1.1 PROBLEM STATEMENT

The increasing frequency of oil spills originating from accidents involving oil tankers is a matter of great environmental concern. These incidents have the potential to cause severe damage, such as polluting ocean waters, harming marine ecosystems, and contaminating coastal areas. It is vital to swiftly and accurately detect these spills to facilitate prompt response actions, prevent additional harm, and safeguard our delicate marine environments and coastal populations from the devastating consequences of such accidents.

1.2.1 PROJECT SCOPE

The scope of the project is to address the above-mentioned issue by developing a system for offshore oil spill detection, including data collection, image preprocessing, and machine learning-based detection methods. The project focuses on various image sources and geographical locations.

1.2.2 OBJECTIVES

The primary objective of this project is to develop a robust system for accurate offshore oil spill detection. This includes enhancing data quality through preprocessing methods, enabling the detection of oil spills in various geographical locations, and facilitating timely environmental protection measures.

1.3 LITERATURE SURVEY

"Scientific Bases Development for Oil Spill Accidents Automated Detection Using Drones" by Aleksey Vytovtov, Denis Corolev, et al. (2023) [1]

This research focuses on the effective utilization of unmanned aerial systems (UAS) for oil pipeline monitoring. It establishes the scientific foundation for detecting oil spill incidents and outlines the key technical specifications of aircraft suitable for this purpose. The study addresses the practical needs of the organizations involved by selecting serial photographs as the primary data source for analysis. It identifies optimal monitoring conditions and provides a mathematical model for capturing frames at an appropriate frequency. The research also introduces an automated oil spill detection algorithm, emphasizing the integration of this algorithm with UAS operations. This methodology streamlines the process of identifying and responding to oil spills in an automated fashion, enhancing the efficiency and accuracy of oil spill detection and monitoring.

"Multi-source knowledge graph reasoning for ocean oil spill detection from satellite SAR images" by Xiaojian Liu, Yongun Zhang, et al. (2023) [2]

This paper provides a comprehensive survey of marine oil spill detection methods, emphasizing the use of synthetic aperture radar (SAR) imagery, deep learning, and feature-based techniques. It discusses challenges related to imbalanced datasets and the integration of auxiliary data. The introduction of multi-source knowledge graphs for integrating various data types is a key innovation. The paper explores feature engineering, graph neural networks, and rule inference techniques. It also discusses the creation and evaluation of datasets and the broader applicability of knowledge graphs in other domains.

"Oil Spill Contextual and Boundary-Supervised Detection Network Based on Marine SAR Images" by Qiqi Zhu, Yanan Zhang, et al. (2021) [3]

This research focuses on marine oil spill detection using synthetic aperture radar (SAR) imagery. It addresses issues with noise and blurred boundaries in SAR images. The study introduces the Contextual and Boundary-Supervised Detection Network (CBD-Net) and the Deep-SAR Oil Spill (SOS) dataset. CBD-Net enhances oil spill region extraction through multiscale features and the spatial and channel squeeze excitation (scSE) block. It outperforms other models in terms of mIoU and F1 score, showcasing its potential in marine oil spill decision support systems.

"Realtime Oil Spill Detection By Image Processing of Synthetic Aperture Radar Data" by Subhrangshu Adhikary, Surya Prakash Tiwari, et al. (2022) [4]

This research addresses real-time ship oil spill detection using Synthetic Aperture Radar (SAR) data from advanced satellites. The study introduces an image processing technique centered on blob detection, reducing computational resource requirements while maintaining high detection accuracy. The proposed method achieves a remarkable 95.3% detection accuracy with swift detection times. It outperforms deep learning techniques in terms of speed with a marginal tradeoff in accuracy. This approach paves the way for automated, cost-effective, real-time ship oil spill detection with minimal infrastructure and maintenance requirements.

“Improved YOLOX-S Marine Oil Spill Detection Based on SAR Images” by Shuai Zhang Jun Xing, Xin Zhe Wong et al. 2022 [5]

Marine oil spills, known for their rapid spread and enduring ecological impact, necessitate efficient monitoring methods. Synthetic Aperture Radar (SAR) is widely employed for this purpose due to its all-weather and continuous observation capabilities. However, the inconsistency in contrast across SAR images poses challenges for feature learning by neural networks. To address this issue, this paper introduces an enhanced YOLOX-S model (IYOLOX-S) for marine oil spill detection. This model employs a truncated linear stretch module to enhance image contrast, employs CspDarknet and PANnet for feature extraction, and utilizes a Decoupled Head for oil spill detection. The addition of the linear stretching module improves contrast and highlights oil spill characteristics for better feature learning. Furthermore, the incorporation of a score loss into the global loss function enhances the model's learning ability, improving detection accuracy. Experimental results on an oil spill dataset show a test set average precision (AP) of 90.02%, demonstrating the IYOLOX-S model's effectiveness in accurately identifying oil spill areas.

“A New Technique for Segmentation of the Oil Spills From Synthetic-Aperture Radar Images Using Convolutional Neural Network” by Fatemeh Mahmoudi Ghara, Shahriar Baradaran Shokouhi, 2022 [6]

This paper focuses on utilizing synthetic-aperture radar (SAR) imaging for efficient oil spill detection, employing deep neural networks, namely U-NET and DeeplabV3, for image segmentation. Due to resource limitations, the authors chose these networks to enhance accuracy with a limited dataset. They increased the dataset to 9801 images using augmentation techniques and conducted experiments on Google Colab. Results indicate 78.8% accuracy for U-NET and 54% for DeeplabV3 in SAR oil spill detection, ultimately concluding that U-NET is more effective. This research highlights the potential of deep learning in environmental monitoring and disaster response.

“Fully Automated Sar Based Oil Spill Detection Using Yolov4” by Yi-Jie Yang, Suman Singha, Roberto Mayerle (2021) [7]

The Eastern Mediterranean Sea, marked by high marine traffic and a growing presence of oil and gas activities, is a significant oil pollution hotspot, necessitating effective monitoring of oil spills. Spaceborne Synthetic Aperture Radar (SAR) is a valuable tool for this purpose due to its wide coverage and all-weather capabilities. However, distinguishing real oil spills from similar-looking features in SAR imagery remains a challenge. This study employs the YOLOv4 object detection algorithm as a one-class oil spill detector within Regions of Interest (ROIs) while considering background information. Preliminary findings suggest the need for a pixel threshold to remove inconspicuous oil spills. The trained model demonstrates good generalization, with average precisions (AP) of 67.80% on the validation set and 65.37% on the test set, indicating no overfitting. The study also proposes data augmentation strategies for potential performance enhancement, contributing to more effective oil spill detection in the Eastern Mediterranean Sea using SAR technology.

"A novel deep learning instance segmentation model for automated marine oil spill detection" by Shamsudeen Temitope Yekeen, et al. (2020) [8]

This paper has predominantly relied on traditional machine learning and semantic segmentation deep learning models, which exhibit limited accuracy when distinguishing oil spills from visually similar "look-alikes" in SAR images. This study introduces a novel deep learning model, based on Mask R-CNN, which surpasses existing approaches. The model's training involves transfer learning with ResNet 101 on the COCO dataset, complemented by the Feature Pyramid Network (FPN) architecture for feature extraction. It achieves an overall accuracy of 98.3% for ship detection and segmentation. Furthermore, it excels in detecting and segmenting oil spills and look-alikes, with oil spill detection outperforming look-alike detection, yielding accuracy rates of 96.6% and 91.0%, respectively. This study underscores the superiority of the proposed deep learning instance segmentation model over traditional machine learning and semantic segmentation methods in oil spill detection and segmentation.

1.4 HARDWARE REQUIREMENTS

- System: MINIMUM i3.
- Hard Disk: 40 GB.
- Ram: 4 GB.
- STORAGE: I TB Storage
- INTERNET: wireless adapter (Wi-Fi)

1.5 SOFTWARE REQUIREMENTS

1. **Python**: The primary programming language for implementing machine learning and image processing tasks in the project.

2. **IDE (Integrated Development Environment)**: A coding platform like Anaconda or Jupyter Notebook to write, test, and run code efficiently.

3. **Machine Learning Libraries**

   - **TensorFlow**: A powerful open-source library for building and training machine learning and deep learning models, vital for creating accurate oil spill detection models.

   - **Keras**: A high-level neural networks API that simplifies model development, often used with TensorFlow for rapid prototyping.

   - **PyTorch**: Another popular deep learning framework that provides flexibility and ease of use in model building.

   - **scikit-learn**: This versatile library offers a wide range of tools for classification, regression, clustering, and model evaluation, which are valuable for oil spill detection model development.

4. **Image Processing Libraries (e.g., OpenCV)**: OpenCV is a comprehensive library for computer vision and image processing. It plays a crucial role in enhancing image quality and segmenting oil spills for accurate detection.

5. **Version Control (Git)**: Git is a version control system that helps manage and collaborate on project code efficiently. It tracks changes and allows multiple team members to work together seamlessly, which is essential for the oil spill detection project.

CHAPTER 2

SYSTEM ANALYSIS

2.1 EXISTING SYSTEM

The prevailing landscape of offshore oil spill detection predominantly relies on manual or semi-automated methodologies, often necessitating human intervention at various stages of data collection, processing, and analysis. These systems primarily harness satellite imagery, occasionally integrating basic image processing techniques. However, they grapple with several notable drawbacks.

2.1.1 DISADVANTAGES OF EXISTING SYSTEM

The limitations of these existing systems are multifaceted. Foremost among these challenges is limited accuracy, particularly when dealing with adverse environmental conditions. Manual and semi-automated processes tend to be time-consuming, potentially leading to delayed responses in cases of oil spills. The systems' inefficiency in handling vast datasets, common in the context of monitoring expansive marine regions, further exacerbates these delays. Additionally, distinguishing oil spills from visually similar features within satellite images remains a critical hurdle. The reliance on human intervention introduces an elevated risk of human errors, which can compromise the precision of the detection process.

2.2 PROPOSED SYSTEM

The proposed system represents a concerted effort to overcome the limitations inherent in existing approaches. It seamlessly integrates cutting-edge machine learning techniques, including deep learning models, to achieve a significantly enhanced level of precision in oil spill detection. The foundation of this system rests on the utilization of satellite imagery for data collection, bolstered by a robust image preprocessing pipeline designed to elevate data quality and reduce noise. A hallmark of the proposed system is its full automation, enabling efficient detection and swift responses to oil spill incidents. This automation not only curtails the likelihood of human-induced errors but also empowers the system to efficiently process substantial datasets, rendering it exceptionally well-suited for the monitoring of extensive marine territories. The integration of advanced machine learning models and state-of-the-art image processing techniques elevates the system's detection capabilities, ensuring superior performance in terms of accuracy and efficiency.

2.2.1 ADVANTAGES OF PROPOSED SYSTEM

The advantages intrinsic to the proposed system are multifaceted and pivotal for revolutionizing offshore oil spill detection. Its ability to deliver high levels of accuracy, even in the face of challenging environmental conditions, marks a substantial improvement over existing methods. The full automation of the system mitigates the risk of human-induced errors, and its proficiency in managing extensive datasets positions it as an ideal choice for overseeing large marine expanses. The adoption of advanced machine learning models, coupled with sophisticated image processing techniques, enhances the system's detection prowess, further underscoring its superior performance in terms of accuracy and efficiency. While real-time capabilities are not the primary focus, the system remains well-equipped to significantly improve the efficiency and accuracy of oil spill detection and response, thus minimizing environmental impact.

CHAPTER 3

SYSTEM DESIGN

3.1 SYSTEM ARCHITECTURE

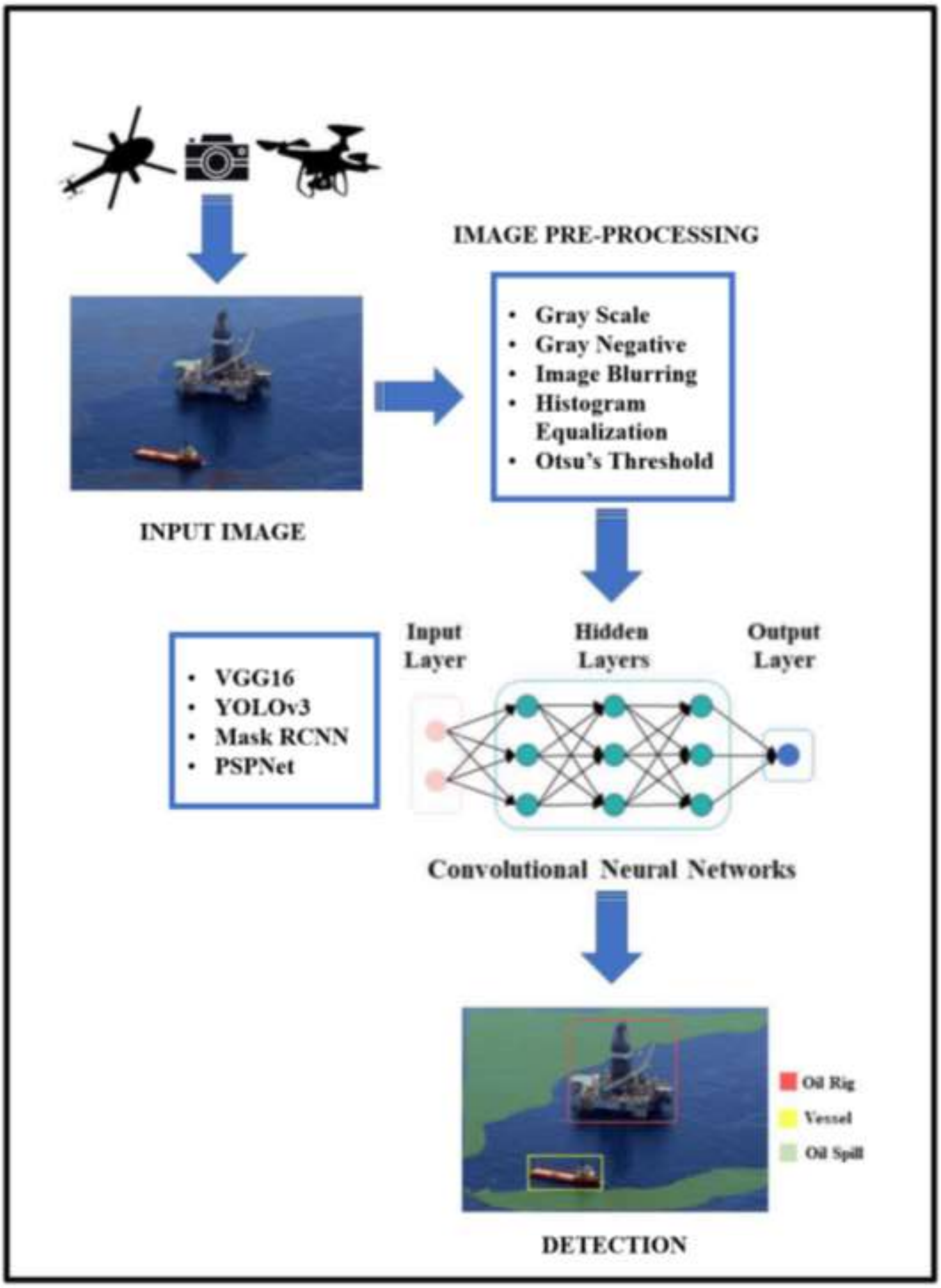

Fig. 3.1 System Architecture

3.2 USE CASE DIAGRAM

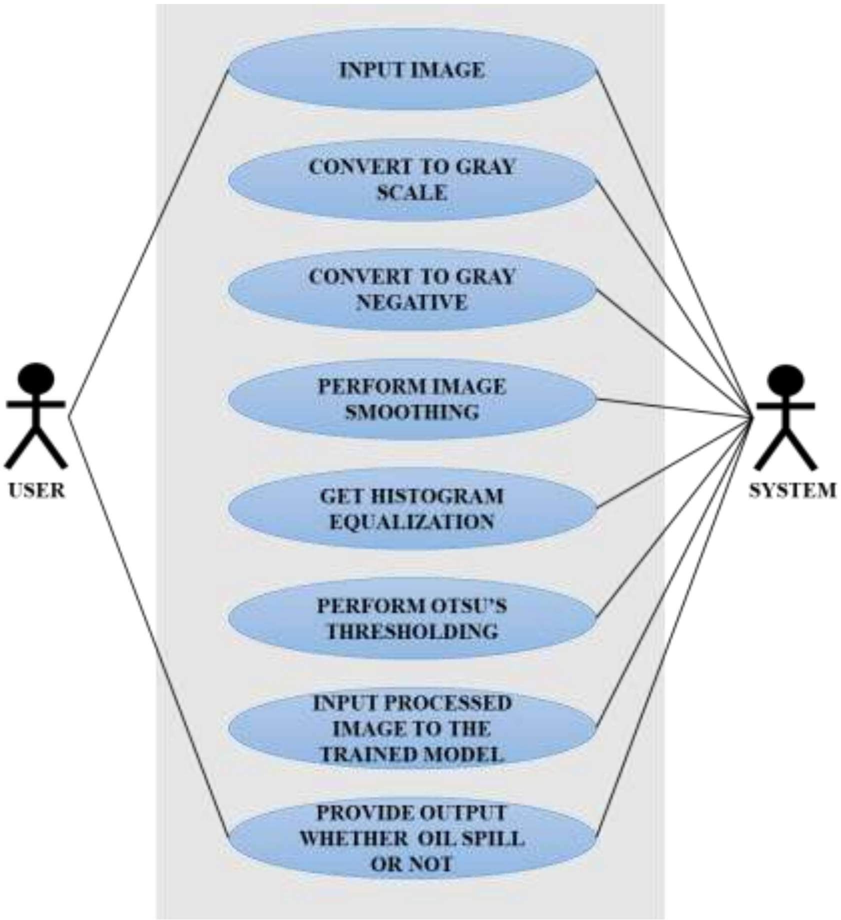

Fig. 3.2 Use case Diagram

3.3 ACTIVITY DIAGRAM

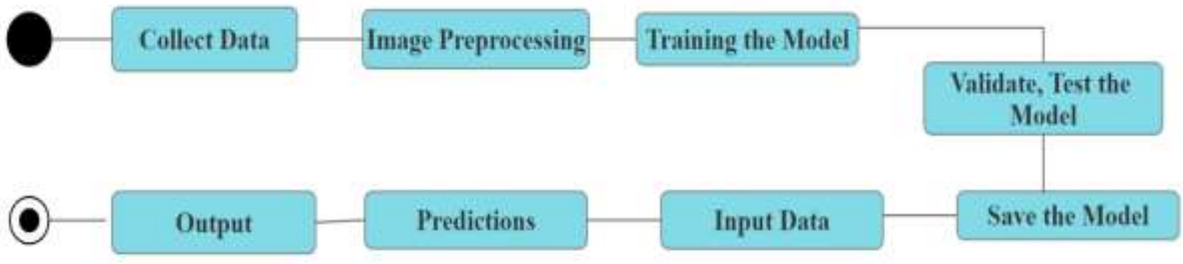

Fig. 3.3 Activity Diagram

3.4 DATA FLOW DIAGRAM

Fig. 3.4 Data flow diagram

In the context of oil spill detection in the ocean, this data flow diagram illustrates a specialized image processing pipeline. Commencing with an oceanic image, it undergoes a sequence of critical transformations, including grayscale conversion, negative conversion, image smoothening, and histogram equalization, all tailored to enhance the image's suitability for analysis. Subsequently, Otsu's thresholding is employed to segment potential oil spill regions. To refine the detection process, a pre-trained Convolutional Neural Network (CNN) is integrated, leveraging its capacity for feature extraction and object recognition to identify and classify oil spills. The CNN's predictions, which may include information about the spill's extent or characteristics, lead to a conclusive output, empowering informed decisions and response strategies in oil spill monitoring and mitigation efforts within oceanic environments. This streamlined workflow is pivotal in improving the precision and efficiency of oil spill detection in the open ocean.

3.5 CLASS DIAGRAM

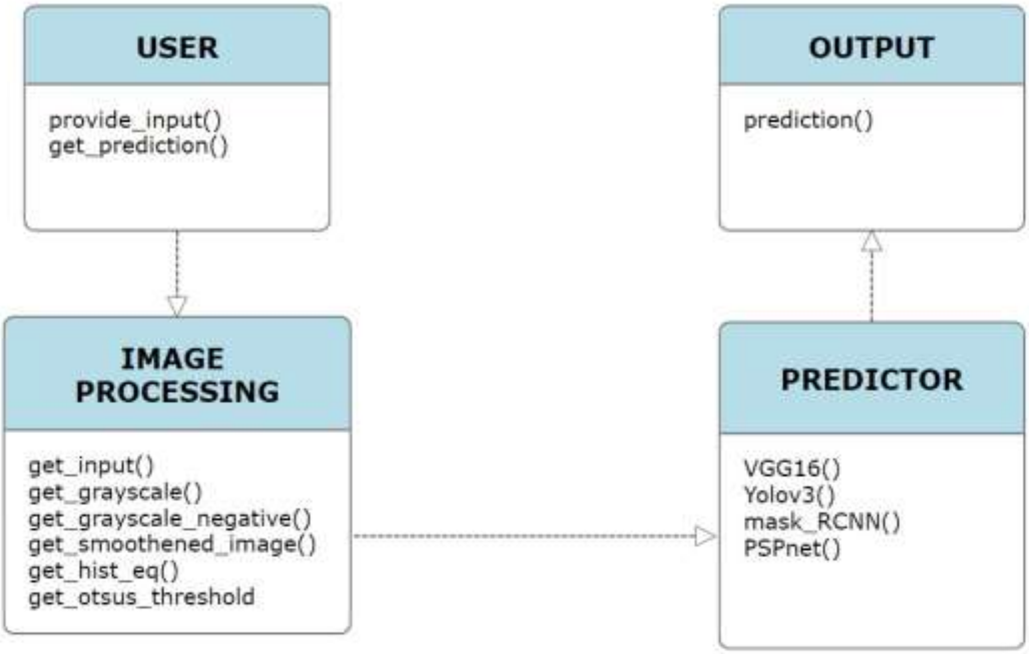

Fig. 3.5 Class diagram

CHAPTER 4

SYSTEM IMPLEMENTATION

4. 1 MODULES

This project involves various steps and processes to detect oil spill with more accuracy. The major modules are listed below.

(1) **Data Collection**: Acquiring relevant data sources, such as satellite and aerial imagery related to oil spills and maritime environments.
(2) **Preprocessing:** Cleaning and preparing the acquired data to ensure its quality and alignment for subsequent analysis, including noise reduction.
(3) **Detection**: Identifying and classifying oil spills within the images using deep learning models like VGG16, PSPNet, Mask R-CNN, and YOLOv3, or other suitable methods.
(4) **Validation and Testing**: Evaluating the models' performance on validation and test datasets to ensure their accuracy and readiness for practical deployment.

4.2 MODULE DESCRIPTION

4.2.1 DATA COLLECTION

An in-house image dataset, gathered through web mining with keywords like "oil spill," "ocean aerial imagery," and "sea aerial view," comprises a total of 1292 images. These images are utilized for training, validation, and testing of various models. The dataset is composed of drone-captured images (from low altitudes), satellite-captured images (from high altitudes), and the remaining are captured from a first-person perspective. It encompasses diverse geographical locations, including the Gulf of Mexico (known for the Deepwater Horizon oil spill), San Francisco Bay in California (associated with the Chevron oil spill), the Persian Gulf (related to the Persian Gulf oil spill), the East China Sea (associated with the Sanchi oil spill), Saldanha Bay in South Africa (connected to the Castillo de Bellver oil spill), the coast of Galicia in Spain (linked to the Prestige oil spill), and the coast of Brittany in France (associated with the Amaco Cadiz oil spill).

4.2.2 PREPROCESSING (IMAGE PROCESSING)

Enhancing the images of oil spills in the ocean offshore is critically important to build an efficient oil spill detection system. In this project various image processing techniques are employed to enhance the images for detecting accurately. In the next stage, a Convolutional Neural Network (CNN) will be employed to inform the competent authorities and reduce the impact of oil spills on the marine ecosystem.

4.2.2.1 CONVERSION OF RGB TO GRAYSCALE IMAGE

The initial step in the image processing pipeline for oil spill detection is the conversion of RGB (Red, Green, Blue) satellite images into grayscale. This transformation simplifies subsequent analysis by representing each pixel with a single intensity value, reducing computational complexity. The choice to convert to grayscale is driven by the recognition that, in the context of oil spill detection, color information may not always be as significant. Grayscale images provide a more straightforward and standardized foundation for analysis, enabling efficient processing and feature extraction..

Fig 4.1 RGB to Grayscale conversion

4.2.2.2 TRANSFORM IMAGE TO GRAY-NEGATIVE

Following the grayscale conversion, a further enhancement is introduced by transforming grayscale images into their negative counterparts. This transformation, often referred to as the gray-negative transformation, is a key feature enhancement technique. Its role is to make specific elements within the image, including potential oil spills and relevant details, more pronounced. By inverting the grayscale image, subtle characteristics that might remain indistinct are accentuated, thereby making them stand out more prominently against the background. This feature enhancement is pivotal in improving the visibility of potential oil spills, which can be crucial for accurate detection.

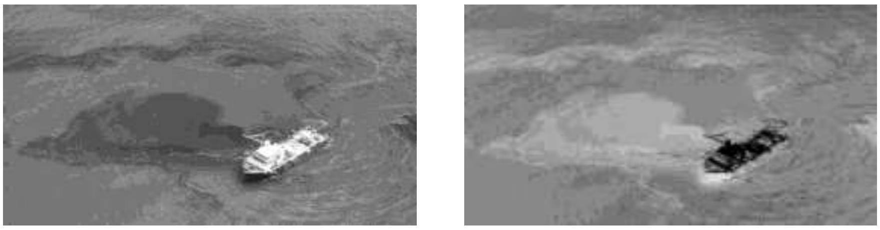

Fig 4.2 Gray negative transformation

4.2.2.3 SMOOTHING IMAGE (IMAGE BLURRING)

Noise reduction represents a critical challenge in offshore imagery, where a variety of artifacts and lighting variations can introduce irregularities and disturbances. To address this issue effectively, a series of smoothing techniques is applied, encompassing Gaussian filtering, median blur, and bilateral filtering. Gaussian filtering involves the computation of a weighted average of neighboring pixel values, which effectively reduces high-frequency noise and provides a smoother image. Median blur, in contrast, replaces pixel values with the median of their local neighborhood, offering an efficient means to remove salt-and-pepper noise while preserving important details. Bilateral filtering represents a more advanced non-linear approach to smoothing, which not only effectively reduces noise but also maintains edge information. This preservation of edge details contributes to a cleaner and more visually usable image, laying a robust foundation for subsequent analysis.

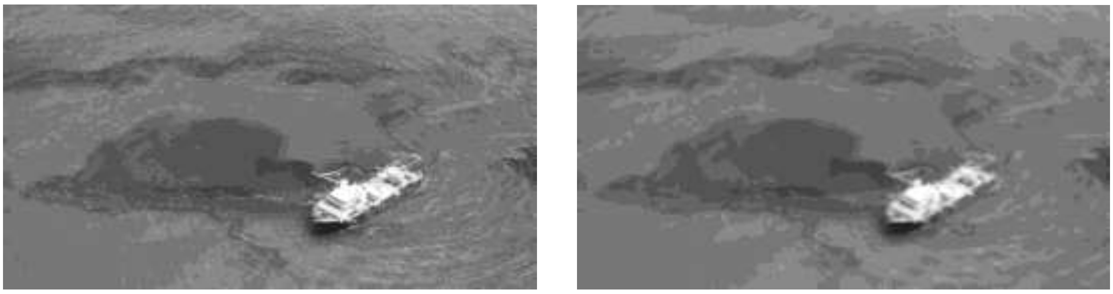

Fig 4.3 Image Smoothening

4.2.2.4 HISTOGRAM EQUALIZATION

Histogram equalization plays a pivotal role in the image processing pipeline by significantly enhancing image contrast. This technique redistributes intensity levels across the image, with the goal of making various features, including the edges and structures associated with potential oil spills, more distinct. Increased contrast is central to the objective of making potential spill regions stand out more prominently within the image. This enhancement is pivotal in ensuring that subtle features, which might otherwise remain unnoticed, become more discernible. Such improved visibility contributes significantly to the accuracy of oil spill detection.

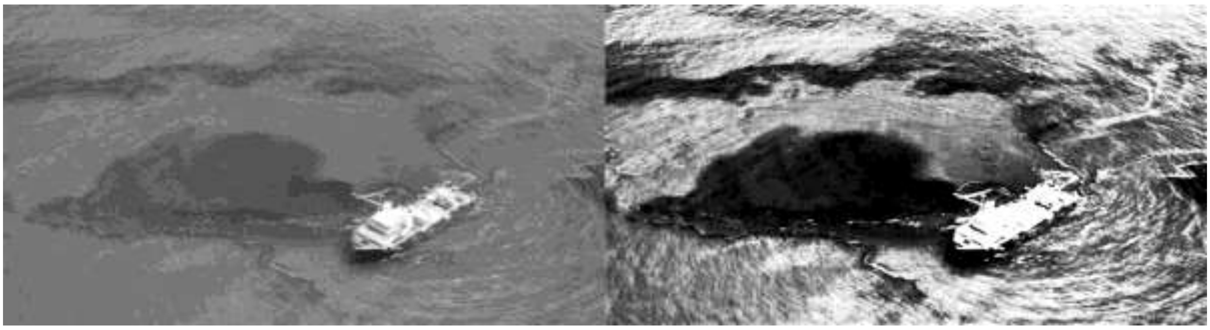

Fig 4.4 Histogram Equalization

4.2.2.5 ADAPTIVE IMAGE THRESHOLDING USING OTSU'S THRESHOLDING METHOD

Image segmentation is a fundamental component of oil spill detection, as it plays a pivotal role in separating the image into different regions of interest. The primary objective of this segmentation is to isolate potential oil spill areas from the rest of the scene, a foundational step in precise detection. Otsu's thresholding method, a key component of this phase, serves as an automated tool for threshold determination. By selecting an optimal threshold that effectively distinguishes these regions with precision, it aids in the creation of a segmented image. This segmented image, post-Otsu thresholding, is well-prepared for further analysis, making it significantly easier to identify and isolate oil spill areas.

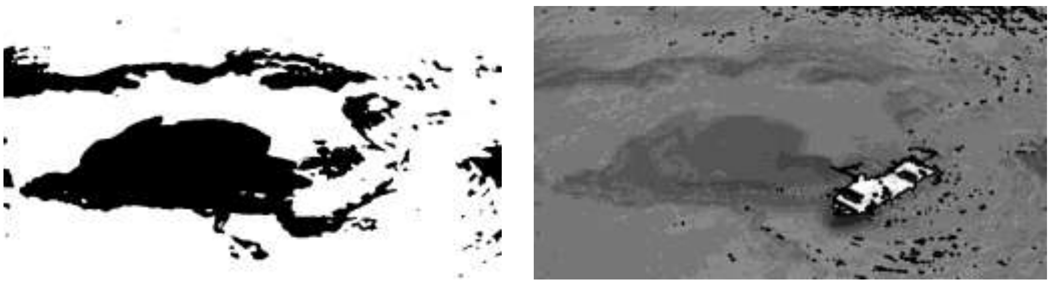

Fig 4.5 Otsu’s Thresholding method

4.2.2.6 EXPERIMENTATION WITH COLOR-SPACE AND CANNY EDGE DETECTION

Beyond the grayscale-based methods, the pipeline introduces a vital component—experimentation with color-space transformations. This experimentation is particularly valuable when oil spills exhibit distinct color characteristics. The exploration of various color spaces can highlight unique color patterns associated with oil spills. This not only enhances their visibility but also aids in the more accurate identification of potential oil spills. In parallel, Canny Edge detection emerges as a crucial element within the image processing pipeline. Canny Edge detection is highly effective at identifying sharp intensity transitions within the image. Such sharp transitions are often indicative of oil spills or their boundaries. The presence of these sharp transitions can signify the existence of oil spills and their boundaries, making Canny Edge detection an invaluable technique for subsequent stages of the project. When combined with advanced methods such as Convolutional Neural Networks (CNNs), it can significantly enhance the accuracy and efficiency of the analysis phase.

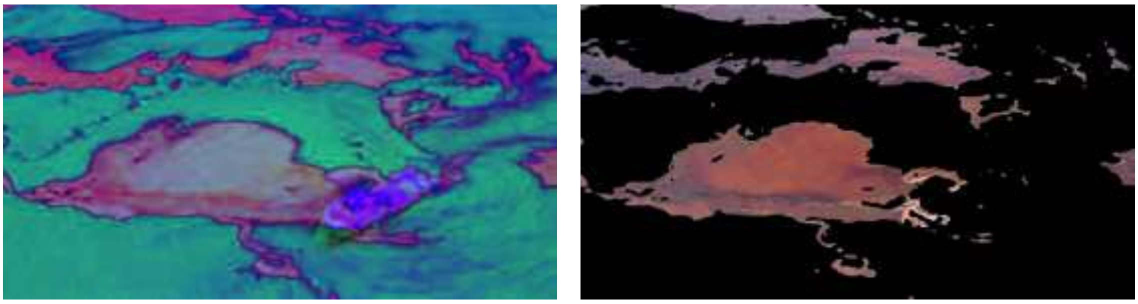

Fig 4.6 Colour-space method to track objects

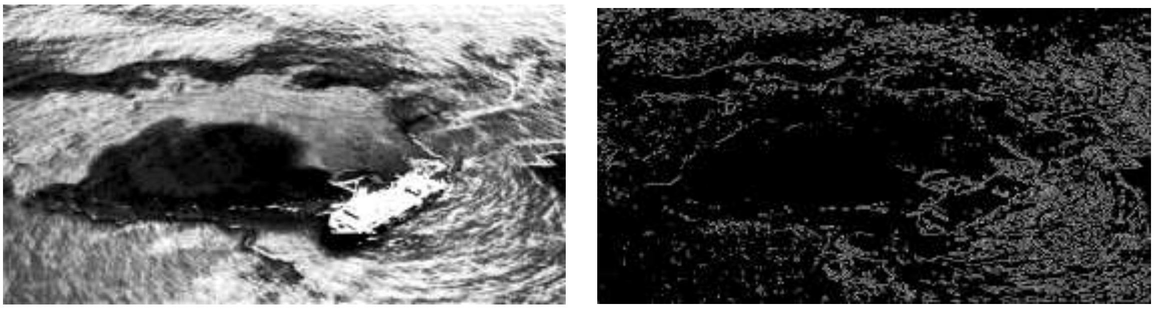

Fig 4.7 Canny Edge detection

Collectively, these image processing methods form a comprehensive pipeline for the preparation and enhancement of satellite imagery, ultimately resulting in data of higher quality. This higher-quality data, in turn, equips subsequent stages of the oil spill detection project with the capability to perform more accurate and efficient detection, even in the challenging offshore environment. Each step within this pipeline is thoughtfully designed to address specific challenges inherent to offshore imagery and to improve the visibility of relevant features, thereby contributing to the overall effectiveness of the detection process.

4.2.3 DETECTION

4.2.3.1 CLASSIFICATON USING VGG16

Adapting the VGG16 architecture for oil spill detection is a process that capitalizes on the strengths of a pretrained deep learning model. The VGG16 model, initially designed for general image classification, serves as the foundation for this task due to its remarkable feature extraction capabilities. To make it suitable for identifying oil spills, the model undergoes a fine-tuning process on a custom dataset exclusively curated for oil spill classification. This dataset comprises labeled images that distinguish between those containing oil spills and those that do not.

Fig 4.8 Classification using VGG16

During fine-tuning, the VGG16 model is meticulously customized, particularly by adjusting the final layers to match the number of classes present in the oil spill dataset, effectively replacing the original classification layers. While fine-tuning, the model's convolutional layers' weights are typically frozen, preserving the valuable knowledge gained during its initial training on extensive datasets like ImageNet. This adaptation allows the model to apply its feature extraction expertise to the intricacies of oil spill identification. Moreover, data augmentation techniques are employed to enhance the model's ability to generalize its learned features. These techniques introduce variations into the training images, such as rotations and zooms, enabling the model to recognize oil spills under diverse conditions.

Additionally, hyperparameters are meticulously fine-tuned, encompassing learning rates, batch sizes, and regularization strategies, to maximize the model's classification accuracy. To ensure the model's effectiveness and prevent overfitting, a validation dataset is utilized for performance monitoring. Once the fine-tuning process is complete, the model is subjected to evaluation on a separate testing dataset, validating its capability to accurately classify oil spills and confirming its readiness for practical deployment. In summary, the adaptation of the VGG16 architecture for oil spill detection harnesses the potential of transfer learning, where a pretrained model's knowledge is redirected and refined for a specific purpose, culminating in a potent and accurate oil spill classification model.

4.2.3.2 OIL SPILL SEMANTIC SEGMENTATION (PSPNet)

Adapting the Pyramid Scene Parsing Network (PSPNet) architecture for oil spill semantic segmentation involves customizing the model to precisely identify and delineate oil spill regions in images. This process requires a dedicated dataset consisting of oil spill images and corresponding ground truth masks. The model is fine-tuned on this data to accurately segment oil spill areas from the background, using loss functions and metrics to assess performance. Data augmentation techniques enhance the model's robustness, while validation and testing confirm its real-world effectiveness. This tailored PSPNet model is a valuable tool for accurately mapping the extent of oil spills, aiding environmental monitoring and response efforts. The availability of a pre-trained model and ground truth masks further supports research and applications in the field of oil spill detection and management.

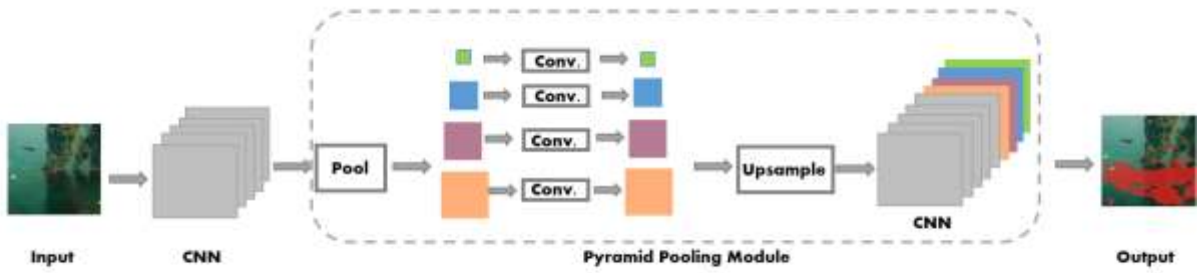

Fig 4.9 Semantic segmentation

4.2.3.3 OIL SPILL INSTANCE SEGMENTATION (Mask R-CNN)

Oil spill instance segmentation, a critical task in environmental monitoring, is achieved by customizing and fine-tuning the Mask R-CNN architecture. This involves adapting the model to delineate individual instances of oil spills within images. The process necessitates a dedicated dataset comprising oil spill images and corresponding ground truth masks, essential for training and evaluating the model's performance. During fine-tuning, the model learns to accurately segment and distinguish oil spill instances, typically with a combination of loss functions. Data augmentation enhances the model's robustness to various spill appearances, and validation and testing confirm its real-world effectiveness. The modified Mask R-CNN model serves as a powerful tool for precise oil spill instance segmentation, supporting research and practical applications in environmental management. Access to a pre-trained model and ground truth masks further aids this endeavour.

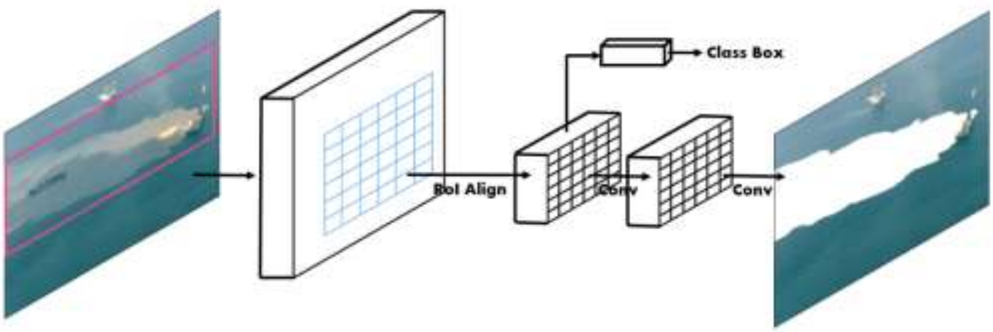

Fig 4.10 Instance segmentation

4.2.3.4 VESSEL AND OIL RIG DETECTION

Vessel and oil rig detection is a vital component of maritime surveillance, and it is accomplished using the YOLOv3 (You Only Look Once) model. This model has been fine-tuned to effectively identify and localize vessels and oil rigs in images and video streams. The trained YOLOv3 model, specialized for this task, is available for download. Additionally, annotations are provided to help evaluate and further improve the model's performance. This approach streamlines the process of monitoring and safeguarding marine environments by accurately detecting vessels and oil rigs, contributing to effective environmental management and safety measures.

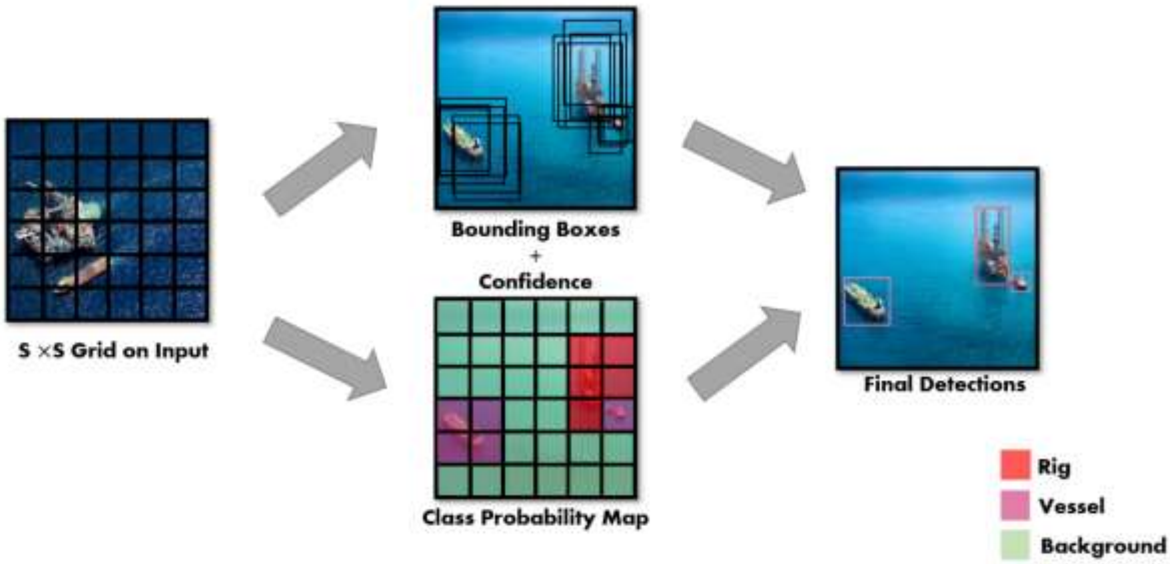

Fig 4.11 Vessel and Oil Rig detection

CHAPTER 5
CONCLUSION

In conclusion, this project offers a robust system for oil spill detection in marine environments. By integrating advanced machine learning techniques and image preprocessing methods, the system excels in accurately detecting oil spills, even under challenging circumstances. While the system's automation reduces the potential for human errors, it efficiently processes large datasets. Although real-time capabilities for immediate response are not explicitly mentioned, its accuracy and efficiency significantly contribute to environmental monitoring, allowing for timely detection and mitigation of oil spills to minimize their impact on marine ecosystems and coastal regions.

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SCREENSHOTS

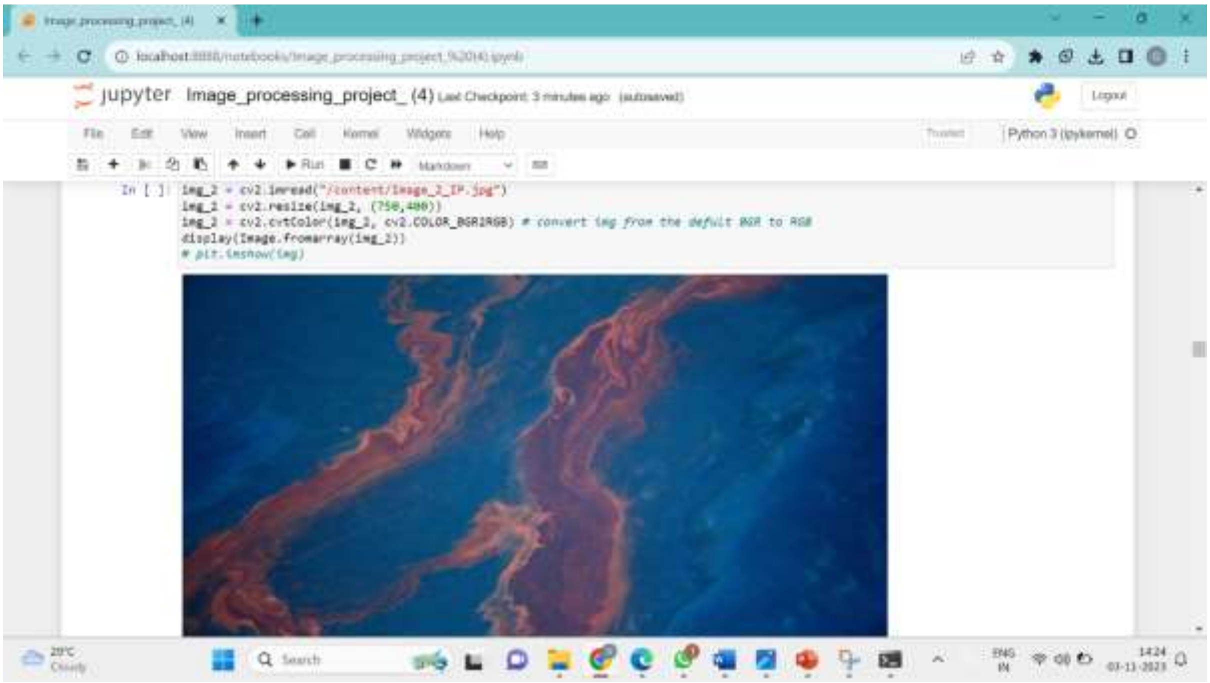

Fig 6.1 Original Input Image

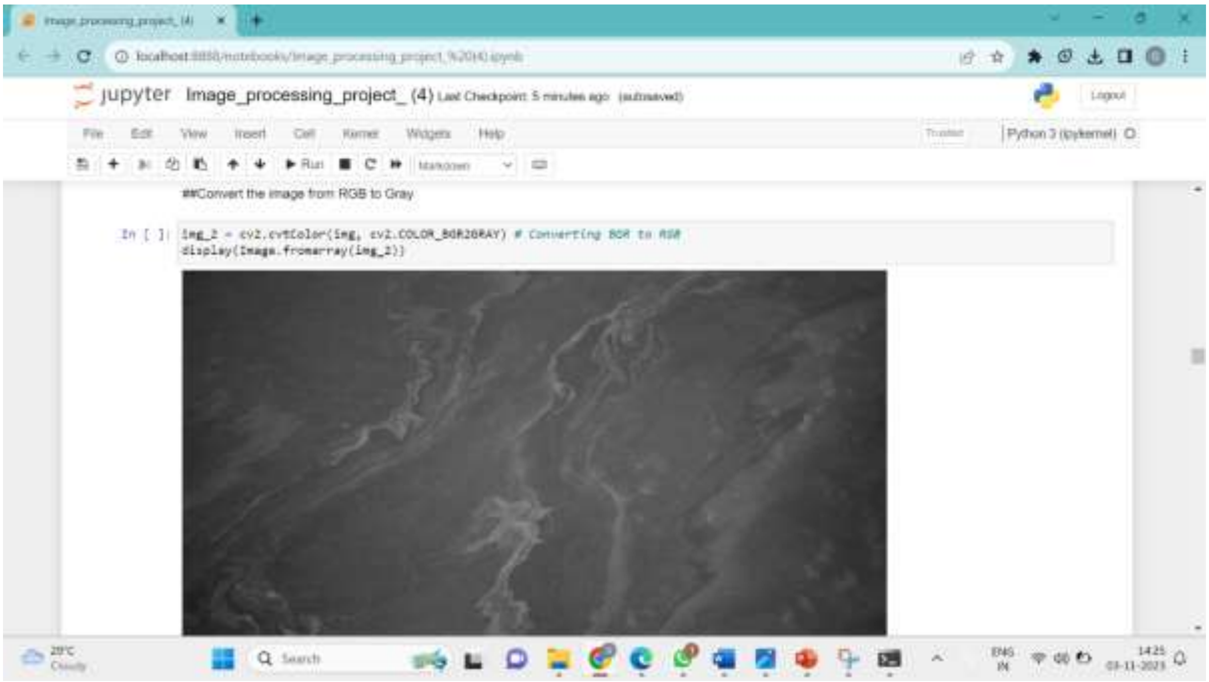

Fig 6.2 RGB to Gray scale output

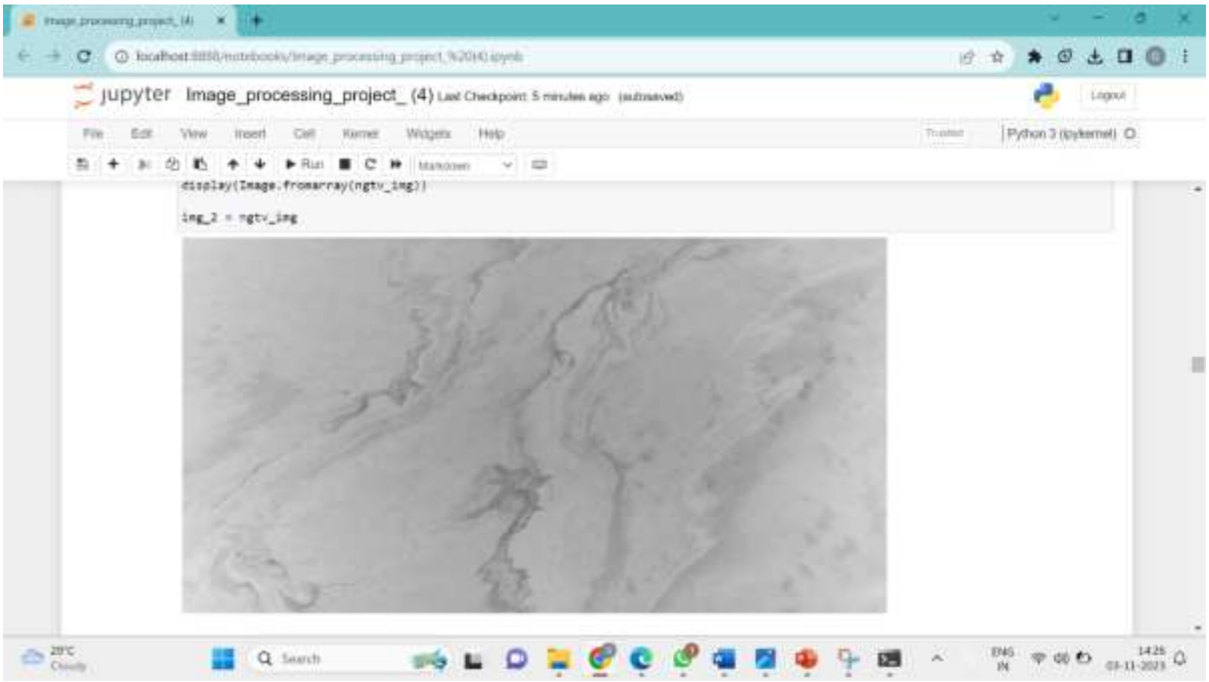

Fig 6.3 Gray negative conversion output

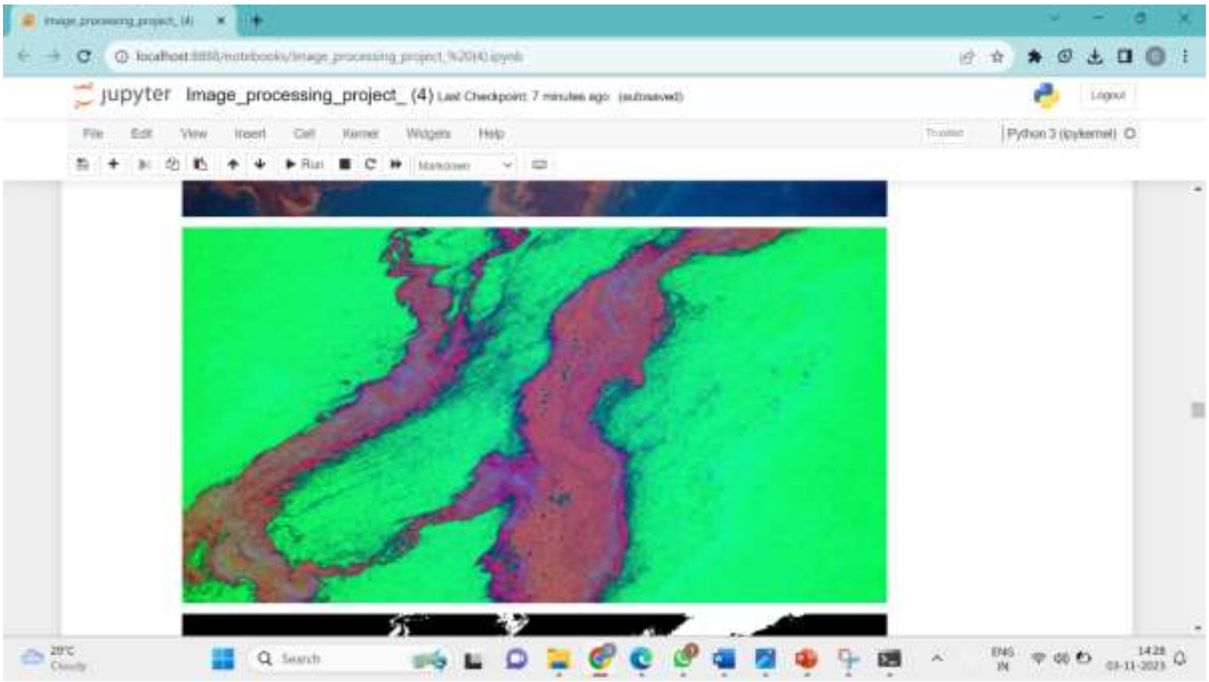

Fig 6.4 Colour-space output

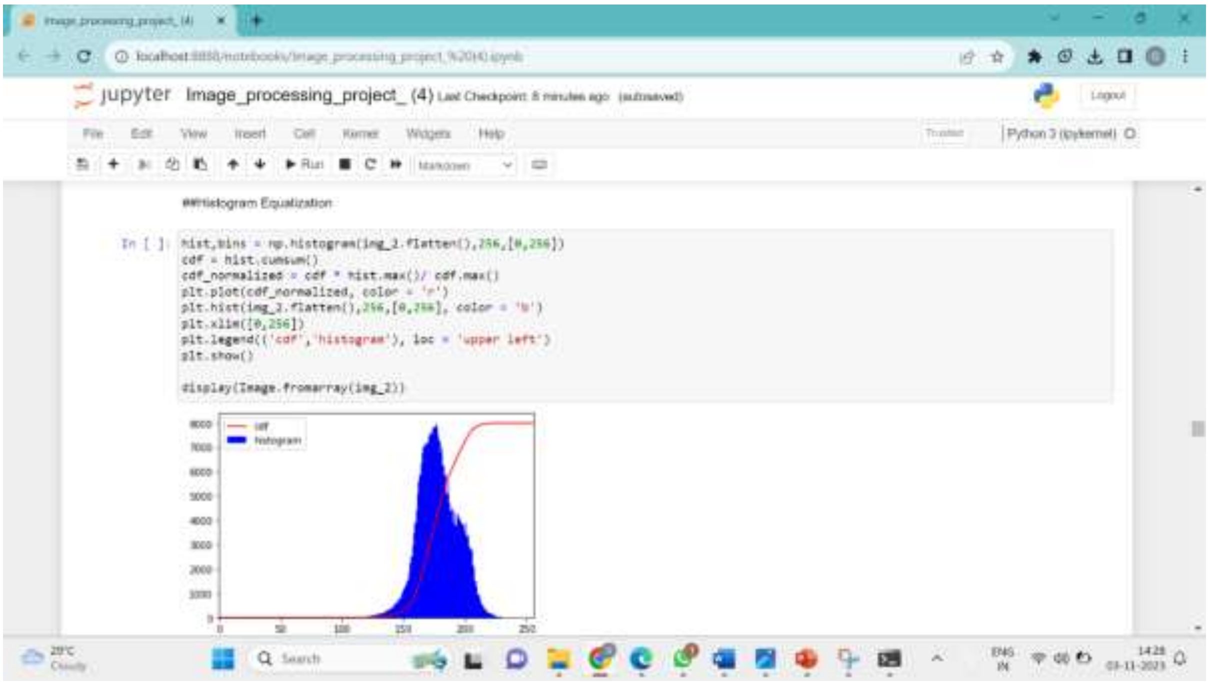

Fig 6.5 Histogram Equalization output

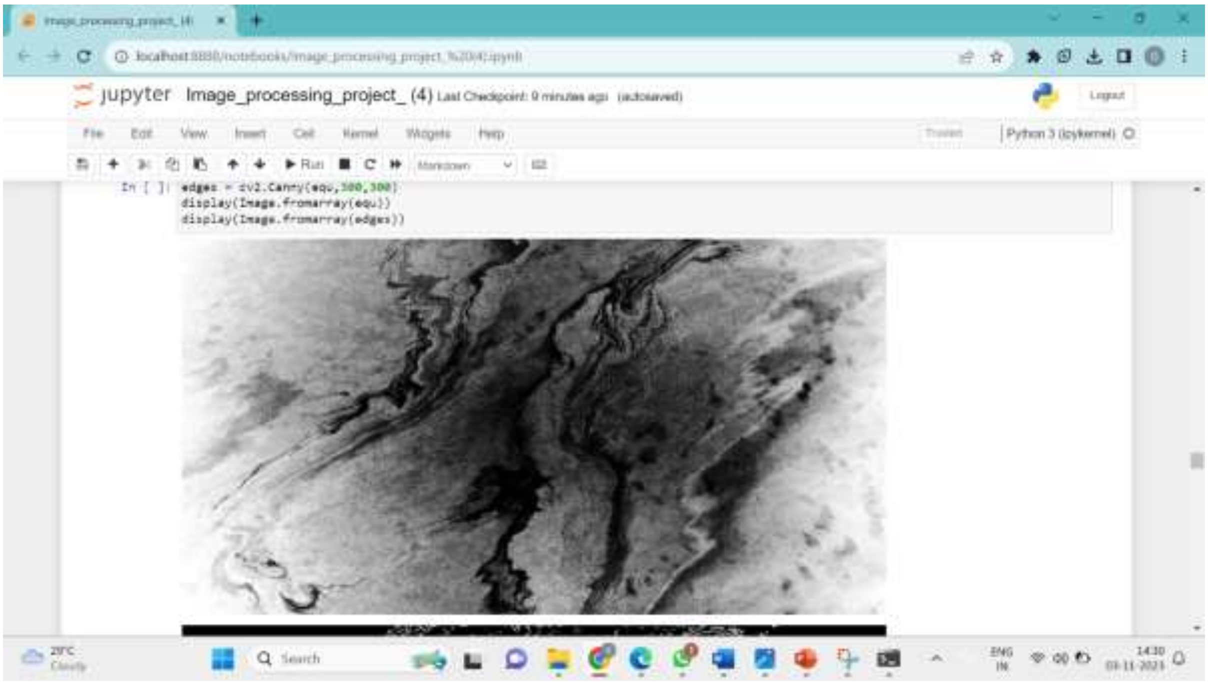

Fig 6.6 Canny Edge detection output

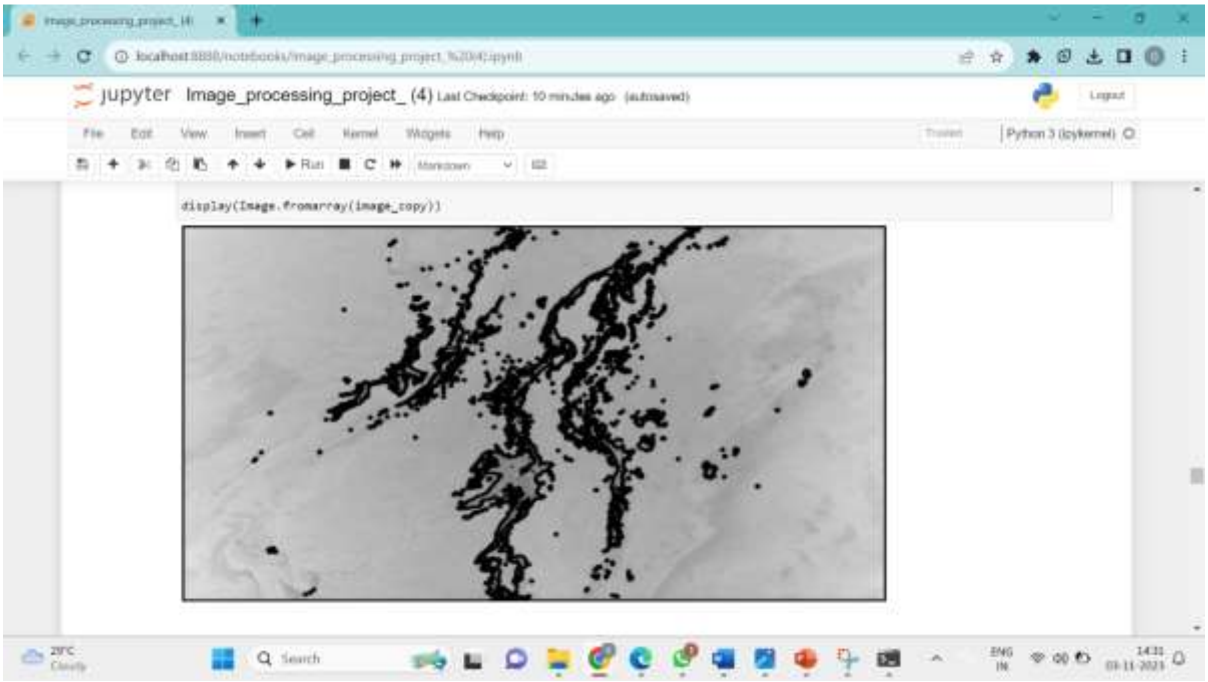

Fig 6.7 Otsu’s thresholding output