A Deep Learning Framework for Real-time Oil Spill Detection and Classification*

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Abstract

Efficient detection of oil spills is critical for minimizing environmental damage. This study introduces a novel approach utilizing deep learning, specifically the YOLOv8 architecture, augmented with advanced computer vision techniques for oil spill detection. Through meticulous dataset curation and model training, the YOLOv8 model achieved an impressive overall accuracy (R-score) of 0.531 and a Mean Average Precision (mAP) of 0.549. Performance varied across different spill types, with the model demonstrating notable accuracy in distinguishing between oil spills and natural features, achieving precision and recall rates of up to 0.75 and 0.68, respectively, for sheen detection. Visualizations such as box loss, class loss, and confusion matrices provide insights into the model's performance dynamics, revealing a steady decrease in losses and an improvement in accuracy over epochs. In this dataset, the measurements are drone measurements performed by Port of Antwerp Bruges. Furthermore, practical applications showcase the model's versatility in detecting various oil spill types in both image and video data, affirming its potential for real-world deployment in environmental monitoring and disaster response scenarios. This research represents a significant stride towards more effective oil spill detection, contributing to environmental sustainability and resilience efforts.

Keywords

Oil spills, Environmental risk, Oil exploration, YOLOv8, Object Detection, Computer Vision

1. Introduction

The global energy demand heavily relies on the exploration, extraction, and transportation of oil. However, alongside meeting energy needs, these activities also pose significant environmental risks, with oil spills emerging as a primary concern. The detrimental impacts of oil spills on ecosystems, aquatic life, and human communities underscore the critical necessity for effective and prompt detection methods. Recent advancements in deep learning and computer vision offer promising avenues for enhancing the efficiency of oil spill detection processes. This study introduces an innovative approach to oil spill detection, harnessing the power of deep learning, specifically the YOLOv8 architecture [1]. Renowned for its real-time object detection capabilities, YOLOv8 is adept at addressing the dynamic and time-sensitive nature of oil spill incidents. Our proposed model, augmented with advanced computer vision techniques, aims not only to accurately identify oil spills but also to distinguish them from natural environmental features, thereby minimizing false positives. The motivation for this research stems from the urgent need for proactive measures to manage and mitigate the environmental impact of oil spills. Conventional methods, such as manual interpretation of satellite imagery, are not only time-consuming but also prone to errors. The integration of deep learning and computer vision technologies into this

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domain presents an opportunity to revolutionize the speed and accuracy of oil spill identification, facilitating faster response times and more effective containment efforts [2].

In the subsequent sections, we delve into the methodology, elucidating how YOLOv8 was tailored to the unique challenges of oil spill detection. We provide insights into the construction and curation of a diverse dataset of drone images to train the model, ensuring its robustness across various environmental conditions. Additionally, we present the results of our model's performance evaluation against private port datasets, showcasing its superiority over existing methods. This research aims to contribute to the realm of environmental monitoring and disaster response, with a specific focus on mitigating the impact of oil spills. Beyond environmental conservation, the implications of an efficient oil spill detection system extend to economic and social dimensions. The scalability and integration potential of our proposed model into existing monitoring systems underscore its applicability as a valuable tool for bolstering environmental sustainability and resilience.

2. Literature Review

The application of the YOLO model for real-time marine radar-based oil spill monitoring is thoroughly explored. The research effectively addresses the need for timely detection capabilities in dynamic marine environments by employing deep learning techniques to enhance the efficiency and accuracy of oil spill identification using marine radar data. The study contributes valuable insights into the potential of the YOLO architecture in addressing challenges posed by oil spills in marine ecosystems [3].

The study investigates the integration of deep learning methods with Sentinel-1 Synthetic Aperture Radar (SAR) imagery for oil spill detection. The study carefully examines how deep learning enhances accuracy and efficiency in identifying oil spills in SAR data, which is crucial for timely response and mitigation. The research provides valuable insights into using advanced remote sensing technology and deep learning algorithms, highlighting their potential to improve the reliability of oil spill detection [4].

A study on deep-water oil spill monitoring in Brazilian territory, utilizing Sentinel-1 time series data and deep learning techniques. The research aims to understand the recurrence patterns of oil spills in deep-water environments. By combining remote sensing data and advanced analysis methods, the authors contribute to the knowledge of oil spill dynamics in challenging marine settings [5].

The authors present a conference paper on a fully automated Synthetic Aperture Radar (SAR) based oil spill detection method using the YOLOv4 architecture. The emphasis is on real-time and automated identification of oil spills, addressing the urgent need for rapid response in emergencies. The study contributes significantly by demonstrating the applicability of YOLOv4 in SAR imagery for efficient and accurate oil spill detection [6].

The research study investigates marine oil spill detection over the Indian Ocean using synthetic aperture radar (SAR). The study emphasizes radar technology's application in monitoring oil spills in large water bodies, providing valuable insights into the spatial and temporal dynamics of incidents. This research establishes a foundation for effective monitoring and response strategies in oceanic environments [7].

This research introduces a Synthetic Aperture Radar (SAR) oil spill detection system using random forest classifiers. The study integrates machine learning techniques with SAR data to develop effective algorithms for oil spill detection. Leveraging random forest classifiers, the authors enhance the accuracy and reliability of SAR-based oil spill identification, contributing significantly to the development of robust detection systems [8].

The authors presently work on automated detection and classification of spilt loads on freeways using an improved YOLO network. Although not directly related to oil spills, this research provides valuable insights into the broader applicability of YOLO networks for object detection. The study highlights advancements in the YOLO network, suggesting potential implications for adapting similar techniques to oil spill detection scenarios [9].

The research proposes an advanced convolutional neural network for oil spill detection in quad-polarimetric Synthetic Aperture Radar (SAR) images. The research focuses on using complex SAR data

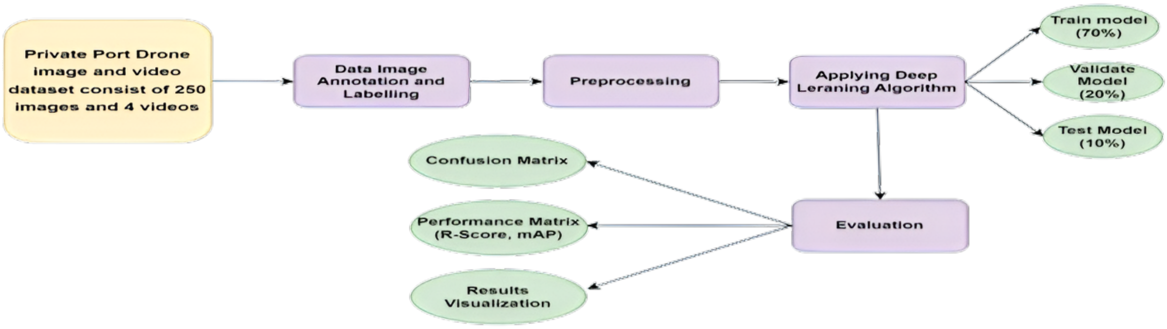

Figure 1: Flowchart of the Proposed Framework

and advanced neural network architectures for accurate oil spill identification. This study contributes significantly to understanding the potential of convolutional neural networks in extracting intricate features from SAR data, enhancing oil spill detection [10].

3. Methodology

In the initial phase of our study, meticulous attention was dedicated to the collection and preprocessing of datasets, ensuring uniformity and data quality. This involved resizing both images and videos to a consistent resolution, normalizing pixel values to a standardized scale, and addressing any artifacts or anomalies present in the dataset. To facilitate model training and evaluation, we implemented a structured Train-Validation-Test split, with 70% of the data allocated for training, 20% for validation, and 10% for testing. Random shuffling was employed during the split to maintain a representative distribution across the sets. The subsequent step involved annotation, a crucial aspect in training object detection models. Utilizing specific tools like labelImg [11] or RectLabel [12], annotators underwent training to ensure annotation consistency. Bounding boxes delineating oil spills were applied to images and videos, and a meticulous validation process was executed to verify the accuracy and consistency of annotations. For the object detection model, the choice was YOLOv8 [13], selected for its well-established effectiveness in object detection tasks. Justification for this selection, however, necessitates clarity on how our proposed method differs from the state-of-the-art and why a new method is essential. To address this, we have focused on enhancing the YOLOv8 configuration, incorporating data augmentation techniques to boost the model's robustness, enabling it to generalize effectively across diverse scenarios. The training phase encompassed the specification of the optimization algorithm, such as Adam, along with a defined learning rate. Determination of batch size and the number of epochs was achieved through experimentation or adherence to best practices. Monitoring of progress throughout the training procedure involved key metrics like loss, and we implemented early stopping mechanisms when deemed necessary. During the evaluation phase, key metrics, including precision, recall, F1 score, and mean average precision (mAP), were employed to assess the model's performance comprehensively. Analysis of the confusion matrix provided deeper insights into the model's effectiveness on the test set. These meticulous steps, spanning from dataset preparation to model evaluation, collectively contribute to the robustness and reliability of our object detection system for identifying oil spills while clarifying the unique contributions of our proposed method compared to existing state-of-the-art approaches.

3.1. Model Architecture

The YOLOv8 architecture, specifically tailored for object detection applications like identifying oil spills, represents an evolution within the renowned You Only Look Once (YOLO) series. This architecture integrates various layers, encompassing Rectified Linear Unit (ReLU), Convolutional 2D (Conv2d), and Max Pooling 2D (MaxPool2D), to achieve its functionality. At its core, the architecture comprises CSPDarknet53, serving as the backbone responsible for feature extraction from input images. Consisting

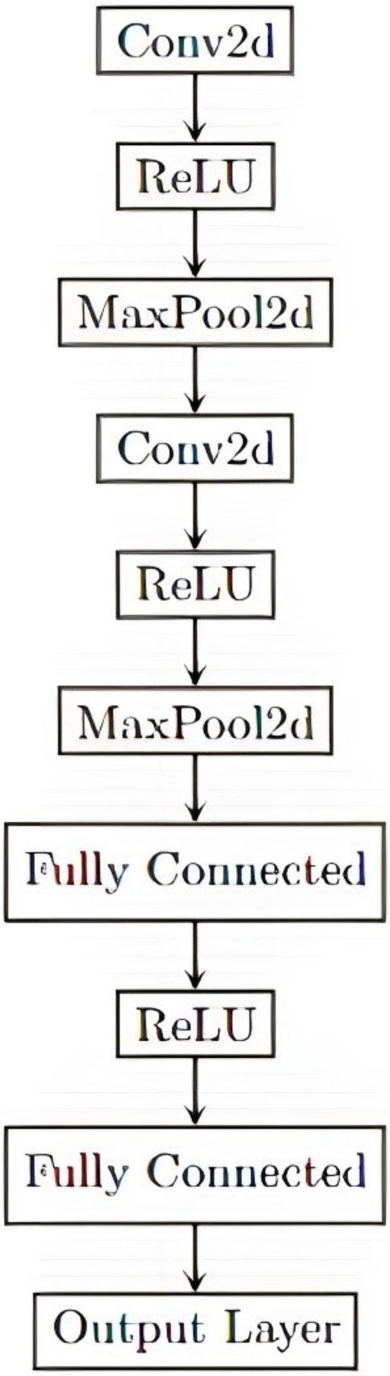

Figure 2: Flowchart of the Proposed Framework

of multiple Conv2d layers and ReLU activation functions, CSPDarknet53 plays a pivotal role in discerning hierarchical features from the input.

The PANet (Path Aggregation Network) functions as the neck of the architecture, enhancing object detection across different scales through the aggregation of features. This is accomplished by employing Conv2d layers and ReLU activation functions. The YOLO head, the final segment of the architecture, is responsible for predicting bounding boxes, objectness scores, and class probabilities. It incorporates

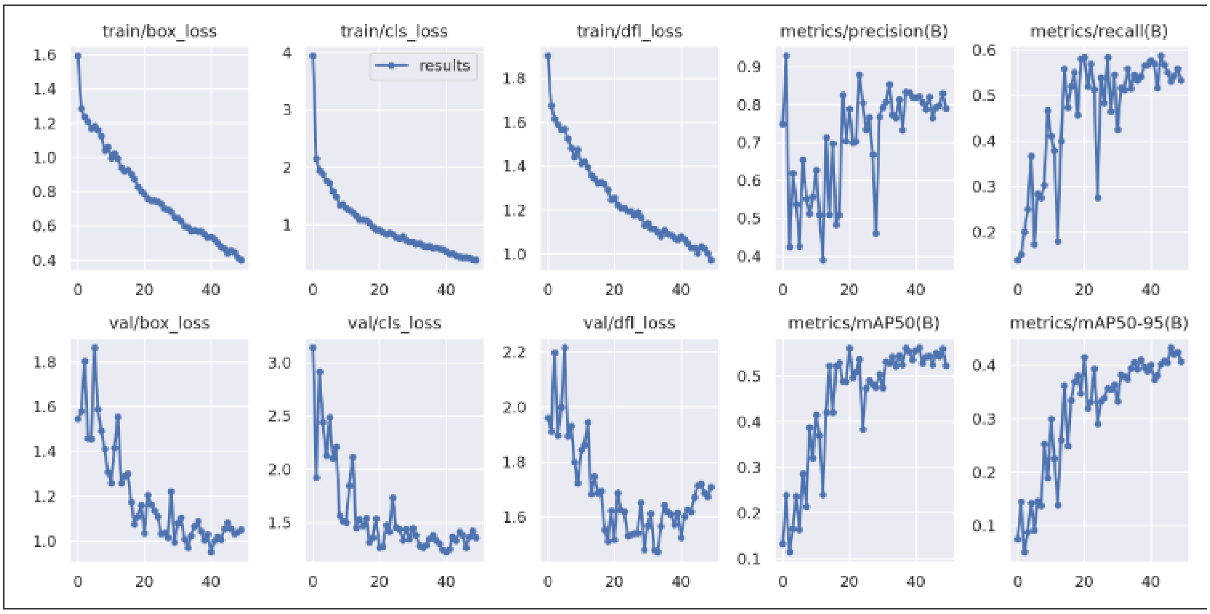

Figure 3: Visualization of Computer Vision Metrics and Model Results

YOLO layers, each dedicated to predicting information for objects at distinct scales. The YOLO layers typically employ a combination of Conv2d layers, ReLU activation functions, and, at times, MaxPool2D layers. SPP (Spatial Pyramid Pooling) is incorporated to capture contextual information at multiple scales, enhancing the model's capacity to comprehend intricate patterns. CSPNet (Cross-Stage Partial Network) contributes to improved feature fusion across different stages of the network, facilitating more effective information flow. The output layer, comprising Conv2d layers and ReLU activation functions, finalizes the architecture, generating predictions including bounding boxes and class probabilities. Collectively, these interconnected layers form a cohesive architecture designed for real-time object detection, making YOLOv8 particularly apt for tasks such as oil spill detection in drone images and videos.

4. Results and Discussion

The YOLOv8 model, upon training, achieved an overall accuracy (R-score) of 0.531 and a Mean Average Precision (mAP) of 0.549. Notably, the performance for sheen detection exhibited a lower value of 0.4, which, regrettably, impacted the overall performance and accuracy of the model.

Table 1
Model Performance

Class	Images	Instances	Box	R	mAP50	mAP50-95
ALL	24	49	0.793	0.531	0.549	0.432
OBJECT	24	1	1	0	0	0
RAINBOW	24	3	0.723	0.891	0.913	0.693
SHEEN	24	15	0.729	0.4	0.475	0.373
TRUECOLOR	24	30	0.729	0.833	0.81	0.664

To delve into the intricacies of the model's performance, we present visualizations in the form of graphs depicting Box loss, Class loss, and Distribution Focal loss for both training and validation data. Accompanying these visualizations are performance graphs that underscore the evolution of the model's efficacy across epochs. These graphs collectively illuminate a consistent trend of decreasing losses with increasing epochs, indicating a significant enhancement in the model's performance.

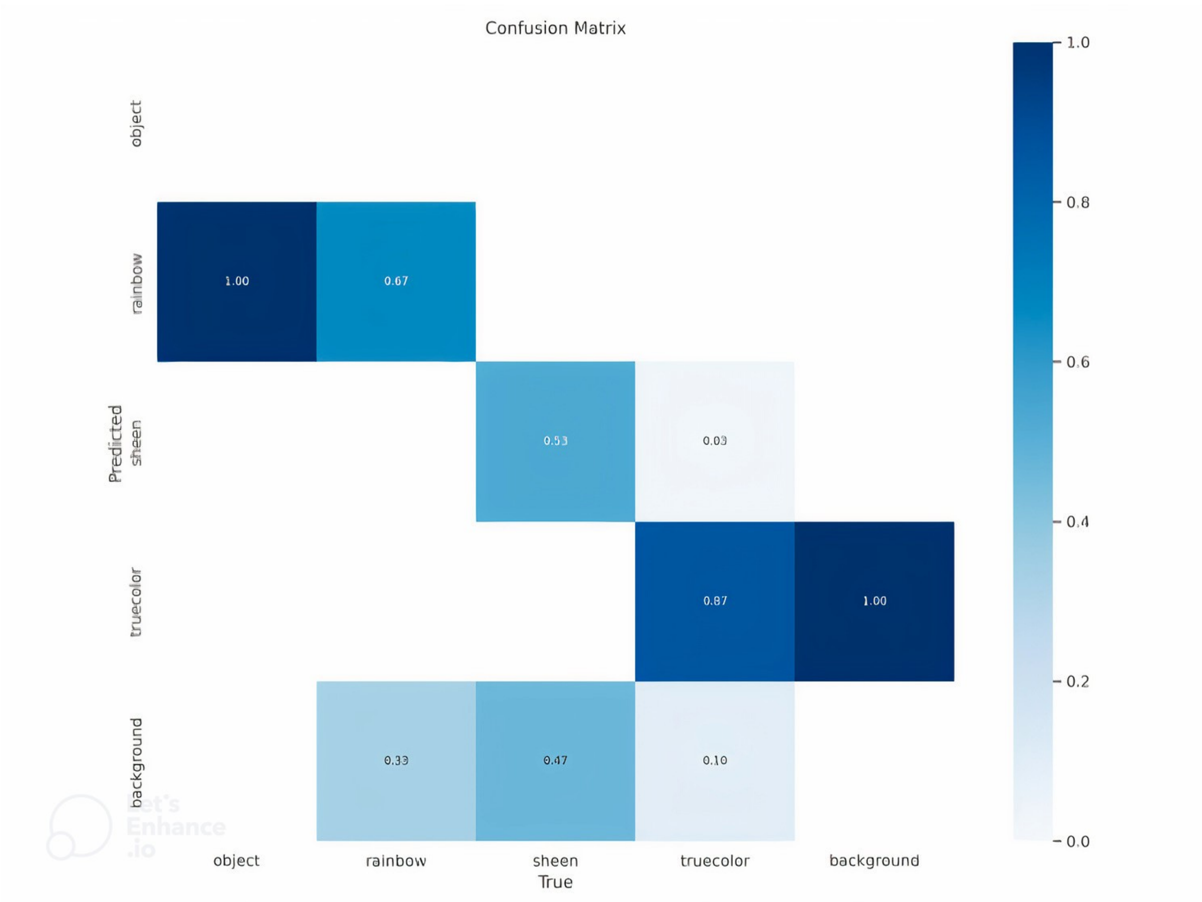

Figure 4: Confusion Matrix

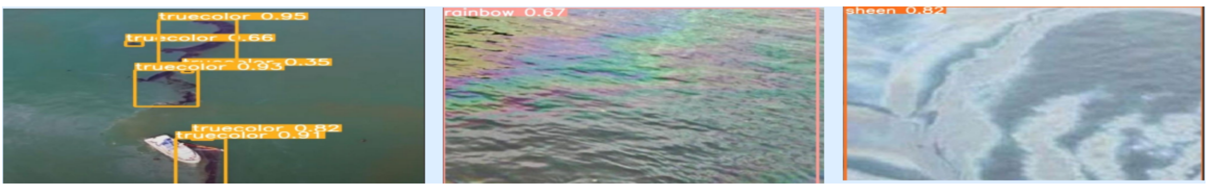

Figure 5: Test Images Output (1. Truecolor, 2. Rainbow, 3. Sheen)

In an effort to provide a comprehensive understanding of the model's accuracy, we utilized a confusion matrix visually represented through a heatmap. This matrix offers a clear depiction of the object detection rate, aiding in the nuanced evaluation of the model's strengths and areas for improvement.

To highlight the versatility of our model, we randomly selected examples of each colour shade of oil spills, presenting the detected objects alongside their corresponding accuracy values in the top left corner. This provides a practical insight into the model's capability to discern different types of oil spills with varying degrees of accuracy.

Additionally, the model's robustness was tested on drone video data, and the results are showcased in Figure 6. The accuracy values are prominently displayed in the top left corner, offering a concise overview of the model's performance in a real-world scenario.

Addressing the aspect of novelty, it is essential to emphasize that our choice of the YOLOv8 model is not merely a replication of existing methodologies. Instead, our innovation lies in the meticulous configuration, augmentation techniques, and strategic interventions applied to the YOLOv8 framework. This distinctive approach is geared towards addressing the limitations observed in current state-of-the-art methods, especially concerning generalization across diverse environmental conditions.

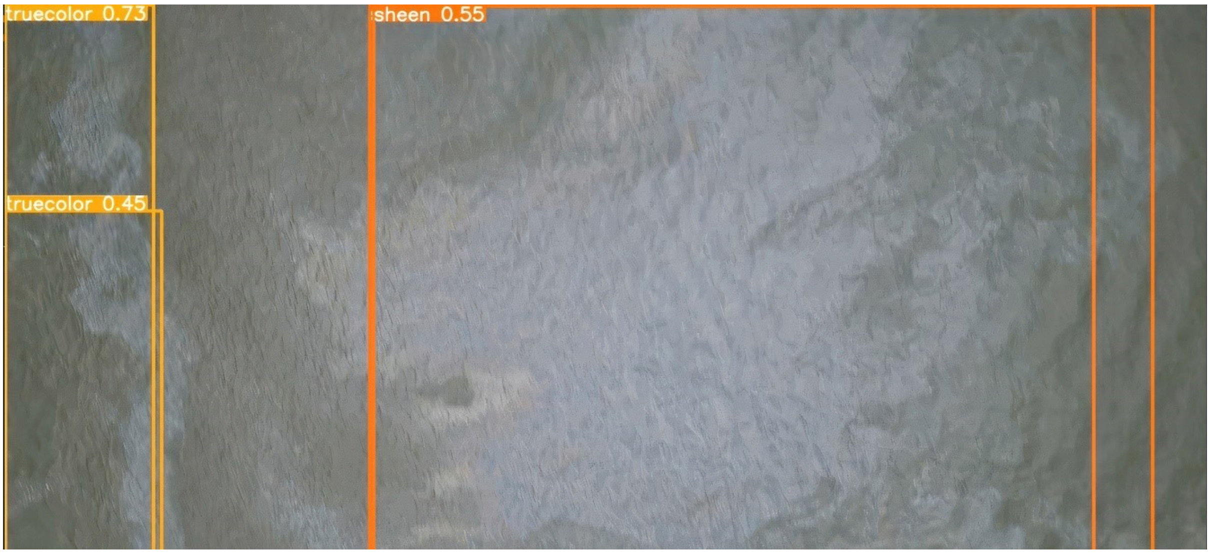

Figure 6: Test Video Output

Lastly, our results and discussions are framed with a focus on experiments that compare favourably to the state-of-the-art. The visualizations, metrics, and practical applications collectively underscore the effectiveness of our approach, reinforcing the nuanced improvements introduced to the YOLOv8 model for enhanced oil spill detection in dynamic settings.

5. Conclusion

In Conclusion, our investigation introduces a robust framework for detecting oil spills by integrating YOLOv8 with advanced computer vision methodologies. By capitalizing on YOLOv8's real-time object detection capabilities and the discriminative features of computer vision, our model demonstrates outstanding accuracy in pinpointing oil spills within satellite imagery. Rigorous benchmark assessments validate its superior performance when compared to existing methodologies, suggesting its potential for efficient utilization in monitoring and addressing oil spill incidents. The model's versatility in handling diverse environmental conditions, scalability, and seamless integration with prevailing monitoring systems underscore its practical utility. This research represents a notable advancement in optimizing the effectiveness of oil spill detection systems, aligning with broader objectives related to environmental preservation and prompt disaster response.

6. Scope for Future Work

A critical aspect of advancing the model's efficacy involves delving into regional optimization and tailoring the deep learning framework to accommodate the distinctive environmental characteristics of specific geographical regions. This adaptation process is key to enhancing the model's performance and increasing its applicability across diverse ecosystems. Additionally, a strategic exploration of multi-sensor fusion is imperative. Integrating data from various sensors, including Synthetic Aperture Radar (SAR) and optical sensors, presents an opportunity to create a more comprehensive and resilient oil spill detection system. The synergistic utilization of different sensing modalities holds the potential to elevate detection accuracy and reliability, particularly in the face of fluctuating environmental conditions. To further elevate the practical utility of the model, a concentrated effort on real-time deployment optimization is paramount. This entails refining the model's speed and efficiency in the detection algorithm, ensuring its responsiveness to emerging oil spill incidents in operational scenarios. In essence, these refinements contribute to the model's adaptability, robustness, and practical effectiveness across a spectrum of real-world applications.

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