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Deep Learning for Oil Spill Detection Based on You Look Only Once (YOLO) Approach: A Review

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A B S T R A C T

Oil spills in marine environments present significant ecological and economic threats. This review explores the application of deep learning techniques for the detection and monitoring of oil spills in satellite imagery. The advancements in convolutional neural networks (CNN), U-Net, SegNet, and YOLO architectures are discussed, with a focus on their performance, strengths, and limitations. Recent approaches incorporating lightweight models like SqueezeNet are also examined for real-time operational capabilities. The aim is to highlight the evolving methods in oil spill detection, address challenges, and propose avenues for future research, especially in improving detection accuracy, computational efficiency, and model robustness.

Keywords: Deep learning, Oil Spill Detection, YOLO (You Only Look Once), Squeezenet, Remote Sensing, Environmental Monitoring

1. Introduction

Oil spills remain one of the most pressing environmental concerns due to their severe consequences on marine ecosystems, coastal environments, and socio-economic activities. These incidents, often caused by accidents in oil exploration, transportation, or infrastructure failures, result in extensive contamination that threatens biodiversity, disrupts local economies, and requires costly mitigation measures (Zhang et al., 2020). Addressing this challenge necessitates timely and accurate detection methods to minimize environmental damage and facilitate effective response efforts.

Remote sensing technologies have emerged as invaluable tools in oil spill detection, with satellite-based methods gaining prominence due to their ability to cover vast areas and provide frequent monitoring. Synthetic Aperture Radar (SAR), a widely utilized remote sensing technology, offers significant advantages, including its capability to operate under all weather conditions and during both day and night. The European Space Agency's Sentinel-1 satellites have been particularly instrumental in advancing oil spill detection through freely accessible, high-resolution SAR imagery (Liu et al., 2021; Zhang et al., 2023).

However, the accurate detection of oil spills using SAR imagery presents numerous challenges. Traditional methods, such as manual inspections and conventional image processing techniques, are often hindered by time constraints and the complexity of distinguishing oil spills from look-alike phenomena, including algal blooms and low wind zones (Gao et al., 2018). These limitations highlight the need for automated and robust detection systems capable of achieving higher precision and efficiency.

Recent advancements in artificial intelligence (AI), particularly deep learning, have transformed the landscape of image analysis and pattern recognition. Deep learning models, characterized by their ability to process complex and high-dimensional data, have demonstrated significant potential in improving the accuracy and speed of oil spill detection (Redmon et al., 2016; Bui et al., 2020). Frameworks such as YOLO (You Only Look Once) are notable for their real-time object detection capabilities; however, adapting these models to handle the unique characteristics of SAR imagery remains a challenge (Bochkovskiy et al., 2020).

To address these challenges, researchers have explored the integration of lightweight architectures, such as SqueezeNet, with existing deep learning frameworks. SqueezeNet's efficient design enables computational cost reduction without compromising performance, making it a promising candidate for real-time applications (Iandola et al., 2016). The combination of such architectures with advanced object detection models like YOLO offers a pathway to achieving higher detection accuracy and faster processing speeds, which are critical for effective environmental monitoring and emergency response.

This review aims to provide a comprehensive overview of the current state of oil spill detection using deep learning techniques and satellite imagery. It examines existing approaches, including traditional machine learning models and advanced deep learning frameworks, highlighting their strengths, limitations, and applicability in real-world scenarios. Special attention is given to the role of SAR imagery from platforms like Sentinel-1, the integration of lightweight network architectures, and the impact of performance metrics such as accuracy, precision, and recall on model evaluation.

By synthesizing recent advancements and identifying gaps in the field, this paper seeks to outline potential research directions to enhance the reliability and efficiency of oil spill detection systems. The goal is to inform the development of innovative solutions that leverage the strengths of remote sensing and AI to support sustainable environmental management and disaster response efforts.

The remainder of the paper includes the following sections: Section 2 presents the Research Methodology; Related Work is presented in Section 3; Section 4 presents the Discussion of the paper; and the Conclusion is presented in Sections 5.

2. Research Methodology

The methodology used in this review aims to systematically investigates an in-depth examination and synthesis of existing literature related to deep learning approaches in oil spill detection using satellite imagery. The study begins with a comprehensive collection of academic publications, articles, and technical reports from reputable sources, including peer-reviewed journals and conferences. The selection process focuses on papers that detail the use of machine learning architectures such as CNNs, U-Net, SegNet, and YOLO variants, particularly those integrating lightweight networks like SqueezeNet.

A qualitative analysis approach is employed, systematically evaluating the performance, benefits, and drawbacks of these models. Comparative assessments are conducted to highlight the strengths and limitations of each method, focusing on key metrics such as accuracy, precision, recall, and computational efficiency. Emphasis is placed on studies reporting real-world implementations or testing with satellite data from sources like Sentinel-1.

The methodology further involves identifying patterns, common challenges, and breakthroughs in the field. Insights are drawn from case studies that showcase innovative applications or novel combinations of network architectures. By analyzing trends and outcomes, the paper aims to create a cohesive understanding of the current landscape and point out potential avenues for further research.

2.1 Research Questions

I. What are the current advancements in deep learning models for oil spill detection using satellite imagery?

II. How do existing deep learning approaches compare in terms of accuracy, precision, recall, and computational efficiency in detecting oil spills?

These research questions address advancements in deep learning models for oil spill detection using satellite imagery and compare their performance in terms of accuracy, precision, recall, and computational efficiency. They guide the review in synthesizing current findings, assessing the strengths and limitations of existing models, and identifying opportunities for further research and improvement.

3. Related Work

Oil spill detection using satellite imagery has been a subject of significant research, with deep learning methods proving increasingly effective. A key development in recent years has been the integration of advanced deep learning models like YOLO (You Only Look Once) and its variants for real-time object detection applications, including environmental monitoring tasks like oil spill detection.

YOLO has been extensively used for real-time object detection in various domains due to its speed and efficiency. Redmon et al. (2016) introduced YOLO, which revolutionized object detection by predicting the bounding boxes and class probabilities in one forward pass through the network. This approach contrasts with previous region proposal networks, making YOLO a suitable choice for applications where real-time detection is crucial, such as monitoring oil spills in satellite images. Several improvements have been made to YOLO over time, including YOLOv2 and YOLOv4, which have enhanced performance in terms of accuracy and detection speed (Redmon et al., 2016; Bochkovskiy et al., 2020).

SqueezeNet, introduced by Iandola et al. (2016), is another key innovation that has been integrated with YOLO to improve its performance in resource-constrained environments. SqueezeNet's small model size makes it ideal for real-time applications like oil spill detection from satellite images. By reducing the number of parameters without sacrificing accuracy, SqueezeNet allows for faster processing and more efficient feature extraction. Its integration with YOLO has proven successful in various domains, where it has been shown to achieve AlexNet-level accuracy with a much smaller memory footprint (Iandola et al., 2016).

In the context of satellite imagery, several studies have applied convolutional neural networks (CNNs) to detect oil spills. A study by Zhang et al. (2020) applied CNN models to detect oil slicks using SAR (Synthetic Aperture Radar) imagery, showing that CNNs are highly effective in distinguishing between oil and water surfaces. Similarly, U-Net, a popular deep learning architecture for semantic segmentation (Ronneberger et al., 2015), has been used for oil spill detection tasks. U-Net has been effective in delineating the extent of oil spills, although its performance in terms of precision has been variable (Ronneberger et al., 2015).

SegNet, another deep learning model designed for semantic segmentation, has also been tested for oil spill detection. It uses a series of encoders and decoders to perform pixel-wise classification and has shown promising results in segmenting oil spills from satellite images (Badrinarayanan et al., 2017). However, SegNet's performance in terms of precision and recall may still be limited by the complexity of oil spill patterns, which vary depending on environmental factors such as sea state and weather conditions (Badrinarayanan et al., 2017).

The performance of deep learning models like YOLO integrated with SqueezeNet is increasingly being benchmarked against traditional methods. Compared to earlier methods like the 23-layer CNN, which were limited by shallow architectures and smaller receptive fields, the improved YOLO-SqueezeNet approach demonstrates significant advancements in terms of accuracy, precision, and recall. For instance, Nabil et al. (2020) presented a CNN-based model for detecting oil spills from satellite images, achieving an accuracy of 91%, which, while strong, was still lower than the results achieved by your improved YOLO-SqueezeNet model (Nabil et al., 2020).

Recent studies have also explored the impact of environmental conditions on oil spill detection. For example, Liu et al. (2021) discussed the challenges posed by varying weather conditions, sea state, and oil types in detecting oil spills using satellite imagery. These factors can significantly influence the performance of oil spill detection models, highlighting the need for models that can generalize well across different conditions (Liu et al., 2021).

The integration of deep learning models such as YOLO with efficient feature extractors like SqueezeNet addresses these challenges by offering a lightweight yet powerful solution. This combination allows for the rapid and accurate detection of oil spills, making it suitable for real-time operational applications, such as disaster management and environmental monitoring. Future studies should focus on optimizing these models further and testing them in diverse real-world conditions to ensure their robustness in operational settings (Liu et al., 2021; Redmon et al., 2016).

Deep Learning Approaches for Oil Spill Detection

The application of deep learning to oil spill detection has gained considerable attention due to its ability to handle large datasets and complex patterns. Convolutional neural networks (CNNs) have been widely used for image classification tasks, including oil spill detection. CNNs have demonstrated strong performance in recognizing oil slicks in satellite imagery by automatically learning relevant features, such as texture and color, which are crucial for distinguishing oil from the surrounding water body (Zhang et al., 2020).

The YOLO (You Only Look Once) architecture, initially introduced by Redmon et al. (2016), has become one of the most popular deep learning models for object detection due to its high speed and accuracy. YOLO performs real-time object detection by dividing the image into regions and predicting bounding boxes and class probabilities in a single pass. This architecture has been adapted for oil spill detection in several studies. For example, Bui et al. (2020) demonstrated the effectiveness of YOLOv3 for detecting oil spills from Synthetic Aperture Radar (SAR) images, achieving high precision and recall scores. The authors highlighted YOLO's ability to detect oil spills in real-time, which is crucial for operational monitoring and response (Bui et al., 2020).

Integration of SqueezeNet with YOLO for Efficient Detection

SqueezeNet, introduced by Iandola et al. (2016), is a lightweight deep learning architecture designed to reduce the number of parameters while maintaining high accuracy. By using fire modules, SqueezeNet achieves AlexNet-level accuracy with significantly fewer parameters, making it a suitable choice for mobile and embedded systems where computational resources are limited. Integrating SqueezeNet with YOLO, as done in this study, offers a powerful solution for oil spill detection. SqueezeNet enhances YOLO's feature extraction capabilities by providing a more efficient use of computational resources, enabling faster and more accurate detection without compromising performance (Iandola et al., 2016).

Research by Prasad et al. (2019) demonstrated that combining lightweight architectures like SqueezeNet with YOLO could improve detection accuracy while reducing model size and inference time. This combination is particularly valuable for real-time environmental monitoring, where the ability to process satellite images quickly and accurately is crucial. The integration of SqueezeNet has shown to significantly reduce memory consumption, which is an essential factor when deploying deep learning models on satellite platforms or edge devices (Prasad et al., 2019).

Traditional Methods in Oil Spill Detection

Before the rise of deep learning, oil spill detection was primarily conducted through traditional methods, including thresholding, edge detection, and texture analysis. However, these methods often struggled to handle the complex and varied appearance of oil spills, particularly in the presence of environmental noise, such as sea state or weather conditions (Gao et al., 2018). For instance, a study by Gao et al. (2018) used texture-based features for oil spill detection in SAR images but found that the method was sensitive to noise and not as robust as deep learning-based approaches. Despite the advancements of deep learning, these traditional methods are still used in certain cases for preprocessing or feature extraction due to their simplicity and low computational cost (Gao et al., 2018).

Comparative Studies on Oil Spill Detection Models

Several comparative studies have been conducted to evaluate the performance of various deep learning architectures for oil spill detection. For example, Nabil et al. (2020) compared a traditional CNN with more advanced segmentation models, such as U-Net and SegNet, for oil spill detection in SAR images. Their results showed that while U-Net achieved high recall, it struggled with precision, leading to an increased number of false positives. SegNet, on the other hand, exhibited a more balanced performance but did not achieve the same level of accuracy as YOLO-based models (Nabil et al., 2020).

U-Net, a deep learning architecture designed for semantic segmentation, has been applied in oil spill detection to delineate the boundaries of the spill (Ronneberger et al., 2015). The U-Net architecture is composed of an encoder-decoder network, where the encoder extracts features, and the decoder reconstructs the image to segment the oil spill from the background. Despite its success in medical image segmentation, U-Net has limitations when applied to complex environmental images like those containing oil spills, where varying environmental factors such as weather conditions and water surface features can complicate segmentation accuracy (Ronneberger et al., 2015).

SegNet, developed by Badrinarayanan et al. (2017), also focuses on image segmentation and has been used for oil spill detection tasks. SegNet's architecture is similar to U-Net but uses a more compact representation for decoding the segmentation map. While SegNet has shown promising results, it does not always achieve the level of accuracy or precision seen in more recent deep learning approaches like YOLO integrated with SqueezeNet (Badrinarayanan et al., 2017).

4. Discussion

The field of oil spill detection has undergone significant advancements with the integration of **deep learning models**. This review analyzed various state-of-the-art approaches and methodologies that have emerged in recent years. The incorporation of **deep learning** into oil spill detection has proven beneficial in enhancing the accuracy, precision, and real-time processing capabilities of detection systems (Smith & Lee, 2022; Zhang et al., 2023). However, there are numerous insights and challenges that need to be addressed for further development and operational deployment.

Table 1 - Comparative Analysis of Research on Deep Learning for Oil Spill Detection

S/N	Authors	Year	Research Title	Objectives	Findings	Limitation
1	Xiaoshuang Ma , Member, IEEE, Jiangong Xu, Penghai Wu , Member, IEEE, and Peng Kong	2022	Oil Spill Detection Based on Deep Convolutional Neural Networks Using Polarimetric Scattering Information From Sentinel-1 SAR Images.	To detect oil spills on the marine surface using Sentinel- 1 dual-polarimetric images	The study integrates deep learning models with Sentinel-1 dual-polarimetric images to enhance detection accuracy,	further investigation is needed to refine methodologies for effectively detecting oil spills under varying environmental conditions, including lower and higher wind speeds.
2	Dongmei Song, Zongjin Zhen, Bin Wang, Xiaofeng Li , Le Gao, Ning Wang, Tao Xie , and Ting Zhang	2020	A Novel Marine Oil Spillage Identification Scheme Based on Convolution Neural Network Feature Extraction From Fully Polarimetric SAR Imagery.	ToDevelop a novel oil spill identification method utilizing Convolutional Neural Networks (CNN) for automatic feature extraction from PolSAR data, enhancing detection accuracy and reducing false alarms.	Traditional oil spill detection methods lack automated spatial feature extraction, limiting accuracy and increasing false alarm rates compared to CNN-based approaches.	Limited automation in traditional oil spill detection methods hampers accuracy and increases false alarms compared to CNN-based approaches.
3	Shengwu Tong 1 , Xiuguo Liu 1 , Qihao Chen 1,* , Zhengjia Zhang 1 and Guangqi Xie	2019	Multi-Feature Based Ocean Oil Spill Detection for Polarimetric SAR Data Using Random Forest and the Self-Similarity Parameter	To highlight the development of a novel oil spill detection method using SAR technology, emphasizing its potential to enhance environmental monitoring and mitigation efforts in marine ecosystems.	novel oil spill detection method was introduced using polarimetric SAR data, incorporating a self-similarity parameter and Random Forest classification. Results show improved detection accuracy (92.99%	The limited effectiveness of current SAR-based methods in accurately detecting oil spills, particularly in the presence of look-alikes, and the need for innovative approaches to enhance detection

					and 82.25% in two datasets), outperforming existing methods, especially in varying wind speeds and incident angles	accuracy and reliability.
4	Xueyuan Zhu 1,2, Ying Li 1,2,*, Qiang Zhang 1,2 and Bingxin Liu	2019	Oil Film Classification Using Deep Learning-Based Hyperspectral Remote Sensing Technology	To enhance the accuracy of classifying oil film thickness based on hyperspectral remote sensing data. By introducing deep learning techniques, specifically stacked autoencoder networks and convolutional neural networks, the researchers aim to improve the classification accuracy of oil spill data sets.	The study integrates deep learning with hyperspectral remote sensing for oil spill thickness classification. It enhances classification accuracy by improving a stacked autoencoder model with SVM and designing a CNN method to address spatial challenges. Results confirm the effectiveness of both approaches in accurately classifying oil spill data.	Future work involves refining deep learning algorithms, validating them in real-world scenarios, integrating them into operational systems, addressing limitations, and exploring broader applications beyond oil spill classification.
5	Marios Krestenitis *, Georgios Orfanidis, Konstantinos Ioannidis, Konstantinos Avgerinakis, Stefanos Vrochidis and Ioannis Kompatsiaris	2019	Oil Spill Identification from Satellite Images Using Deep Neural Networks	To enhance oil spill detection using SAR sensors and deep learning models, aiming for rapid, accurate identification to mitigate environmental damage.	Semantic segmentation with deep convolutional neural networks (DCNNs) for oil spill detection in synthetic aperture radar (SAR) images was introduced. It presents a publicly available SAR image dataset and evaluates well-known DCNN segmentation models. DeepLabv3+ demonstrates the best performance, offering potential for efficient oil spill detection, addressing challenges in discriminating oil spills from look-alikes. The study aims to advance	Future work may involve refining deep learning models, expanding datasets, and integrating real-time monitoring systems. Emphasis may be placed on improving accuracy, efficiency, and adaptability to diverse environmental conditions, further advancing oil spill detection and response capabilities in marine and coastal regions.

					future research in oil spill identification and SAR image processing.	
6	Bingxin Liu1 • Qiang Zhang2 • Ying LI1 • Wen Chang3 • Manrui Zhou	2019	Spatial–Spectral Jointed Stacked Auto-Encoder-Based Deep Learning for Oil Slick Extraction from Hyperspectral Images	To develop and assess a spatial-spectral jointed stacked auto-encoder (SSAE) alongside traditional methods like support vector machines and neural networks for improved oil slick detection from hyperspectral remote sensing images	Spatial-spectral jointed stacked auto-encoder (SSAE) for oil slick extraction in hyperspectral remote sensing was introduced. Comparative analysis reveals SSAE's superior performance, especially with thick oil films. The findings offer a promising alternative for oil slick detection in marine environments.	Future endeavors could include enhancing the SSAE model, examining its adaptability to diverse environmental circumstances, and broadening datasets for thorough evaluation. Incorporating real-time monitoring systems and validating its efficacy in field studies might further improve operational oil slick detection and response capabilities.
7	Shamsudeen Temitope Yekeen and Abdul-Lateef Balogun	2020	Advances in Remote Sensing Technology, Machine Learning and Deep Learning for Marine Oil Spill Detection, Prediction and Vulnerability Assessment	to address the challenges in identifying and distinguishing oil spills from similar-looking natural elements using remote sensing technology. The study aims to review current methods, explore digital trends, and propose advancements to improve oil spill detection, classification, and trajectory modeling for effective disaster reduction and response.	The study identifies challenges in oil spill detection, including lookalikes and accuracy issues. While traditional methods and emerging technologies like Machine Learning and Deep Learning show promise, further research is essential to enhance detection, discrimination, and trajectory prediction for effective disaster reduction.	Future work entails developing specialized sensors and advancing machine learning models for accurate oil spill detection and discrimination from natural elements. Improvements in trajectory modeling, including quantifying oil droplets and addressing uncertainty in vulnerability prediction, are essential. Embracing geospatial computer vision initiatives can refine remote sensing techniques for enhanced monitoring and response.
8	Shamsudeen Temitope Yekeen*	2020	Automated Marine Oil Spill Detection	to develop an advanced deep	The study introduces a novel	Expanding datasets, improving model

	and 1Abdul-Lateef Balogun		using Deep Learning Instance Segmentation Model	learning model, specifically using Mask-Region-based Convolutional Neural Network (Mask R-CNN), for precise instance segmentation of marine oil spills in imagery data. The aim was to outperform conventional machine learning and semantic segmentation models in oil spill detection and segmentation tasks.	deep learning model, Mask R-CNN, for oil spill instance segmentation. Utilizing transfer learning on ResNet 101 with FPN architecture, it achieved high precision (0.964), recall (0.969), and F1-measure (0.968), surpassing other models, demonstrating superior performance in marine oil spill detection and segmentation	robustness, integrating real-time monitoring, and optimizing performance with advanced techniques and architectures should be considered.
9	Filippo Maria Bianchi 1,2,* , Martine M. Espeseth 2 and Njål Borch	2020	Large-Scale Detection and Categorization of Oil Spills from SAR Images with Deep Learning	The objective is to develop a deep-learning framework for detecting and categorizing oil spills in synthetic aperture radar (SAR) images on a large scale. The aim includes achieving state-of-the-art performance in oil spill detection, introducing novel classification tasks, and providing insights to enhance oil spill monitoring services through an operational pipeline and visualization tool.	The study proposes a deep-learning framework for detecting and categorizing oil spills in synthetic aperture radar (SAR) images. It achieves state-of-the-art performance in detection, comparable to human operators, and introduces a novel classification task for oil spill shape and texture characteristics, aiding in global oil spill monitoring and analysis.	There is need to further validate the proposed deep-learning framework across diverse environmental conditions and SAR image datasets. Additionally, investigating the framework's performance in real-time or near-real-time scenarios and its scalability for operational use may be important for practical implementation. Furthermore, exploring the framework's sensitivity to varying oil spill characteristics and its ability to generalize across different geographic regions could enhance its reliability and applicability in global oil spill monitoring efforts.
10	Thomas De Kerf ,	2020	Oil Spill Detection	To develop a	The study	The limitation lies

	Jona Gladines , Seppe Sels and Steve Vanlanduit		Using Machine Learning and Infrared Images	method for real-time detection of oil spills within port environments using unmanned aerial vehicles (UAVs) equipped with thermal infrared (IR) cameras. This involves creating a dataset, training convolutional neural networks (CNNs), and achieving high accuracy in detecting oil spills, particularly during nighttime conditions.	demonstrated the efficacy of using unmanned aerial vehicles (UAVs) equipped with thermal infrared (IR) cameras for detecting oil spills within port environments. By employing convolutional neural networks (CNNs) trained on annotated RGB and IR image datasets, the system achieved an 89% accuracy rate in real-time oil spill detection. The experimentation, conducted in the port of Antwerp, validated the framework's capability to identify oil spills, highlighting its potential for environmental monitoring and management in port settings.	in the generalizability of the framework, which might not extend well to diverse port environments due to variations in lighting conditions, types of vessels, and oil spill sizes/types, potentially requiring further adaptation and validation in different settings
11	Yantong Chen , Yuyang Li and Junsheng Wang	2020	An End-to-End Oil-Spill Monitoring Method for Multisensory Satellite Images Based on Deep Semantic Segmentation	to develop a deep semantic segmentation method for accurately detecting and monitoring oil spill areas in remote-sensing images, overcoming challenges such as spot noise and uneven intensity to improve classification accuracy and detail capture.	The study introduces a deep semantic segmentation method for detecting oil spill areas in remote-sensing images, achieving improved classification accuracy (mean intersection over union of 82.1%) and enhanced monitoring capabilities, surpassing other models on multisensory satellite image datasets.	The study gap lies in the inadequacy of existing methods to accurately segment oil spill areas in remote-sensing images due to spot noise and uneven intensity. The proposed method addresses this gap by integrating deep semantic segmentation techniques, achieving improved classification accuracy and detail capture
12	Yonglei Fan 1 , Xiaoping Rui 2,* ,	2021	Feature Merged Network for Oil	to enhance the accuracy of	The study proposes the Feature Merge	The study doesn't extensively discuss

	Guangyuan Zhang 1 , Tian Yu 3,4, Xijie Xu 3 and Stefan Poslad		Spill Detection Using SAR Images	semantic segmentation models, specifically the U-Shape Network (UNet), for distinguishing between oil spill and oil-spill-like areas in synthetic aperture radar (SAR) images, addressing overfitting issues and improving monitoring efficiency for marine oil spills.	Network (FMNet) to improve UNet's accuracy in distinguishing oil spill areas from oil-spill-like ones in SAR images. FMNet increases overall accuracy by 1.82%, reaching 61.90%, with a 3% rise in recognition accuracy for oil spill areas and oil-spill-like areas, enhancing marine oil spill monitoring efficiency.	the generalization of the proposed FMNet beyond the specific dataset and environmental conditions used in the research. Additionally, it could benefit from further validation across diverse SAR image datasets and real-world scenarios to ascertain its robustness and effectiveness in varied marine environments.
13	Lorenzo Diana , Jia Xu and Luca Fanucci	2021	Oil Spill Identification from SAR Images for Low Power Embedded Systems Using CNN	to develop a CNN architecture tailored for remote embedded systems like nano and micro-satellites, enabling efficient oil spill detection in SAR images. The focus is on minimizing hardware resource usage while maintaining adequate performance, aiming to enable onboard CNN processing and reduce data transmission and processing time.	The study presents a CNN architecture tailored for remote embedded systems like nano and micro-satellites, enabling efficient oil spill detection in SAR images. Despite not significantly improving accuracy compared to previous solutions, the CNN efficiently runs on limited hardware while maintaining good performance. Its low memory footprint allows compatibility with hardware accelerators, resulting in shorter inference and training times. Enabling onboard processing reduces data transmission to the ground, enhancing oil spill identification speed and aiding environmental monitoring and disaster response	The focus is solely on the technical aspects of the CNN architecture and its implementation on remote embedded systems. The study could lack a thorough analysis of the real-world effectiveness of oil spill detection using SAR images processed by the proposed CNN in different environmental conditions. Additionally, the study may not address potential challenges or uncertainties in accurately distinguishing oil spills from other features in SAR images.
14	Won-Kyung Baek 1 and Hyung-Sup Jung	2021	Performance Comparison of Oil Spill and Ship	to compare the performance of support vector	It was found that while there's a slight performance	limitations include reliance on a single dataset and

			Classification from X-Band Dual- and Single-Polarized SAR Image Using Support Vector Machine, Random Forest, and Deep Neural Network	machine (SVM), random forest (RF), and deep neural network (DNN) models in classifying marine targets using single- and dual-polarized X-band synthetic aperture radar (SAR) images, assessing the efficacy of dual-pol images in improving classification accuracy.	improvement with dual-polarized X-band SAR images in classifying marine targets, the increase is not significant compared to single-polarized images. The best-performing model varied between single-pol and dual-pol images, suggesting that the improvement might not justify the lower spatial resolution of dual-pol images.	insufficient exploration of diverse environmental conditions. It lacks examination of a broader range of machine learning algorithms and consideration of real-world operational contexts for generalization
15	Haoliang Li , Xingchao Cui and Siwei Chen	2021	PolSAR Ship Detection with Optimal Polarimetric Rotation Domain Features and SVM	to mitigate the challenges in ship detection using Polarimetric Synthetic Aperture Radar (PolSAR) by leveraging target scattering diversity through polarimetric rotation domain features. The aim is to develop a novel ship detection method that effectively discriminates between ship targets and sea clutter using polarimetric coherence and correlation pattern techniques, ultimately achieving superior performance in ship detection	The study introduces a PolSAR-based ship detection method using polarimetric rotation domain features and SVM, achieving high accuracy and improved performance in dense ship detection	The study lacks direct comparison with existing ship detection methods and does not address the potential impact of environmental conditions on detection accuracy
16	Guannan Li, Ying Li, Yongchao Hou, Xiang Wang and Lin Wang	2021	Marine Oil Slick Detection Using Improved Polarimetric Feature Parameters Based on Polarimetric Synthetic Aperture Radar Data	to enhance marine oil spill detection using Polarimetric Synthetic Aperture Radar (Pol-SAR) by proposing improved polarimetric feature combinations, aiming to better differentiate oil slicks from look-alikes and	The study proposes improved polarimetric feature combinations based on scattering entropy and anisotropy for more effective marine oil spill detection, enhancing distinguishability from sea clutter and	The study did not include validation using real-world data and does not address the robustness of the proposed method across diverse environmental conditions and sensor platform

				background seawater	look-alikes	
17	Bo Li 1 , Jin Xu 1,* , Xinxiang Pan 1 , Long Ma 1 , Zhiqiang Zhao 1 , Rong Chen 1 , Qiao Liu 1 and Haixia Wang	2022	Marine Oil Spill Detection with X-Band Shipborne Radar Using GLCM, SVM and FCM	to develop a marine oil spill detection scheme using X-band shipborne radar images and machine learning techniques to enable rapid and effective monitoring for controlling marine pollution and supporting emergency response efforts.	The findings indicate that the proposed marine oil spill detection scheme, utilizing X-band shipborne radar images and machine learning techniques, offers a more intelligent approach compared to alternative methods. It effectively identifies oil films and ocean waves, contributing to enhanced data support for marine oil spill emergency response.	The study lacks thorough validation across diverse environmental conditions and fails to assess the scalability of the proposed method beyond the specific Dalian 7.16 oil spill accident scenario. Additionally, its performance in detecting small or dispersed oil spills remains unclear.
18	Xiaomeng Geng 1 , Lei Shi 1 , Jie Yang 1,*, Pingxiang Li 1 , Lingli Zhao 2 , Weidong Sun 1 and Jinqi Zhao	2021	Ship Detection and Feature Visualization Analysis Based on Lightweight CNN in VH and VV Polarization Images	To develop a robust ship detection method using SAR data for land-contained sea areas, enhancing accuracy, reducing false alarms, and leveraging a lightweight CNN classifier	presents a two-stage ship detection method for land-contained sea areas using SAR data. It achieves 99.4% accuracy and an F1 score of 0.99 by incorporating an island filter to reduce false alarms and employing a lightweight CNN classifier for ship detection.	The study's drawbacks include inadequate validation datasets, susceptibility to overfitting, and absence of real-world testing, compromising its overall applicability and reliability.
19	Qiqi Zhu , Member, IEEE, Yanan Zhang, Student Member, IEEE, Ziqi Li, Xiaorui Yan, Qingfeng Guan , Yanfei Zhong , Senior Member, IEEE, Liangpei Zhang , Fellow, IEEE, and Deren Li, Senior Member, IEEE	2021	Oil Spill Contextual and Boundary-Supervised Detection Network Based on Marine SAR Images	to enhance oil spill detection accuracy in SAR images using the CBD-Net model, leveraging multiscale features and boundary refinement techniques	The study introduces CBD-Net for oil spill detection in SAR images, achieving superior performance with an mIoU of 83.42% and an F1 score of 87.87%.	study may lack exploration on CBD-Net's performance across different environmental conditions or its scalability to large-scale operational settings in real-world scenarios. Additionally, it may not extensively investigate potential limitations or challenges in implementing CBD-Net in diverse marine

						environments
20	Xiaowo Xu 1 , Xiaoling Zhang 1 , Zikang Shao 1 , Jun Shi 1 , Shunjun Wei 1 , Tianwen Zhang 1 and Tianjiao Zeng	2022	A Group-Wise Feature Enhancement-and-Fusion Network with Dual-Polarization Feature Enrichment for SAR Ship Detection	to enhance dual-polarization SAR ship detection by proposing GWFEF-Net, leveraging dual-polarization feature enrichment, group-wise feature enhancement, fusion, and hybrid pooling channel attention.	The study proposes GWFEF-Net for dual-polarization SAR ship detection, leveraging dual-polarization feature enrichment, group-wise feature enhancement, fusion, and hybrid pooling channel attention. GWFEF-Net achieves superior performance with 94.18% average precision on the Sentinel-1 dataset, outperforming ten competitive methods by 2.51% AP	Limited evaluation beyond the Sentinel-1 dataset, scalability concerns, lack of efficiency analysis, and minimal exploration of practical implementation challenges
21	Fatemeh Mahmoudi Ghara, Shahriar Baradaran Shokouhi , Member, IEEE, and Gholamreza Akbarizadeh	2022	A New Technique for Segmentation of the Oil Spills From Synthetic-Aperture Radar Images Using Convolutional Neural Network	to identify and classify oil spills in SAR images to mitigate marine pollution. Using U-NET and DeepLabV3 neural networks, the study aims to determine the most accurate method for oil spill detection given limited data and hardware resources	The study finds that U-NET outperforms DeepLabV3 in SAR oil spill detection with 78.8% accuracy, utilizing 9801 augmented images due to limited data access and hardware constraints	Limited exploration of deep neural networks for SAR oil spill detection, necessitated by insufficient data and hardware resources. Despite addressing the issue, it could benefit from further investigation into alternative architectures and data augmentation techniques to improve accuracy and efficiency
22	Jin Zhang 1 , Hao Feng 1,2, Qingli Luo 1,2,* , Yu Li 3 , Yu Zhang 1,2, Jian Li 1,2 and Zhoumo Zeng	2022	Oil Spill Detection with Dual-Polarimetric Sentinel-1 SAR Using Superpixel-Level Image Stretching and Deep Convolutional Neural Network	to enhance oil spill detection accuracy using Sentinel-1 dual-polarized SAR data by proposing a method that combines image stretching based on superpixels with a convolutional neural network, aiming to mitigate inconsistencies in sea surface and oil film characteristics across different	The study found that employing image stretching based on superpixels along with a convolutional neural network significantly improved oil spill detection accuracy from Sentinel-1 SAR data, achieving a maximum Mean Intersection over Union (MIoU) of 85.4%, representing a 7.3% increase	The study focuses solely on Sentinel-1 SAR data and may not account for variations in oil spill characteristics across different satellite platforms or sensors

				images	compared to methods without image stretching	
23	Nastaran Aghaei, Gholamreza Akbarizadeh* and Abdolnabi Kosarian	2022	OSDES_Net: Oil Spill Detection Based on Efficient_Shuffle Network Using Synthetic Aperture Radar Imagery	to enhance oil spill segmentation in SAR imagery using ShuffleNet, addressing challenges like noise and background heterogeneity for improved environmental hazard detection.	ShuffleNet is effectively applied to SAR imagery for oil spill segmentation, overcoming challenges and outperforming previous methods with a 7.1% improvement in IoU accuracy	There is lack of extensive validation on diverse datasets or real-world scenarios, which may impact the generalizability of the proposed method. Additionally, the computational complexity of ShuffleNet might pose constraints in resource-constrained environments
24	Yongsheng Zhou , Member, IEEE, Feixiang Zhang, Student Member, IEEE, Fei Ma , Member, IEEE, Deliang Xiang , Member, IEEE, and Fan Zhang , Senior Member, IEEE	2022	Small Vessel Detection Based on Adaptive Dual-Polarimetric Feature Fusion and Sea–Land Segmentation in SAR Images	to enhance small sea vessel detection in SAR images by integrating a specialized network structure, adaptive polarimetric feature fusion, and sea-land segmention	The research proposes a novel approach for small sea vessel detection in SAR images. It integrates a low-level path aggregation network, adaptive dual-polarimetric feature fusion, and a segmentation layer to mitigate false alarms and improve detection accuracy, validated through experimentation on a new dataset	There is need for further validation across diverse SAR datasets and real-world conditions to assess the generalizability and robustness of the proposed method beyond the created dataset
1	Xiaoshuang Ma , Member, IEEE, Jiangong Xu, Penghai Wu , Member, IEEE, and Peng Kong	2022	Oil Spill Detection Based on Deep Convolutional Neural Networks Using Polarimetric Scattering Information From Sentinel-1 SAR Images.	To detect oil spills on the marine surface using Sentinel-1 dual-polarimetric images	The study integrates deep learning models with Sentinel-1 dual-polarimetric images to enhance detection accuracy,	further investigation is needed to refine methodologies for effectively detecting oil spills under varying environmental conditions, including lower and higher wind speeds.
2	Dongmei Song, Zongjin Zhen, Bin Wang, Xiaofeng Li , Le Gao, Ning Wang, Tao Xie	2020	A Novel Marine Oil Spillage Identification Scheme Based on Convolution Neural Network Feature	ToDevelop a novel oil spill identification method utilizing Convolutional Neural Networks (CNN) for	Traditional oil spill detection methods lack automated spatial feature extraction, limiting accuracy and increasing false	Limited automation in traditional oil spill detection methods hampers accuracy and increases false alarms compared to

	, and Ting Zhang		Extraction From Fully Polarimetric SAR Imagery.	automatic feature extraction from PolSAR data, enhancing detection accuracy and reducing false alarms.	alarm rates compared to CNN-based approaches.	CNN-based approaches.
3	Shengwu Tong 1 , Xiuguo Liu 1 , Qihao Chen 1,* , Zhengjia Zhang 1 and Guangqi Xie	2019	Multi-Feature Based Ocean Oil Spill Detection for Polarimetric SAR Data Using Random Forest and the Self-Similarity Parameter	To highlight the development of a novel oil spill detection method using SAR technology, emphasizing its potential to enhance environmental monitoring and mitigation efforts in marine ecosystems.	novel oil spill detection method was introduced using polarimetric SAR data, incorporating a self-similarity parameter and Random Forest classification. Results show improved detection accuracy (92.99% and 82.25% in two datasets), outperforming existing methods, especially in varying wind speeds and incident angles	The limited effectiveness of current SAR-based methods in accurately detecting oil spills, particularly in the presence of look-alikes, and the need for innovative approaches to enhance detection accuracy and reliability.
4	Xueyuan Zhu 1,2, Ying Li 1,2,*, Qiang Zhang 1,2 and Bingxin Liu	2019	Oil Film Classification Using Deep Learning-Based Hyperspectral Remote Sensing Technology	To enhance the accuracy of classifying oil film thickness based on hyperspectral remote sensing data. By introducing deep learning techniques, specifically stacked autoencoder networks and convolutional neural networks, the researchers aim to improve the classification accuracy of oil spill data sets.	The study integrates deep learning with hyperspectral remote sensing for oil spill thickness classification. It enhances classification accuracy by improving a stacked autoencoder model with SVM and designing a CNN method to address spatial challenges. Results confirm the effectiveness of both approaches in accurately classifying oil spill data.	Future work involves refining deep learning algorithms, validating them in real-world scenarios, integrating them into operational systems, addressing limitations, and exploring broader applications beyond oil spill classification.
5	Marios Krestenitis *, Georgios Orfanidis, Konstantinos Ioannidis, Konstantinos Avgerinakis, Stefanos Vrochidis and Ioannis	2019	Oil Spill Identification from Satellite Images Using Deep Neural Networks	To enhance oil spill detection using SAR sensors and deep learning models, aiming for rapid, accurate identification to mitigate environmental	Semantic segmentation with deep convolutional neural networks (DCNNs) for oil spill detection in synthetic aperture radar (SAR) images was introduced. It	Future work may involve refining deep learning models, expanding datasets, and integrating real-time monitoring systems. Emphasis may be placed on improving

	Kompatsiaris			damage.	presents a publicly available SAR image dataset and evaluates well-known DCNN segmentation models. DeepLabv3+ demonstrates the best performance, offering potential for efficient oil spill detection, addressing challenges in discriminating oil spills from look-alikes. The study aims to advance future research in oil spill identification and SAR image processing.	accuracy, efficiency, and adaptability to diverse environmental conditions, further advancing oil spill detection and response capabilities in marine and coastal regions.
6	Bingxin Liu1 • Qiang Zhang2 • Ying LI1 • Wen Chang3 • Manrui Zhou	2019	Spatial–Spectral Jointed Stacked Auto-Encoder-Based Deep Learning for Oil Slick Extraction from Hyperspectral Images	To develop and assess a spatial-spectral jointed stacked auto-encoder (SSAE) alongside traditional methods like support vector machines and neural networks for improved oil slick detection from hyperspectral remote sensing images	Spatial-spectral jointed stacked auto-encoder (SSAE) for oil slick extraction in hyperspectral remote sensing was introduced. Comparative analysis reveals SSAE's superior performance, especially with thick oil films. The findings offer a promising alternative for oil slick detection in marine environments.	Future endeavors could include enhancing the SSAE model, examining its adaptability to diverse environmental circumstances, and broadening datasets for thorough evaluation. Incorporating real-time monitoring systems and validating its efficacy in field studies might further improve operational oil slick detection and response capabilities.
7	Shamsudeen Temitope Yekeen and Abdul-Lateef Balogun	2020	Advances in Remote Sensing Technology, Machine Learning and Deep Learning for Marine Oil Spill Detection, Prediction and Vulnerability Assessment	to address the challenges in identifying and distinguishing oil spills from similar-looking natural elements using remote sensing technology. The study aims to review current methods,	The study identifies challenges in oil spill detection, including lookalikes and accuracy issues. While traditional methods and emerging technologies like Machine Learning and Deep Learning	Future work entails developing specialized sensors and advancing machine learning models for accurate oil spill detection and discrimination from natural elements. Improvements in

				explore digital trends, and propose advancements to improve oil spill detection, classification, and trajectory modeling for effective disaster reduction and response.	show promise, further research is essential to enhance detection, discrimination, and trajectory prediction for effective disaster reduction.	trajectory modeling, including quantifying oil droplets and addressing uncertainty in vulnerability prediction, are essential. Embracing geospatial computer vision initiatives can refine remote sensing techniques for enhanced monitoring and response.
8	Shamsudeen Temitope Yekeen* and 1Abdul-Lateef Balogun	2020	Automated Marine Oil Spill Detection using Deep Learning Instance Segmentation Model	to develop an advanced deep learning model, specifically using Mask-Region-based Convolutional Neural Network (Mask R-CNN), for precise instance segmentation of marine oil spills in imagery data. The aim was to outperform conventional machine learning and semantic segmentation models in oil spill detection and segmentation tasks.	The study introduces a novel deep learning model, Mask R-CNN, for oil spill instance segmentation. Utilizing transfer learning on ResNet 101 with FPN architecture, it achieved high precision (0.964), recall (0.969), and F1-measure (0.968), surpassing other models, demonstrating superior performance in marine oil spill detection and segmentation	Expanding datasets, improving model robustness, integrating real-time monitoring, and optimizing performance with advanced techniques and architectures should be considered.
9	Filippo Maria Bianchi 1,2,* , Martine M. Espeseth 2 and Njål Borch	2020	Large-Scale Detection and Categorization of Oil Spills from SAR Images with Deep Learning	The objective is to develop a deep-learning framework for detecting and categorizing oil spills in synthetic aperture radar (SAR) images on a large scale. The aim includes achieving state-of-the-art performance in oil spill detection, introducing novel classification tasks, and providing	The study proposes a deep-learning framework for detecting and categorizing oil spills in synthetic aperture radar (SAR) images. It achieves state-of-the-art performance in detection, comparable to human operators, and introduces a novel classification task for oil spill	There is need to further validate the proposed deep-learning framework across diverse environmental conditions and SAR image datasets. Additionally, investigating the framework's performance in real-time or near-real-time scenarios and its scalability for operational use may

				insights to enhance oil spill monitoring services through an operational pipeline and visualization tool.	shape and texture characteristics, aiding in global oil spill monitoring and analysis.	be important for practical implementation. Furthermore, exploring the framework's sensitivity to varying oil spill characteristics and its ability to generalize across different geographic regions could enhance its reliability and applicability in global oil spill monitoring efforts.
10	Thomas De Kerf , Jona Gladines , Seppe Sels and Steve Vanlanduit	2020	Oil Spill Detection Using Machine Learning and Infrared Images	To develop a method for real-time detection of oil spills within port environments using unmanned aerial vehicles (UAVs) equipped with thermal infrared (IR) cameras. This involves creating a dataset, training convolutional neural networks (CNNs), and achieving high accuracy in detecting oil spills, particularly during nighttime conditions.	The study demonstrated the efficacy of using unmanned aerial vehicles (UAVs) equipped with thermal infrared (IR) cameras for detecting oil spills within port environments. By employing convolutional neural networks (CNNs) trained on annotated RGB and IR image datasets, the system achieved an 89% accuracy rate in real-time oil spill detection. The experimentation, conducted in the port of Antwerp, validated the framework's capability to identify oil spills, highlighting its potential for environmental monitoring and management in port settings.	The limitation lies in the generalizability of the framework, which might not extend well to diverse port environments due to variations in lighting conditions, types of vessels, and oil spill sizes/types, potentially requiring further adaptation and validation in different settings

4.1 Significant Advancements in Deep Learning Techniques

Recent years have seen the adoption of various deep learning architectures for oil spill detection, including **convolutional neural networks (CNNs)**, **U-Net**, **YOLO**, and **SegNet** (Gonzalez et al., 2021; Thompson et al., 2022). Each of these architectures brings unique strengths:

I. **CNNs** are foundational in feature extraction and classification but may lack precision in object localization when compared to more sophisticated object detection networks (Huang & Chen, 2021).

II. **U-Net** has demonstrated strong segmentation capabilities due to its encoder-decoder structure, making it particularly effective in detailed mapping of oil spill regions (Rao & Mahdi, 2020).

III. **YOLO** networks, known for real-time object detection, have emerged as leading contenders for fast and efficient oil spill monitoring, especially when combined with lightweight architectures like **SqueezeNet** to balance speed and performance (Johnson et al., 2022).

Integrating models like **YOLO** with **SqueezeNet** or other lightweight architectures has shown promising results in terms of computational efficiency and real-time application, addressing the challenges of deployment on limited-resource systems, such as edge devices (Kim et al., 2021).

4.2 Emerging Trends in the Field

Several key trends have emerged in recent research that highlight the future trajectory of oil spill detection:

I. **Hybrid Deep Learning Models**: Combining architectures (e.g., YOLO with SqueezeNet or integrating U-Net for segmentation tasks) has proven effective in enhancing performance by leveraging the strengths of each model (Ali & Omotola, 2023).

II. **Multimodal Data Fusion**: The use of **synthetic-aperture radar (SAR) data** from sources like **Sentinel-1** has been pivotal in oil spill detection due to its high resolution and ability to operate in varying weather conditions (Nguyen et al., 2021). The fusion of SAR with optical data has also been explored to improve detection accuracy and robustness (Martin & Hussein, 2022).

III. **Lightweight Architectures for Edge Deployment**: The development of models that can operate efficiently on **edge devices** is crucial for real-time monitoring. Architectures such as **MobileNet** and **SqueezeNet** have gained attention for their minimal computational requirements and high efficiency (Lee et al., 2022).

IV. **Transfer Learning and Pre-trained Models**: Leveraging pre-trained models has become a common practice to enhance training efficiency, especially when working with limited labeled datasets (Sanchez & Bravo, 2023).

4.3 Challenges and Limitations

Despite the substantial progress, several challenges remain in the application of deep learning to oil spill detection:

I. **Data Scarcity and Variability**: The availability of diverse and labeled datasets remains a significant challenge. Although **Sentinel-1** provides high-quality SAR data, obtaining a comprehensive dataset that covers all potential environmental variations (e.g., different sea states, weather conditions) is difficult (Wu & Garcia, 2021).

II. **False Positives and Model Interpretability**: While models such as **YOLO** and **SegNet** achieve high accuracy, false positives remain an issue, particularly when interpreting dark patches in SAR imagery. Enhancing model interpretability through techniques like **attention mechanisms** and **explainable AI** is crucial for building trust in automated systems (Ahmed & Patel, 2022).

III. **Computational Load and Real-Time Constraints**: Even with lightweight models, balancing detection accuracy with computational efficiency is challenging, especially for real-time operations on limited-resource platforms (Chen et al., 2022).

IV. **Generalizability Across Regions**: The effectiveness of trained models across different geographical and environmental conditions can vary. Research has highlighted that models trained in one region may not generalize well to other regions with different oceanic and atmospheric characteristics (Smith & Wong, 2023).

4.4 Future Directions for Improvement

Based on the synthesis of recent studies, several areas for future research have been identified:

I. **Development of Comprehensive Datasets**: Collaborative efforts are needed to build larger, annotated datasets that capture a wide range of environmental scenarios and oil spill characteristics (Johnson et al., 2023). Utilizing synthetic data and **data augmentation techniques** can also help mitigate data scarcity (Rao et al., 2021).

II. **Integration with IoT and Edge Computing**: The real-time detection and monitoring of oil spills can benefit from the integration of **IoT** and **edge computing** technologies (Kim & Lopez, 2023). This would enable immediate response actions, leveraging lightweight models for faster decision-making in remote locations.

III. **Advancements in Explainable AI**: To ensure greater adoption in operational settings, there is a growing need for models that provide **transparent and interpretable** outputs, enabling better decision-making and minimizing false alarms (Ahmed & Patel, 2022).

IV. **Exploring Other Lightweight Architectures**: Future studies could explore more efficient and accurate architectures, such as **EfficientNet** or variants of **Transformers** adapted for image tasks, to improve both detection performance and resource management (Nguyen et al., 2023).

V. **Robustness Under Dynamic Conditions**: Research focusing on enhancing the robustness of detection models to operate effectively under various weather, sea states, and other environmental conditions would further strengthen their operational value (Chen et al., 2022).

4.5 Practical Implications and Potential Applications

The improved detection capabilities of advanced deep learning models have practical implications for environmental protection and disaster management. Enhanced real-time monitoring can significantly aid in **early response efforts**, minimizing the environmental and economic impact of oil spills (Smith & Lee, 2022). The deployment of such technologies can be extended to include **maritime surveillance**, **pipeline monitoring**, and **port safety**, providing a comprehensive system for managing oil-related hazards (Martin & Hussein, 2022).

5. Conclusion

This paper presents a comprehensive review of the state-of-the-art research works in the field of oil spill detection, highlighting the integration of advanced deep learning models and techniques. The review covers the significant progress made with different architectures such as **YOLO**, **U-Net**, **CNNs**, and lightweight models like **SqueezeNet**. These models have contributed to improved precision, accuracy, and speed in detecting oil spills, facilitating timely and effective environmental response.

Emerging trends emphasize the potential of **hybrid models**, **multimodal data fusion**, and the application of **edge computing** to enhance real-time monitoring capabilities. However, challenges related to **data scarcity**, **model interpretability**, and **deployment under dynamic conditions** remain areas needing further exploration. Addressing these limitations through collaborative efforts and future research focused on **explainable AI**, **robust architectures**, and **comprehensive datasets** will be crucial for advancing the practical application of these technologies.

In conclusion, while significant progress has been made, continued innovation and interdisciplinary cooperation will drive the development of more efficient, reliable, and scalable oil spill detection systems. Such advancements will contribute to environmental safety, early disaster response, and the overall resilience of monitoring systems in maritime and coastal management.

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