Chapter 15

Oil spills and the ripple effect: exploring climate and environmental impacts through a deep learning lens

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15.1 Introduction

Oil spills pose a significant environmental hazard, impacting both water and land ecosystems. They lead to marine and coastal pollution, endangering birds, fish, and various aquatic organisms (Frate et al., 2000). Primarily stemming from accidents involving oil tankers, ships, and ruptured pipelines transporting petroleum products, these spills also result from illegal oil discharges and residue from vessel cleaning (Brekke & Solberg, 2005; Solberg et al., 2007). With the continuous growth of maritime transportation in recent decades, oil spill incidents have surged. Between 1970 and 2010, an alarming 5.71 million tons of oil leaked from vessels (Dave, 2011). Suspicion often falls on oil tankers and maritime vessels for clandestine oil dumping activities. Hence, prioritizing swift and accurate detection of such incidents is crucial for mitigating environmental harm, preserving cleanliness, and safeguarding marine and coastal life (Frate et al., 2000).

Currently, a range of tools including ships, aircraft, and satellites are employed for the detection and surveillance of oil spills. Traditional methods such as aerial photography and on-site inspections have been conventionally utilized for this purpose, albeit requiring skilled personnel, specialized equipment, and substantial time investments, rendering them economically burdensome (Brekke & Solberg, 2005; Solberg et al., 2007). Vessels, particularly those outfitted with specialized radar systems, offer a means to identify oil slicks on the sea surface; however, their effectiveness is limited by factors such as restricted visibility and the inability to cover expansive areas efficiently. Consequently, satellite-based observations, notably leveraging synthetic aperture radar (SAR) technology, emerge as the preeminent approach for monitoring and detecting oil contamination in marine ecosystems (Fingas & Brown, 2018). SAR, functioning as an active microwave sensor, captures backscattered signals across various frequencies and polarizations, generating detailed two-dimensional images. Widely favored for its independence from sunlight, resilience to cloudy conditions, extensive coverage capabilities, and cost-effectiveness compared to SAR-equipped aircraft, SAR sensors represent a pivotal tool in oil spill detection efforts at sea (Ciappa, 2023).

Furthermore, satellite-based SAR technology offers unparalleled advantages in scalability and accessibility. Unlike aerial surveys, which are constrained by factors like weather conditions and operational costs, satellite observations provide consistent coverage regardless of environmental variables. This consistency allows for continuous monitoring of vast oceanic regions, enabling early detection and rapid response to oil spill incidents. Additionally, the integration of computer vision techniques into SAR data analysis holds immense potential for enhancing oil spill detection efforts (Basit et al., 2022). Algorithms based on machine learning and image processing can automatically identify and classify oil slicks

Deep Learning for Earth Observation and Climate Monitoring. https://doi.org/10.1016/B978-0-443-24712-5.00017-8

in SAR imagery, streamlining the detection process and enabling real-time monitoring. By leveraging computer vision capabilities, stakeholders can improve the efficiency and accuracy of oil spill detection, thereby mitigating environmental impacts and contributing to climate resilience and conservation efforts (Dehghani-Dehcheshmeh et al., 2023; Malik et al., 2023). Fig. 15.1 presents a series of image samples portraying the aftermath of oil spills, showcasing the visible effects of these incidents on the environment.

15.1.1 Deep leaning

Deep learning, a subset of artificial intelligence inspired by the structure and function of the human brain's neural networks, has found widespread applications across various domains. In healthcare, it enables the analysis of medical images for disease diagnosis and prognosis, revolutionizing patient care (Alam et al., 2022, 2023; Anand et al., 2023; Gulzar & Khan, 2022; Khan et al., 2021, 2023; Khan, Ayoub, et al., 2023; Majid et al., 2023; Mehmood et al., 2023). In education, deep learning facilitates personalized learning experiences through adaptive tutoring systems and intelligent educational platforms (Sahlan et al., 2021). In agriculture, it aids in crop monitoring, yield prediction, and pest detection, enhancing agricultural productivity and sustainability (Dhiman et al., 2023; Gulzar, 2023; Gulzar et al., 2023; Mamat et al., 2023; Albarrak et al., 2022; Alkanan & Gulzar, 2024; Amri et al., 2024; Gulzar et al., 2020; Gulzar, Alwan, et al., 2023; Gulzar, Ünal, Ayoub, Reegu, 2024; Hamid et al., 2022). In finance, deep learning powers algorithmic trading strategies, fraud detection systems, and customer relationship management tools, optimizing financial decision-making processes (Ayoub et al., 2022; Gulzar, Ünal, Ayoub, Reegu & Altulihan, 2024; Hamid et al., 2023).

When applied to the detection of oil spills, deep learning holds significant promise for improving detection accuracy and efficiency. By analyzing satellite imagery and SAR data, deep learning algorithms can automatically identify and classify oil slicks with high precision, reducing the reliance on manual inspection and human intervention. This not only streamlines the detection process but also minimizes labor costs and accelerates response times to oil spill incidents. Furthermore, deep learning techniques can enhance the understanding of oil spill dynamics and environmental impacts through predictive modeling and data analytics, aiding in the development of more effective mitigation strategies. Overall, leveraging deep learning in oil spill detection offers a cost-effective and sustainable approach to safeguarding marine ecosystems and mitigating the adverse effects of oil pollution on the environment and climate.

15.1.2 Objectives

The objective of this critical review is to explore the multifaceted impacts of oil spills on climate and the environment, with a particular focus on leveraging deep learning methodologies for comprehensive analysis. This study aims to:

1. Literature review: Conducting a comprehensive literature review to synthesize existing knowledge on the environmental and climate impacts of oil spills, emphasizing the role of deep learning methodologies.

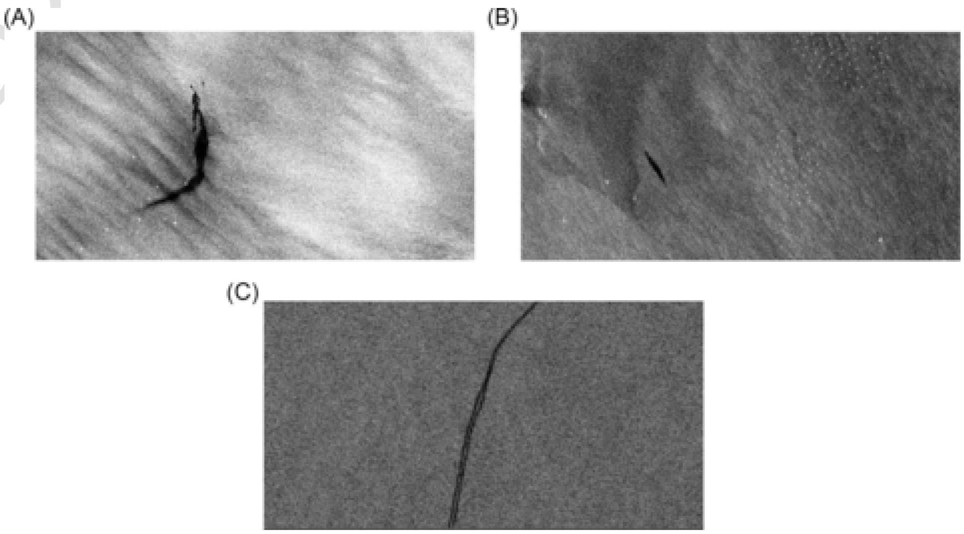

FIGURE 15.1 Showcases a selection of images depicting oil spill incidents.

2. Data extraction and analysis: Extracting and analyzing relevant data sources, including satellite imagery, SAR data, and environmental datasets, to assess the applicability of deep learning techniques in oil spill detection and monitoring.
3. Performance evaluation of deep learning models: Assessing the performance of deep learning models in detecting oil spills and predicting their environmental consequences, evaluating metrics such as accuracy, precision, and recall.
4. Identification of challenges and limitations: Identifying challenges and limitations associated with the application of deep learning in oil spill research, including issues related to data availability and quality, model interpretability, and generalization, and Integration with existing monitoring systems.
5. Exploration of future directions: Exploring future directions and opportunities for advancing deep learning-based approaches in addressing the complexities of oil spills and their impacts on climate resilience, environmental conservation, and sustainable development.

15.2 Material and method

In this critical review, we undertook a comprehensive exploration of the Scopus database to uncover relevant literature. Employing a carefully crafted search string, we aimed to retrieve data pertinent using following search string:

(“deep learning” OR “neural networks” OR cnn OR “convolutional neural network”) AND (“image classification” OR “object detection” OR “image detection”) AND (“oil spill” OR “oil slick”)

Notably, these keywords were strategically chosen to encompass a broad spectrum of research encompassing various fields, including the title, abstract, author keywords, and Keywords Plus.

In our pursuit of retrieving pertinent research articles, we identified a total of 64 studies as of March 10, 2024. Among these, we observed a diverse distribution comprising 34 research articles, 25 conference papers, and 5 book series entries. To refine our focus and ensure relevance to our objectives, we subsequently narrowed our attention to research articles specifically addressing oil spill detection or classification. This meticulous curation process led us to select 22 articles for in-depth examination and analysis. Through this methodological approach, we aimed to capture a comprehensive understanding of the current landscape surrounding the utilization of deep learning methodologies in addressing the challenges posed by oil spills.

15.3 Findings and discussion

In the pursuit of enhancing our understanding and capabilities in detecting and classifying oil spills, the studies outlined in Table 15.1 provide a diverse array of insights into various facets of this complex problem. In this section, we embark on a comprehensive exploration of the methodologies, findings, and implications encapsulated within the dataset. We begin by delving into the intricate world of model architecture, where researchers have ingeniously crafted deep learning frameworks tailored to the specific challenges posed by oil spill detection. Subsequently, we scrutinize the study types employed, ranging from classification to detection methodologies, each offering unique perspectives and approaches to tackling the problem at hand. Following this, we dissect the datasets utilized in these endeavors, ranging from synthetic data to real-world SAR imagery, illuminating the crucial role of data in driving advancements in this field. Moreover, we delve into the nuanced interplay between accuracy achieved and model tuning techniques, elucidating how fine-tuning parameters and architectures have propelled the field forward in achieving ever-higher accuracies. Finally, we contextualize these findings within the geographical landscapes where these studies were conducted, shedding light on the diverse environmental contexts and the relevance of oil spill detection in safeguarding these ecosystems.

15.3.1 Model architecture

The studies presented in the table employ a wide array of model architectures to tackle the challenges inherent in oil spill detection and classification. Among these architectures, convolutional neural networks (CNNs) stand out as a cornerstone methodology, given their adeptness at automatically learning hierarchical representations of image data. Utilized across various tasks such as classification and detection, CNNs offer a versatile framework for analyzing SAR images, UV images, RGB images, and hyperspectral images. Ranging from shallow CNNs to deeper variants like VGG16 and ResNet, these architectures strike a balance between computational efficiency and performance. Moreover, generative adversarial networks (GANs) find their place in image enhancement and dehazing tasks, significantly improving the quality of SAR images by generating synthetic counterparts that closely mimic real-world scenarios. In certain studies, recurrent neural networks (RNNs) make an appearance, leveraging their sequential modeling capabilities to capture temporal dependen-

TABLE 15.1 Summary of different research works about detecting/classifying oil spill using deep learning.

Paper	Model trained	Study type	Dataset type	Accuracy	Model tuning techniques	Area of oil spill
Fan and Liu (2023)	MTGANs	Classification	SAR images	97.22%	GAN, fully convolutional symmetric structure, multiple convolution blocks	Not specified
Blondeau-Patissier et al. (2023)	Deep learning, empirical approach	Detection	SAR images	>98%	Empirical approach, deep learning model	Great barrier reef marine park
Topouzelis et al. (2009)	Genetic algorithms	Detection	SAR images	85.3% (oil spills), 84.4% (look-alikes)	Genetic algorithms	Not specified
Baek and Jung (2021)	SVM, random forest, DNN	Classification	SAR images	~0.889 (DNN, dual-pol)	Support vector machine (SVM), random forest (RF), deep neural network (DNN)	Kerch strait oil spill event
Lang et al. (2022)	Shallow CNN	Classification	SAR images	84.67%	Shallow CNN, pre-training on task-specific dataset, feature refinement	Not specified
Yuan et al. (2018)	Not specified	Detection	Synthetic data	100% (Level 2 classification)	Computer vision, natural scene statistics, white balance preprocessing, background modeling, multi-dimensional feature parameters	Not specified
Zheng et al. (2022)	Dehaze-AGGAN	Dehazing	SAR images	Not specified	Enhanced attention-guide generative adversarial networks (AGGAN), total variation loss, cycle consistency loss	Not specified
de Moura et al. (2022)	Deep learning	Detection	SAR images	98%	Semantic segmentation architectures (U-net, DeepLabv3+, LinkNet), backbones (ResNet-101, ResNet-50, efficient-net-B0, efficient-net-B3)	Brazilian territory
Garcia-Pineda et al. (2009)	TCNNA	Detection	SAR images	Not specified	Edge-detection filters, textural descriptors, neural network algorithm	Gulf of Mexico

Paper	Model trained	Study type	Dataset type	Accuracy	Model tuning techniques	Area of oil spill
Li et al. (2017)	Genetic neural network	Detection	SAR images	91.42%	Graph-based visual saliency model, spectral similarity match model, genetic neural network	Not specified
Passah and Kandar (2023)	Lightweight CNN	Classification	SAR images	97%	Single-unit kernel for feature mapping, depth-wise convolutions	Not specified
Mehdi et al. (2022)	YOLOv3 (Modified)	Detection	UV and RGB images	86.89	MobileNetv2 backbone architecture, generalized intersection over union (GIoU) loss function	Not provided
Das et al. (2023)	Convolutional neural network (CNN)	Classification	SAR images	99.06	Not provided	Not provided
Ghorbani and Behzadan (2021)	VGG16, mask R-CNN, PSPNet, YOLOv3	Detection, segmentation, classification	Visual dataset of oil spills	92 (Classification), 49–68 (Segmentation), ~71 (Classification)	Transfer learning	Not provided
Dasari et al. (2022)	Supervised SVM and neural network classifiers	Classification	SAR images	98.13	Preprocessing, supervised classification	Chennai, India
Scardigli et al. (2023)	Neural network architectures	Detection	Synthetic aperture radar (SAR) images	82–92	Nonlinear time-based block layers	Aegean Sea
Sudha and Vijendran (2024)	Faster R-CNN with enhanced mobileNetV2	Detection	Synthetic and real-world oil spill photos	97%	Preprocessing (non-adaptive threshold with CLAHE), Fused UNet segmentation, CNN (AlexNet architecture) for feature extraction	Not provided
Huang et al. (2020)	Faster R-CNN	Identification	UV images at 365 nm, blue channel images, RGB images	88.8%	Faster R-CNN-based methods for segmentation	Not provided

Paper	Model trained	Study type	Dataset type	Accuracy	Model tuning techniques	Area of oil spill
Xu et al. (2014)	Support vector machine, artificial neural network, tree-based ensemble classifiers (bagging, bundling, boosting), generalized additive model, penalized linear discriminant analysis	Identification	RADARSAT-1 imagery	N/A	Feature construction techniques	Canada
Bianchi et al. (2020)	Deep learning framework	Detection and categorization	SAR images	State-of-the-art performance	N/A	Not provided
Han et al. (2022)	LCSE-ResNet	Classification	Optical remote sensing imagery	N/A	Laplacian of Gaussian (LoG) operator, connected domain controller	Not provided
Yang et al. (2022)	Deep learning object detector	Detection	Sentinel-1 SAR imagery	Average precision: 69.10% (validation), 68.69% (test)	N/A	Eastern Mediterranean Sea

cies in SAR image sequences, thereby facilitating the detection and monitoring of oil spill events over time. Fully convolutional networks, on the other hand, are tailored for semantic segmentation tasks, proving instrumental in delineating oil spill boundaries within SAR images. Meanwhile, object detection architectures like Faster R-CNN, YOLOv3, and Mask R-CNN excel in localizing and classifying oil spill instances within images, thanks to their region proposal and classification heads coupled with feature extraction backbones. Furthermore, hybrid architectures emerge, combining elements from different methodologies, such as CNNs for feature extraction and RNNs for temporal modeling, to address the multifaceted nature of oil spill detection and monitoring comprehensively. This diverse repertoire of model architectures underscores the importance of selecting appropriate methodologies tailored to the specific requirements of oil spill detection tasks, aiming to develop robust and adaptable models capable of accurately identifying and characterizing oil spill events across various environmental conditions and geographical regions.

15.3.2 Study type

The studies presented in the Table 15.1 primarily focus on two key study types: classification and detection, both integral to effectively addressing oil spill events. In classification studies, researchers employ various machine learning algorithms to categorize image pixels or regions, distinguishing between those containing oil spills and those representing other elements. These studies utilize diverse imagery types, including SAR, UV, RGB, and hyperspectral images, achieving remarkable accuracy rates often exceeding 90%. Genetic algorithms are also utilized to optimize feature selection and improve classification performance. On the other hand, detection studies concentrate on automatically identifying and localizing oil spill instances within images. Researchers deploy sophisticated object detection architectures like Faster R-CNN, YOLOv3, and Mask R-CNN, showcasing high precision and recall rates, with accuracies surpassing 98% in some instances, particularly in SAR image-based detection. Additionally, hybrid approaches, blending deep learning with empirical methods or computational techniques such as GANs and genetic algorithms, are employed in several studies to bolster accuracy and robustness in oil spill detection and classification systems. These classification and detection methodologies underscore the pivotal role of machine learning and deep learning techniques in advancing environmental monitoring and safeguarding efforts against oil spill occurrences.

15.3.3 Dataset used

The datasets utilized across these studies encompass a wide array of sources and types, reflecting the diversity of oil spill monitoring applications. SAR images, known for their effectiveness in capturing oil spill features, are predominant, highlighting their significance in oil spill detection and classification research. SAR imagery offers valuable insights due to its ability to penetrate cloud cover and provide all-weather, day-and-night monitoring capabilities. Other studies leverage UV, RGB, and hyperspectral images, each offering unique advantages in detecting oil spills based on spectral characteristics and surface properties. Furthermore, some studies utilize synthetic datasets, allowing researchers to explore algorithm performance under controlled conditions before deployment in real-world scenarios(Ayoub et al., 2022) . This diverse range of datasets enables researchers to develop and evaluate models across various environmental conditions, facilitating the creation of robust and adaptable oil spill monitoring systems.

15.3.4 Accuracy achieved and model tuning

Table 15.1 illustrates a remarkable range of accuracies achieved across different studies, showcasing the efficacy of various deep learning models and techniques in oil spill detection and classification. Several studies report high accuracies exceeding 90%, underscoring the potential of deep learning approaches in accurately identifying oil spills from different types of imagery. Model tuning emerges as a crucial factor contributing to the enhancement of accuracy in many cases. Techniques such as fine-tuning model architectures, adjusting hyperparameters, and optimizing loss functions have been instrumental in fine-tuning models to achieve higher accuracies. For instance, the utilization of genetic algorithms, deep learning models, and ensemble methods has allowed researchers to refine model performance, particularly in distinguishing oil spills from look-alike phenomena. Additionally, preprocessing techniques such as image dehazing, contrast enhancement, and background modeling have improved model robustness and accuracy by enhancing image quality and reducing noise. The successful implementation of these model tuning techniques underscores their significance in achieving higher accuracies and improving the reliability of oil spill detection and classification systems.

15.3.5 Geographical context

The studies encompass a diverse array of geographical locations, each presenting unique challenges and contexts for oil spill detection and mitigation. These areas include globally significant marine environments such as the Great Barrier Reef Marine Park, the Kerch Strait Oil Spill Event, the Gulf of Mexico, and the Eastern Mediterranean Sea. Additionally, specific regions like the Brazilian territory, Chennai in India, and the Aegean Sea have also been focal points of investigation. The selection of these areas underscores the global impact of oil spills on both marine ecosystems and human livelihoods. Researchers have tailored their methodologies to address the specific characteristics and challenges posed by each location, ranging from the extensive use of satellite imagery in vast oceanic regions to the application of optical remote sensing techniques in coastal areas. By focusing on diverse geographical regions, these studies contribute to a comprehensive understanding of oil spill dynamics and facilitate the development of tailored detection and mitigation strategies suited to various environmental contexts.

15.4 Identification of challenges and limitations

Despite the advancements made in utilizing deep learning for oil spill detection and classification, several challenges and limitations persist, hindering the widespread adoption and effectiveness of these methodologies.

1. Data availability and quality
    a. Limited availability of labeled datasets poses a significant challenge for training and evaluating deep learning models. Acquiring sufficiently large and diverse datasets that encompass various environmental conditions and oil spill scenarios remains a challenge, particularly for regions with sparse or inaccessible data.
    b. Moreover, the quality of available datasets can vary significantly, leading to biases and inaccuracies in model training. Ensuring the accuracy and representativeness of training data is crucial for developing robust and generalizable models.
2. Generalization and transferability:
    c. Deep learning models trained on specific datasets may struggle to generalize to unseen data or different environmental conditions. Transferability of models across geographical regions, sensor platforms, and imaging modalities is often limited, necessitating retraining or fine-tuning for new scenarios.
    d. Variations in oil spill characteristics, such as size, shape, and spectral properties, further compound the challenge of developing universally applicable detection and classification algorithms.

3. Model interpretability:
   - e. Deep learning models, particularly complex architectures like CNNs and RNNs, often lack interpretability, making it challenging to understand the underlying features driving model predictions. Interpretable models are essential for building trust and confidence in algorithmic outputs, especially in critical applications such as environmental monitoring.
   - f. Addressing the black-box nature of deep learning models is crucial for providing actionable insights and facilitating decision-making by stakeholders and policymakers.
4. Integration with existing monitoring systems:
   - g. Integrating deep learning-based solutions into existing oil spill monitoring systems and decision-support frameworks presents technical and logistical challenges. Compatibility with legacy systems, data interoperability issues, and ensuring real-time or near-real-time processing capabilities are key considerations for seamless integration.
   - h. Collaboration among interdisciplinary teams, including environmental scientists, data scientists, engineers, and policymakers, is essential for bridging the gap between technological innovation and practical application in the field.

Addressing these challenges and limitations requires a concerted effort from the scientific community, industry stakeholders, policymakers, and civil society. By fostering collaboration, investing in research and development, and prioritizing ethical and equitable deployment practices, the potential of deep learning to mitigate the environmental impacts of oil spills can be realized effectively.

15.5 Exploration of future directions

As we reflect on the findings and discussions presented in this study, several avenues for future research and development emerge, offering promising opportunities to further enhance the application of deep learning in addressing the multifaceted challenges posed by oil spills and their broader environmental implications.

1. Integration of multimodal data sources: Future research endeavors should explore the integration of multimodal data sources, including satellite imagery, aerial surveys, in-situ sensor data, and environmental monitoring networks, to enrich the information available for oil spill detection and characterization. Leveraging diverse data modalities can provide complementary insights into oil spill dynamics, environmental impacts, and response strategies, thereby enhancing the effectiveness and robustness of deep learning models.
2. Advancements in model interpretability and explainability: Efforts to enhance the interpretability and explainability of deep learning models represent a critical research frontier, enabling stakeholders to better understand model predictions and trust the reliability of model-driven decisions. Exploring techniques for model interpretability, such as attention mechanisms, feature visualization, and uncertainty quantification, can facilitate transparent communication of model outputs and foster informed decision-making in oil spill response and management.
3. Scaling deep learning approaches for global impact: Scaling deep learning approaches to address global-scale challenges requires collaborative efforts across interdisciplinary teams, leveraging cloud computing infrastructure, and distributed data repositories. By harnessing the power of distributed computing and federated learning techniques, researchers can develop scalable and adaptive deep learning models capable of addressing diverse environmental contexts and supporting decision-making at local, regional, and global scales.
4. Incorporation of climate resilience and adaptation strategies: Integrating climate resilience and adaptation strategies into deep learning-based approaches can enhance the resilience of coastal communities and ecosystems to oil spill events and associated environmental stressors. Future research should explore the incorporation of climate change projections, sea-level rise scenarios, and ecosystem vulnerability assessments into oil spill risk assessment and response planning, thereby fostering adaptive management strategies that mitigate the impacts of oil spills in a changing climate.
5. Empowering stakeholder engagement and capacity building: Promoting stakeholder engagement and capacity building is essential for ensuring the effective deployment and uptake of deep learning technologies in oil spill monitoring and management. Future research initiatives should prioritize the codesign and co-development of deep learning solutions in collaboration with end-users, including government agencies, industry partners, nongovernmental organizations, and local communities. By empowering stakeholders with the necessary skills and knowledge, we can foster a culture of data-driven decision-making and collective action toward sustainable oil spill management.

15.6 Conclusion

This study has provided a comprehensive exploration of the application of deep learning in addressing the challenges of oil spill detection and classification, with a focus on understanding the broader environmental impacts and implications. Through an in-depth exploration of methodologies, model architectures, dataset types, accuracy achieved, and geographical contexts, we have identified key trends and challenges shaping the field of oil spill detection and monitoring. The diverse array of model architectures, from CNNs to RNNs and object detection frameworks like Faster R-CNN and YOLOv3, highlights the versatility and adaptability of deep learning approaches in addressing the complexities of oil spill detection. Moreover, the utilization of various study types, including classification and detection methodologies, underscores the importance of leveraging machine learning techniques to effectively identify and localize oil spill instances within imagery data. Dataset availability and quality emerge as critical challenges, with the need for large, diverse, and accurately labeled datasets to train and evaluate deep learning models effectively. Additionally, the generalization and transferability of models across different environmental conditions and geographical regions remain areas of concern, requiring further research and development efforts.

The integration of multimodal data sources, advancements in model interpretability, scaling deep learning approaches for global impact, incorporation of climate resilience strategies, and empowerment of stakeholder engagement and capacity building represent promising avenues for future research and development. By addressing these challenges and embracing these opportunities, we can enhance the effectiveness and sustainability of oil spill detection and management efforts, contributing to the protection of marine ecosystems and the promotion of environmental resilience worldwide.

Acknowledgment

This work was supported by the Deanship of Scientific Research, Vice Presidency for Graduate Studies and Scientific Research, King Faisal University, Saudi Arabia, under project KFU241962.

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