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AI-enhanced real-time monitoring of marine pollution: part 1-A state-of-the-art and scoping review

Navya Prakash[1,2]* and Oliver Zielinski[2,3]

[1]Marine Sensor Systems, Institute for Chemistry and Biology of the Marine Environment (ICBM), Carl von Ossietzky University of Oldenburg, Oldenburg, Lower Saxony, Germany, [2]Marine Perception, German Research Center for Artificial Intelligence (DFKI) GmbH, Oldenburg, Lower Saxony, Germany, [3]Leibniz Institute for Baltic Sea Research Warnemuende (IOW), Rostock, Mecklenburg-Western Pomerania, Germany

Marine pollution, especially from oil spills and litter, poses significant threats to marine ecosystems, aquaculture and fisheries. The proliferation of pollutants requires advanced monitoring techniques to enhance early detection and mitigation efforts. Artificial Intelligence revolutionizes environmental monitoring by enabling rapid and precise pollution detection using remote sensing and machine learning models. This review synthesizes 53 recent studies on Artificial Intelligence applications in marine pollution detection, focusing on different model architectures, sensing technologies and preprocessing methods. The most deployed models of Random Forest, U-Network, Generative Adversarial Networks, Mask Region-based Convolution Neural Network and You Only Look Once demonstrated high prediction rate for detecting oil spills and marine litter. However, challenges remain, including limited training datasets, inconsistencies in sensor data and real-time monitoring constraints. Future research should improve Artificial Intelligence model generalization, integrate multi-sensor data and enhance real-time processing capabilities to create more efficient and scalable marine pollution detection systems.
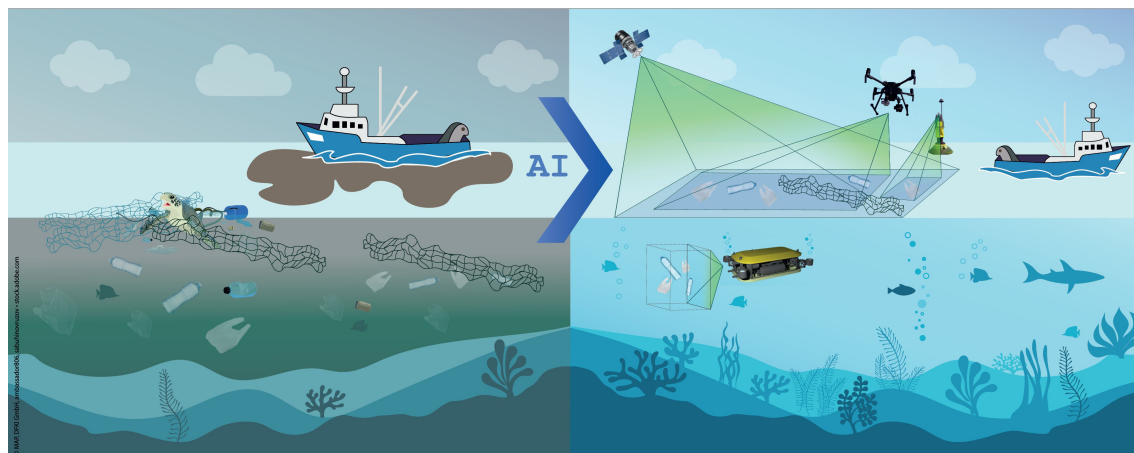
GRAPHICAL ABSTRACT

1 Introduction

Pollution is the release of harmful substances into the environment, leading to adverse changes in the ecosystem. Marine contamination is a significant part of global environmental pollution, as water covers a vast area of the Earth's surface (NASA, 2023). The annual European Union (EU) Blue Economy Report (MARE, 2021) reported oil spills, litter, plastic debris, and ship emissions as significant harmful contaminants affecting the marine ecosystem. Another annual EU Blue Economy Report (EU, 2019) that followed discussed that 9 million tons of plastic litter are deposited on beaches and afloat in oceans, degrading marine ecosystems. Subsequently, the United Nations (UN) report (UN, 2022) mentioned that 17 million metric tons of plastic litter entered the ocean in 2021, and it is predicted to increase exponentially by 2040.

Furthermore, the research of Patil et al. (2016) addressed that the Caribbean Sea has dead zones with nearly 2.7 to 4.8 million tons of plastic litter entering annually. According to the research studies of Chinglenthoiba et al. (2023); Diem et al. (2023), and Fagiano et al. (2023), plastic contaminants are abundant in marine ecosystems. The maximum percentage of marine plastics and litter recorded are from the fishing fleet, merchant ships, recreational fishing, boats, coast guards, beachgoers, and industry wastes (COAPS, 2022; NAOO, 2022; OECD, 2022; UNEP, 2022). Furthermore, several studies, such as those of Leistenschneider et al. (2023); Ferreira et al. (2023); Kalter and Passow (2023), and Tedesco et al. (2024), have revealed that plastic litter and oil spills are two major marine pollutants that cause severe hazards to the ecosystem. Specifically, oil spills suffocate marine organisms, disrupt photosynthesis in aquatic plants, and lead to long-term contamination of marine habitats. Plastic litter, on the other hand, entangles marine animals, is ingested by fish and seabirds, leading to internal injuries and starvation, and degrades into microplastics that accumulate in the food chain, posing risks to marine biodiversity and human health

(Diez et al., 2019). Additionally, Diez et al. (2019) reported on marine plastics and oil spill impact in the Caribbean Sea, with a concentration of 200,000 pieces of plastics measured per square kilometer in the northern region and around 250 oil spills estimated to occur yearly due to ship traffic.

However, several approaches from COAPS (2022); NAOO (2022); OECD (2022), and UNEP (2022) have proposed a Triple Planetary Crisis (TPC) (UNEP, 2022) to prevent and monitor pollution. TPC proposes measures for contamination, nature biodiversity loss, and climate change (Ford et al., 2022; Lincoln et al., 2022; UNFCCC, 2024; Sharma et al., 2023). The strategies to resolve TPC include the Sustainable Development Goals (SDGs), Marine Strategy Framework Directive (MSFD), and Good Environmental Status (GES). The UN defined the SDGs (UN, 2022), notably Goal-6 of "Clean Water and Sanitation", to ensure water and sanitation availability with sustainable management and, in addition, Goal-14 of "Life Below Water" to conserve and sustainably use the ocean, sea, and marine resources for sustainable development (UNEP, 2022). According to the annual SDGs Report (UNEP, 2022), plastic or litter, overfishing, ocean warming, acidification, and eutrophication are primary reasons to implement SDG Goal-14. Additionally, it reported increasing acidification (CO_2) from maritime traffic emissions and industrial wastes, threatening the marine ecosystem and consequently limiting the ocean's capacity to moderate climate change (UN, 2022). The TPC's next strategy, MSFD, aims to protect the marine environment across Europe (MSFD, 2008) and achieve good environmental conditions (GES, 2020). The main propositions of the GES are to protect the marine environment, prevent deterioration, and restore the damaged ecosystem. The primary GES descriptors are marine litter, contaminants, eutrophication, and biodiversity. The European Commission proposed the Sustainable Blue Economy (Pauli, 2010; EU, 2019) for all economic activities related to oceans, seas, and coasts. It is an

initiative to use the sea sustainably, including preventing marine pollution, especially plastics (EU, 2019; Smail et al., 2019).

Furthermore, preventing and eliminating marine pollution is necessary (Meyerjürgens et al., 2023; Nama et al., 2023; Su et al., 2023), so the intention to incorporate artificial intelligence (AI) (refer to Supplementary Material) with remote sensing satellite imagery for marine pollution analysis existed in 1990 (Muller-Karger, 1992). However, according to the following reports and studies (UN, 2022; COAPS, 2022; OECD, 2022), marine pollution still exists worldwide. Thus, recently developed marine sensor technologies (Zielinski et al., 2009; Helinski et al., 2021; Salgado-Hernanz et al., 2021) are deployed for real-time investigation of marine contamination. Moreover, new technologies have been developed to determine marine pollution, predominantly using AI. The conjunction of optical sensors with AI models for monitoring and analyzing marine oil and plastics can assist in achieving the TPC goals of preventing marine pollution. The research of Moorton et al. (2022) supports using deep learning (refer to Supplementary Material, Figure_dl) to locate debris in the ocean as it does not harm aquatic life and adapt it for marine pollution prediction as AI is extensively used in various environmental disciplines (Zhang et al., 2023; Konya and Peyman, 2024). Hence, this study accumulated 53 research articles to compare state-of-the-art AI models that predicted marine pollution and proposes scoping methodologies for future research. The outline of the proposed review methodology for recent studies and technological advancements in machine learning applications for marine oil spills and litter pollution is discussed in Section 2. Furthermore, in Section 3, AI's effectiveness for marine pollution analysis is discussed and current methodologies and limitations are summarized. Section 4 concludes this review with a brief outlook and future research directions.

2 Proposed state-of-the-art and scoping review methodology

The proposed study aims to comprehensively review recent (2016–2023) and ongoing research on state-of-the-art machine-learning-based (refer to Supplementary Material, Figure_ml) marine oil spills and litter models. It compares and briefly summarizes the effectiveness of different neural network model architectures, discusses the data types, and evaluates these technologies to contribute to more effective marine litter management strategies. Through the proposed review, we highlight the progress in recent marine pollution research and identify areas that require further research and innovation to combat the growing threat of marine litter and oil spill pollution. Therefore, the proposed study approach can be categorized as a state-of-the-art and scoping review (Grant and Booth, 2009).

The review methodology comprises two phases as depicted in Figure 1:

1. Literature search method: The literature search method fulfilled the main criteria for this systematic review of recent developments in AI-based research methods to analyze marine pollution. Thus, published articles were chosen from journals and conferences. This search included websites such as Google Scholar, ResearchGate, arXiv, JSTOR, SpringerLink, ScienceDirect, Academia.edu, Scopus, PubMed, and Web of Science. The following search filters were applied: the article selection consisted of "review" or "research" keywords with publication years from 2016 until 2023. All review and research articles were considered for the initial stage of scrutiny; the publication years were limited to 2016 until 2023 as this review aims to discuss progress in AI with recent marine research (Jia et al., 2023a, 2023b; Politikos et al., 2023; Pérez-Beltrán et al., 2024), followed by a high number of articles published with the importance of utilizing AI in various environmental research fields (Konya and Peyman, 2024). Furthermore, the subject area filters were "environmental science" or "computer science". All open-access and locked-access publications from conference proceedings and journal articles were considered for the search. The keywords for the title search included with conjunctions of "and" and "or" are as follows: "marine pollution", "machine learning", "deep learning", "marine litter", "pollution detection", "litter detection", "marine plastic", "marine waste", "marine debris", "oil spills", and "marine oil". The literature analysis involved a systematic and thorough examination of all articles. The initial process included reading and understanding each article in the following order: abstract, conclusion, experimental results, introduction, and other sections. The initial process order was formulated intentionally and proved feasible and efficient by saving time and resources. The corresponding author of this article scrutinized the research methods of each article to ensure the inclusion of machine learning (refer to Supplementary Material, Figure_ml) or deep learning (refer to Supplementary Material, Figure_dl) models for marine pollution analysis. The second process involved thoroughly reading and understanding every article to identify its comparative analysis and any successive publications. In a few cases, the proposed study used the chain or snowball sampling method to identify related research articles.

2. Literature review protocols: The literature review protocols included various state-of-the-art AI techniques emphasizing machine learning and deep learning algorithms for marine pollution analysis of two significant contaminants: oil spills and plastics or litter. The proposed study articulated optical sensors, datasets (spectra, images, videos, multispectral data, hyperspectral data), pollutant classes, pre-processing methods, and model architectures with performance

analysis. The optical sensors were a significant criterion for this review scrutiny because of their extensive use in marine pollution analysis over the past few decades, especially with satellite remote sensing (Zielinski et al., 2009). Another significant criterion was that data acquisition had to be from a real-world or natural environment caused by ship traffic, ship collisions, or oil rig accidents. Similarly, the litter data acquisition should include either of the following: litter, plastics, macro- or micro-plastics, floating plastics, underwater litter, deformed litter, beach litter, debris, beach debris, and laboratory (artificially created or simulated) or real-world or natural environment pollution. Lastly, 53 research articles fulfilled these proposed protocols and were scrutinized and compared.

2.1 AI-based spectral marine oil pollution analysis

Oil spill incidences such as the Bravo blowout on the Ekofish fields in 1977 at the North Sea led to the formation of the Norwegian Clean Seas Association for Operating Companies (NOFO) in 1978 to develop oil spill response technologies and skimmers. This was followed by the Deep Water Horizon (DWH) oil rig explosion in the Gulf of Mexico in 2010, creating a massive leak. These incidents have formed state-of-the-art data acquisition locations for extensive research and majorly analyzed with remote sensing satellites such as Synthetic Aperture Radar (SAR) images (Topouzelis and Psyllos, 2012; Guo and Zhang, 2014). A cumulative literature review is represented in Table 1, and its connected graph
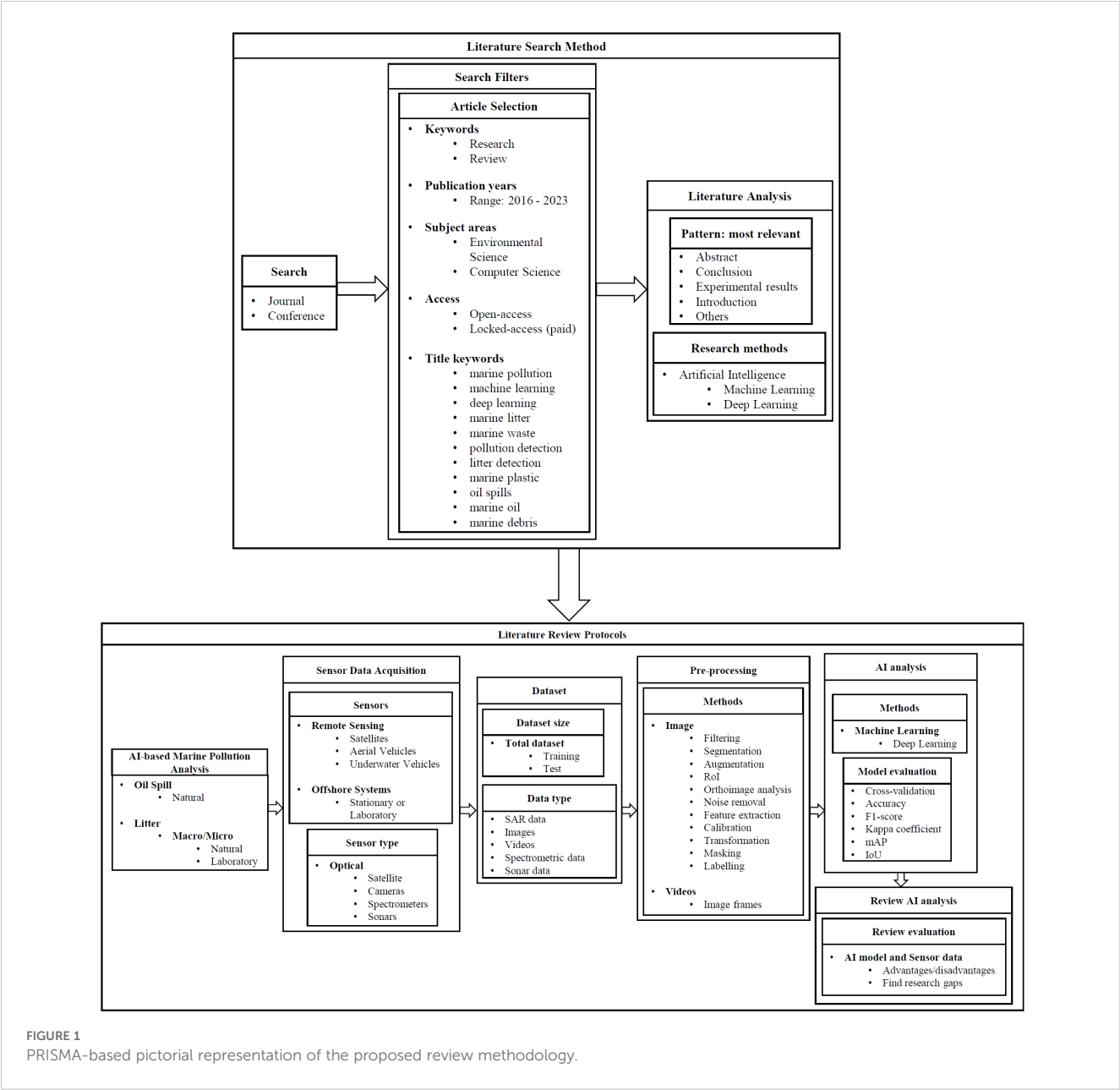

FIGURE 1
PRISMA-based pictorial representation of the proposed review methodology.

of research citations is in Figure 2. The following subsections compare recent research on marine oil pollution analysis methods with distinguished data acquisition techniques such as remote sensing with aerial vehicles and satellites.

2.1.1 Remote sensing with aerial vehicle

In recent studies on oil spill detection, various methods have been employed to enhance the accuracy (McHugh, 2012) (refer to Supplementary Material, Equation (1)) and efficiency of identifying and classifying oil spills with spectral data. One such approach developed by Liu et al. (2016) used an airborne visible infrared imaging spectrometer (AVIRIS) to detect oil spills from the DWH incident, employing a decision tree (Quinlan, 1986) classifier enhanced with minimum noise fraction (MNF) (Green et al., 1988; ENVI, 2022) transformation for noise reduction and feature extraction. This method classified oil spill thickness levels but was influenced by environmental factors. Furthermore, using the same dataset of the DWH incident, Hu (2022) developed an advanced approach by developing a multi-scale convolutional neural network (CNN) integrating 1D-CNN for spectral features and 2D-CNN for spatial features, achieving high classification accuracy with F1-scores of up to 0.99. Moreover, De Kerf et al. (2020) introduced MobileNet-FCN8 for unmanned aerial vehicle (UAV)-based controlled oil spill detection using visible and thermal infrared images, incorporating extensive pre-processing techniques and hyperparameter optimization. The ensemble of MobileNet-FCN8 (Sandler et al., 2018) with RMSprop (Hinton et al., 2012) achieved the highest mean IoU of 0.89, demonstrating superior performance over traditional methods. These studies collectively highlight advancements in oil spill detection from hyperspectral analysis to deep learning-based UAV monitoring.

Manual inspection versus convolutional neural networks: Jiao et al. (2019) proposed UAV-based oil spill detection using deep learning and image processing techniques, significantly reducing detection costs by 57.2% compared to manual inspection. A DJI Phantom 4 Pro UAV captured high-resolution images pre-processed using Otsu (Otsu, 1979) and MSER (Matas et al., 2004) techniques combined with a deep learning model to enhance the detection accuracy. Furthermore, Ren et al. (2016) developed a faster regional-convolution neural network (R-CNN) (Girshick et al., 2014) pre-trained on ImageNet (Deng et al., 2009) with transfer learning (Goodfellow et al., 2016), which achieved the highest mean average precision (mAP) of 0.9930. Comparative evaluations with other models, including You-Only-Look-Once (YOLO) (Redmon et al., 2015) (0.9918 mAP) and Fast R-CNN (0.8771 mAP), confirmed Faster R-CNN's superior performance. The study highlighted the efficiency, accuracy, and cost-effectiveness of integrating UAV technology with deep learning for oil spill monitoring.

Earlier studies, such as that of Liu et al. (2016), utilized MNF-decision tree analysis for hyperspectral oil spill detection, while Hu (2022) improved the classification accuracy with a multi-scale CNN. De Kerf et al. (2020) introduced MobileNet-FCN8 for UAV-based monitoring, achieving a high mean IoU of 0.89. Collectively, these advancements highlight the transition from

traditional spectral analysis to AI-driven UAV and CNN models, enhancing oil spill detection with higher accuracy, efficiency, and real-time capabilities.

2.1.2 Remote sensing with satellite

Traditional machine learning techniques and convolutional neural networks have been employed to detect marine oil pollution using SAR data from different satellite missions. A summary of their comparative analysis is discussed in this subsection.

Machine learning model comparisons: State-of-the-art machine learning algorithms, including SVM, decision trees, random forest, and k-nearest neighbor (k-NN) (Fix and Hodges, 1951; Cover and Hart, 1967), have been applied to detect marine oil pollution using sensor and remote sensing data. A random forest classifier developed by Tong et al. (2019) using PolSAR data from RADARSAT-2 and UAVSAR effectively distinguished oil slicks from look-alikes with F1-scores of 0.92 and 0.82, respectively, after pre-processing with LEE filtering (Lee et al., 2003) and multi-polarimetric feature extraction. Similarly, Trujillo-Acatitla et al. (2022) trained k-NN, random forest, and SVM on Landsat multispectral data for binary oil spill classification, where k-NN achieved 1.00 accuracy but lacked validation against overfitting. Additionally, an SVM model with active learning (Burr, 2010; Mohri et al., 2018) was developed by Cao et al. (2016) which classified oil spills and look-alikes from SAR images of RADARSAT-1 and RADARSAT-2 with an AUC value of 0.66, demonstrating its capability to reduce training data dependency. These studies highlight the effectiveness of ML models in oil spill detection, leveraging different data sources and feature extraction techniques.

CNNs for oil spill detection: Various CNN models have been developed for oil spill detection using Synthetic Aperture Radar data—for example, Cantorna et al. (2019) proposed a six-layer CNN (Hou and Zhao, 2017) trained on ENVISAT and Sentinel-1 data, achieving an AUC value of 0.99 and outperforming clustering algorithms like k-means (Faber, 1994; Hastie et al., 2009) and Logistic Regression (Cramer, 2002). A CNN with multi-scale convolution of Seydi et al. (2021) detected oil spills from Landsat-5 SAR data, achieving F1-scores of 0.93 (cloud-free) and 0.88 (cloudy). Song et al. (2020) developed a deep CNN (DCNN) (Rosenblatt, 1958) for polarimetric SAR (PolSAR) images, integrating PCA and RBF-SVM, achieving F1-scores of 0.98, 0.94, and 0.80 across different datasets. This was followed by a 23-layer CNN by Shaban et al. (2021) trained on Sentinel-1 SAR images that outperformed U-Net and SegNet with an F1-score of 0.79 but which struggled with multi-class classification. Furthermore, Chen et al. (2017a) applied SAE and DBN to RADARSAT-2 data, with SAE achieving 98.92% accuracy. Chaudhary and Kumar (2020) utilized UAVSAR and RISAT-1 data, where Wishart Supervised Classification (Wishart, 1928) outperformed SVM with an accuracy of 0.845. These studies demonstrate the effectiveness of deep learning and machine learning techniques in oil spill detection, leveraging SAR data with advanced pre-processing techniques.

TABLE 1   Cumulative literature of recent AI-based spectral marine oil pollution analysis (2016–2023).

Source	Sensors	Dataset (size)	Pollutant classes	Pre-processing methods	AI techniques	Performance analysis	Others
Cao et al., 2016	RADARSAT-1, RADARSAT-2	SAR images	Oil spill	Sixfold cross-validation	Active learning-boosted SVM	For all 6 AL: AUC = 0.66	Ensembled with other CNNs and more training samples could improve performance
Liu et al., 2016	AVIRIS	RGB, infrared images, spectrometric data	Oil spill—thin, thick, medium	Dimension reduction, denoising, feature extraction, radiometric calibration, atmospheric correction, mask processing	Minimum noise transform-decision tree	Eigenvalue spectra: 0.69—thin oil	FLAASH of ENVI for pre-processing, RoI
Chen et al., 2017a	RADARSAT-2	Polarimetric RGB images (24,000 samples)	Oil spill, biogenic look-alikes	Sixfold cross-validation, coherency matrix	SAE, DBN	Accuracy: SAE = 0.98	Other models trained: SVM and ANN
Orfanidis et al., 2018	Sentinel-1 (training: 571, testing: 106 images), EMSA-CleanSeaNet	SAR images	Oil spill, look-alikes	Segmentation	DCNN (like DeepLab)	Overall accuracy = 0.81	Ensembled with VGG-16 or U-net CNN, it could improve performance
Cantorna et al., 2019	Envisat, Sentinel-1	ASAR images (training: 107, test: 23 images)	Oil spill	Data normalization, eliminating land zones	CNN	F1-score = 0.89	Other models trained: k-means, FCM, SKFCM, logistic regression
Krestenitis et al., 2019	Sentinel-1	SAR images	Oil spills, look-alikes, ships, land, sea surface	ROI cropping, image scaling, radiometric calibration, speckle-median filters, linear transformation	DeepLabv3+	For all classes: DeepLabv3 + 0.65 mean IoU	U-Net performed best for oil spills with 53.79 mean IoU; other models trained: U-Net, Link-Net, PSPNet, DeepLabv2.
Jiao et al., 2019	UAV	RGB (1241 images)	Oil spills	Otsu and MSER	DCNN with Faster R-CNN and VGG16	mAP = 0.99	YOLO had a similar mAP
Tong et al., 2019	RADARSAT-2, UAVSAR	PolSAR data	Crude oil, emulsion, vegetable oil, water	LEE filter	Random forest	F1-score: RADARSAT-2 – 0.92	Random forest used a self-similarity factor
Chaudhary and Kumar, 2020	UAVSAR	PolSAR data (11 samples)	Oil spills, water	ROI, LEE, and speckle filtering	Wishart Supervised Classification and RBF-SVM	Accuracy: Wishart Supervised Classifier = 0.84	SVM did not perform better
De Kerf et al., 2020	UAV	RGB and thermal infrared images	Oil, no oil	Image augmentation, image resizing, extraction of the image center, masking outer regions, ROI identification, thresholding, edge detection, transformation, estimation of oil density	MobileNet-FCN8-RMSprop	Mean IoU = 0.89	Feature extractors: MobileNet, ResNet 50, VGG, FCN, SegNet; image segmentation models such as Unet, PSP, Segnet, FCN
Song et al., 2020	RADARSAT-2	PolSAR (3 images)	Oil, plant oil, seawater	Coherency matrix	Feature fusion: DCNN-PCA, Classification: RBF-SVM	F1-score: Dataset 1– 0.98	Ensembled with autoencoders could improve performance

(Continued)

TABLE 1 Continued

Source	Sensors	Dataset (size)	Pollutant classes	Pre-processing methods	AI techniques	Performance analysis	Others
Zeng and Wang, 2020	ENVISAT, ERS, COSMO Sky-Med SAR	SAR images (336)	Oil spills, look-alikes	Segmentation, intensity estimation, dark patch extraction, data augmentation	OSCNet	Average F1-score = 0.84	Other models trained: VGG-16, VGG-19, AlexNet
Shaban et al., 2021	Sentinel-1	SAR data (310 images)	Oil spill, look-alikes, ships, land, sea	ROI cropping, image scaling, radiometric calibration, speckle-median filters, linear transformation	CNN	F1-score = 0.79	Other models trained: U-Net, SegNet; Labeled: 3D color mask segmentation
Seydi et al., 2021	Landsat-5	SAR data (2 multispectral images)	Oil spills	Radiance values, brightness temperature, atmospheric correction	CNN-SAE	F1-score = 0.93	Other models trained: Random Forest, 2D-CNN, 2D-Res-CNN
Chen and Wang, 2022	Sentinel-1	PolSAR (35 images), wind speed information	Oil spill, look-alikes	Polarimetric entropy, anisotropy, mean scattering angles	AUOSD	F1-score = 0.92	Other model trained: SVM
Wang et al., 2022	RADARSAT-2	Quad PolSAR (training: 3 images)	Oil spill, look-alikes	Coherency matrix, scattering matrix, entropy	BO-DRNet	Mean accuracy = 0.74	Other models trained: FCN-8s, DeepLabv3+Xception, DeepLabv3+ResNet18
Ghara et al., 2022	Sentinel-1, EnviSat	SAR (99 images)	Oil spill, look-alikes	SNAP software, labeled with Supervisely software, augmentation	U-Net	Accuracy = 0.78	Other mode trained: DeepLabv3
Hu, 2022	AVIRIS	RGB, infrared images, spectrometric data (2 images)	Oil spills—discontinuous, thin, emulsified; seawater	Radiometric calibration, atmospheric correction	CNN	Average F1-score = 0.99 (discontinuous oil spills)	Pre-processing: FLAASH-ENVI software
Trujillo-Acatitla et al., 2022	Landsat (4-5 TM, 7 ETM+, 8)	SAR data (175 images)	Oil, plastic, vegetation, soil, water	Reflectance, masking clouds	k-NN	Accuracy = 1.00	Pre-processing: QGIS software; feature extractors: PCA, t-SNE; other model trained: Random Forest
Zhang et al., 2022	Sentinel-1	SAR (8 images)	Oil spill, look-alikes, clean sea, land and ship	LEE filter, scattering matrix, semantic segmentation	ResNet	Mean IoU = 0.85	Feature extraction: calculated superpixels and polarimetric parameters, image stretching
Dehghani-Dehcheshmeh et al., 2023	Sentinel-1	SAR (training: 3,900 images of smaller dimensions, testing: 420 images)	Oil spill (long, linear), look-alikes	ROI cropping, image scaling, radiometric calibration, speckle-median filters, linear transformation	DeepLabv3-ViT	F1-score = 0.78	Other models trained: FC-DenseNet, U-Net
Fan and Liu, 2023	Sentinel-1, ERS-1/2 and GF-3	SAR data (total: 120)	Oil spill, look-alikes	ROI cropping, image scaling, radiometric calibration, speckle-median filters, linear transformation, coherent spot filtering, LEE filter, terrain correction, semantic segmentation	GAN	Average accuracy = 0.83	Other models trained: classification—SVM, k-NN, Decision Tree, Random Forest, Naïve Bayes; segmentation—SegNet, U-Net, DeepLabv3

(Continued)

TABLE 1 Continued

Source	Sensors	Dataset (size)	Pollutant classes	Pre-processing methods	AI techniques	Performance analysis	Others
Fan et al., 2023	Sentinel-1	SAR images (total: 82)	Oil spill, look-alikes	LEE filter, multilooking, terrain correction	MFSCNet	F1-score = 0.79	Other models trained: AlexNet, SegNet, Faster R-CNN, YOLOv4, and Mask R-CNN
Hasimoto-Beltran et al., 2023	EnviSat	ASAR (16 images), wind speed information	Oil spill (small, middle, large), not oil (seawater, look-alikes)	ROI cropping, image scaling, radiometric calibration, speckle-median filters, linear transformation, variance filter	DNN	F1-score = 0.98	Outperformed DeepLabv3+

Advancements in CNN architectures: Several studies have explored deep learning models for marine oil spill detection using Sentinel-1 and RADARSAT-2 SAR images. Orfanidis et al. (2018) and Krestenitis et al. (2019) demonstrated that DeepLab (Chen et al., 2017b)-based CNNs performed well in segmenting oil spills, with DeepLabv3+ (Chen et al., 2018) achieving a mean IoU of 0.6506. Ghara et al. (2022) showed that U-Net outperformed DeepLabv3, achieving 0.78 accuracy, while Dehghani-Dehcheshmeh et al. (2023) found that the DeepLabv3-ViT (Dosovitskiy et al., 2020) hybrid achieved the highest F1-score of 0.78. Wang et al. (2022) introduced BO-DRNet (Frazier, 2018), which surpassed FCN-8s (Jégou et al., 2017; Long et al., 2015) and DeepLabv3+ with a mean accuracy of 0.75. Additionally, U-Net variants like OSCNet by Zeng and Wang (2020), ResNet-based DNN by Hasimoto-Beltran et al. (2023), and Attention U-Net by Chen and Wang (2022) have shown high classification accuracy, with F1-scores ranging from 0.84 to 0.98. Zhang et al. (2022) used ResNet (He et al., 2015) for Persian Gulf SAR data, achieving a mean IoU of 0.85. The MFSCNet of Fan et al. (2023) integrated multi-feature learning and outperformed other CNNs with an F1-score of 0.79. Fan and Liu (2023) employed a GAN-based classifier, achieving 0.97 accuracy in distinguishing oil spills from look-alikes. Therefore, this comparative analysis reveals that U-Net, DeepLab, and hybrid CNN-ViT models have consistently outperformed traditional machine learning techniques like SVM and random forest, proving their effectiveness in oil spill detection in SAR imagery.

The significant research gaps identified from these 24 research articles in recent AI-based spectral marine oil pollution analysis are as follows:

- Limited generalization and small datasets—Most studies rely on limited datasets (often less than 1,000 images), which reduce model generalization across diverse oil spill conditions, SAR sensors, and geographical regions. The need for more extensive, standardized, and diverse datasets remains a critical gap.
- Insufficient multi-modal data integration—While some studies incorporate wind speed and polarimetric SAR features, few leverage multi-sensor fusion (e.g., optical, infrared, and hyperspectral data) to improve oil spill detection accuracy under varying environmental conditions.
- Challenges in differentiating oil spills from look-alikes—Despite a high classification accuracy, many models struggle with distinguishing oil spills from look-alike phenomena (e.g., biogenic slicks, low wind areas) due to limited spectral and textural differences in SAR imagery.
- Lack of real-time and computationally efficient models—Many deep learning architectures are computationally intensive, making them unsuitable for real-time applications in maritime monitoring systems, necessitating lightweight and edge-compatible AI models.
- Limited benchmarking and standardization—The absence of standardized evaluation metrics, benchmark datasets, and comparative studies across multiple AI models hinders the reproducibility and scalability of these
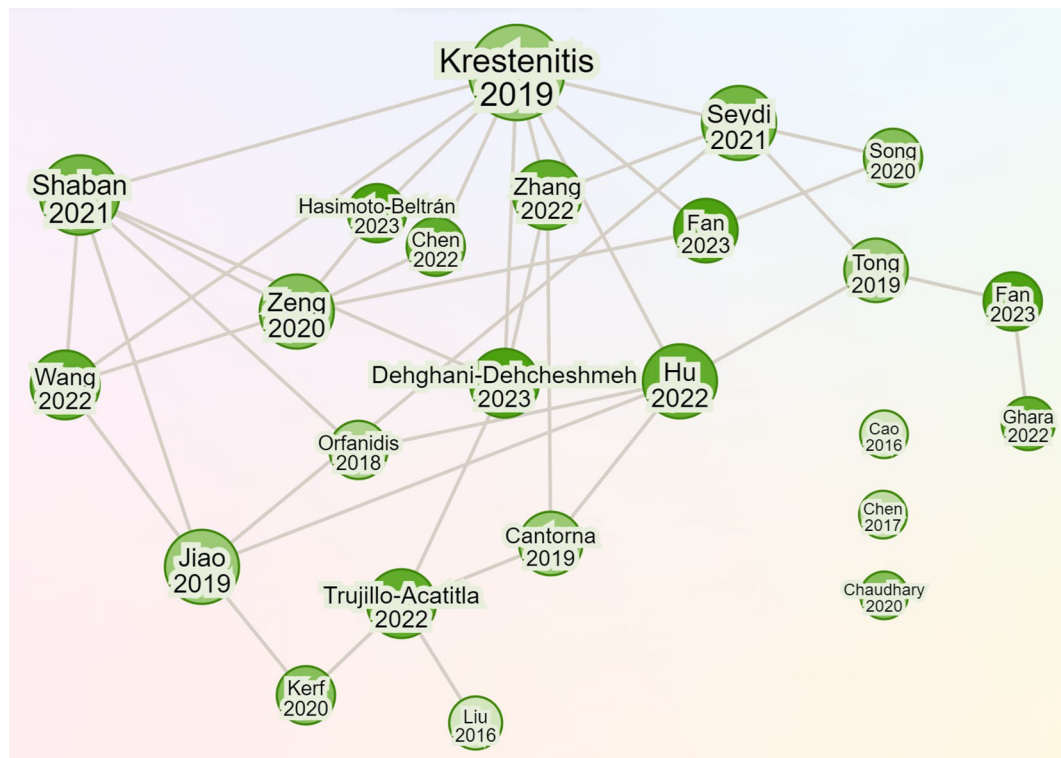
FIGURE 2
Connected graphs for literature of recent AI-based spectral marine oil pollution analysis (2016–2023). The edges represent citations between research articles, the nodes represent the research article, and its size represents the number of citations (a large node size indicates more citations and vice- versa) (graphics from ResearchRabbit.ai).

approaches for operational use in marine oil spill monitoring.

Future research can address the gaps identified in recent research and significantly advance the effectiveness and reliability of marine oil detection and analysis technologies by implementing the improvements listed below:

- Integration of multi-sensor and multi-modal data— Combining SAR with optical, infrared, and hyperspectral data can enhance oil spill detection accuracy by leveraging complementary spectral and spatial information.
- Development of generalized and transferable AI models— Creating deep learning models that generalize well across geographic regions, sensor types, and environmental conditions will improve real-world applicability.
- Enhancing real-time and edge computing capabilities— Implementing lightweight AI models optimized for real-time processing on satellites, drones, and autonomous vessels can enable faster and more efficient oil spill monitoring.
- Advanced feature engineering and hybrid AI approaches— Incorporating physics-based modeling, explainable AI, and hybrid architectures (e.g., CNN-ViT, GANs) can improve

segmentation accuracy and the differentiation of oil spills from look-alikes.
- Establishment of standardized datasets and evaluation metrics—Creating publicly available, high-quality annotated datasets and standardized benchmarking protocols will facilitate the reproducibility and comparability of AI-based oil spill detection models.

2.2 AI-based spectral marine floating litter, plastics, and debris pollution analysis

Recent research has leveraged machine learning and advanced image processing techniques to enhance the detection and classification of marine litter, addressing the limitations of traditional manual monitoring methods. Various models, including support vector machines (SVM), random forest classifiers, and deep learning algorithms, have been applied to high-resolution imaging technologies like reflectance spectrometers and digital cameras to analyze floating, beach, and underwater debris. These AI-driven approaches enable automated, scalable, and real-time marine pollution monitoring using images captured from aerial vehicles, satellites, autonomous underwater

vehicles, and laboratory setups. Deep learning models, in particular, have demonstrated superior accuracy in distinguishing different types of litter, including plastics, ropes, and buoys, even in challenging environments. The integration of these technologies represents a significant advancement in marine litter detection, facilitating large-scale environmental assessments and improving efforts to mitigate ocean pollution. A cumulative literature review in Table 2 and its connected graph in Figure 3 represent citations between research articles. The following subsections compare recent research on marine litter pollution analysis models with different data acquisition strategies such as autonomous underwater vehicles, aerial vehicles, satellites, and from a laboratory.

2.2.1 Remote sensing with autonomous underwater vehicle

2.2.1.1 State-of-the-art CNNs and machine learning ensembled models

Recent advancements in marine debris detection have utilized various CNN-based architectures, each offering unique strengths. Valdenegro-Toro (2016) developed a forward-looking Sonar (FLS) CNN using data for binary and multi-class classification, achieving reasonable accuracy (0.80 and 0.70, respectively) but struggling with deformed plastic detection due to limited training data. Marin et al. (2021) improved the performance by integrating U-Net feature extractors with classifiers like SVM and random forest, where fine-tuned Inception-ResNetV2 achieved the highest F1-score (0.92). Fulton et al. (2019) compared U-Net with YOLO and Faster R-CNN, finding that YOLOv2 provided real-time efficiency, while U-Net yielded superior accuracy for diverse litter types. Xue et al. (2021) further enhanced detection with a hybrid ResNet50-YOLOv3 model, achieving a high Kappa coefficient (0.966) and outperforming Faster R-CNN and SSD in detecting various debris sizes. Specialized models like AquaVision by Panwar et al. (2020) and Mask R-CNN by Politikos et al. (2021) leveraged advanced feature extraction techniques, improving detection in challenging underwater environments. These studies demonstrate the evolution of CNN-based marine debris detection, emphasizing the benefits of ensemble models and transfer learning in improving accuracy and real-time performance.

2.2.2 Remote sensing with aerial vehicle

2.2.2.1 Advancements in ensembled models

Martin et al. (2018) developed an ensembled random forest classifier using orthomosaic litter images from UAV-based surveys along the Saudi Arabian Red Sea coastline. The model, trained with a Histogram of Oriented Gradients (HoG) (Dalal and Triggs, 2005) features, has utilized two binary classifiers to separate litter from background elements and a multi-class classifier to distinguish debris types. While the system detected drink containers (0.44), bottle caps (0.5), and plastic bags (0.037) with varying accuracy, it generated significant false positives, highlighting the impact of image resolution on performance. Comparisons with other classifiers by Fallati et al. (2019), Gonçalves et al. (2020b); Garcia-Garin et al. (2021), and Tran et al. (2022) demonstrated the potential of HoG–random forest models for marine litter

detection with suggestions for improved accuracy through lower UAV flight altitudes.

2.2.2.2 Advancements in CNNs versus manual inspections

Building on Martin et al. (2018), an enhanced model by Martin et al. (2021a, 2021b) used Faster R-CNN with UAV images from 44 beaches in Saudi Arabia, achieving an F1-score of 0.4556, with improved accuracy using DJI Phantom 4 Pro (82%) over Phantom 3 Adv (62%). The PlasticFinder (PlasticFinder, 2017) model by Fallati et al. (2019) trained a CNN on UAV images from the Maldives, outperforming Martin et al. (2018) with an F1-score of 0.63. Furthermore, Gonçalves et al. (2020b) improved marine litter detection with random forest classification on Portuguese beaches (F1-score: 0.75), though it misidentified plants as litter. Gonçalves et al. (2020a) compared random forest (F1-score: 0.70) and DenseNet CNN (F1-score: 0.60), showing random forest's better accuracy in pixel-based classification. Pinto et al. (2021) developed a neural network using UAV orthoimages from Portugal, achieving F1-scores of 0.49 (multi-class) and 0.73 (binary) by leveraging multiple color spaces. Finally, Tran et al. (2022) introduced YOLOv2 CNN for UAV-based litter detection in Taiwan, outperforming previous models with F1-scores of 0.95 (training) and 0.72 (testing), demonstrating the effectiveness of pre-processing techniques in improving marine debris classification.

Several studies have explored AI and deep learning models for detecting marine litter, leveraging datasets from UAVs, satellites, and experimental setups. Kylili et al. (2019) used VGG-16 with Ridge and Lasso regression, achieving 86% accuracy in identifying floating plastics. An improved version by Kylili et al. (2021) trained YOLOv5x and YOLOACT++ on marine litter images, demonstrating better real-time detection (YOLOv5x) and object segmentation (YOLOACT++) with an accuracy of 0.924 for video snapshots. Jakovljevic et al. (2020) applied ResUNet50 for floating pollutant detection in lakes and rivers, achieving an F1-score of 0.88 in multi-class classification. Garcia-Garin et al. (2021) developed a CNN for UAV and aircraft-acquired images, outperforming previous works with an F1-score of 0.86. Comparisons of machine learning methods showed random forest classifiers outperforming SVMs, as demonstrated by Iordache et al. (2022) and Sannigrahi et al. (2022). Iordache et al. (2022) trained a random forest model on multispectral images, achieving an F1-score of 0.93. Hengstmann and Fischer (2020) applied k-means clustering on UAV images for freshwater litter detection, confirming plastics as the dominant pollutant. These studies highlight the effectiveness of AI-driven approaches for marine litter detection, emphasizing the importance of high-quality imagery and dataset augmentation to enhance classification performance.

CNNs, particularly YOLO architectures, have demonstrated superior performance in marine litter detection compared to traditional machine learning classifiers like random forest and SVM. Andriolo et al. (2022) compared different models for UAV-based litter mapping on Portuguese and Spanish coasts, where random forest outperformed CNN for pixel-based beached litter (F1-score: 0.75 vs. 0.60), but CNN achieved the highest F1-score (0.86) for floating litter classification. YOLOv5 has been widely used

TABLE 2 Cumulative literature of recent AI-based spectral marine litter pollution analysis (2016–2023).

Source	Sensors	Dataset (size)	Pollutants/classes	Pre-processing	AI techniques	Performance analysis	Others
Valdenegro-Toro, 2016	Forward-looking Sonar	RGB images (total: 2,000)	Plastic debris	Sliding window, cropping, augmentation	CNN	Accuracy: binary classifier—0.80, multi-class classifier—0.70	Sliding window approach to classify background and debris classes
Acuña-Ruz et al., 2018	HyLogger3 reflectance spectrometer, RGC camera	Reflectance spectrum, RGB images	AMD, styrofoam, plastic buoys, ropes, bottles, containers, fragmented plastics, sand, shells, rocks	Image correction, AMD reflectance estimation	SVM, LDA, and random forest	Average accuracy: linear SVM—0.81	SVM outperformed LDA and RF; the average accuracy of LDA and RF —0.81
Martin et al., 2018	UAV	RGB images (total: 243)	Drink bottles, drums, bottle caps, plastic bags, oil containers, detergent containers, ropes, footwear, boxes–crates–baskets, others	HoG image feature extraction	HoG–random forests	F1-score = 0.13	Three random forest classifiers were ensembled, 2 for binary and 1 for multi-class classification
Fallati et al., 2019	UAV	RGB images	AMD, vegetation, sea, sand, and others	Image alignment, 3D point cloud construction, building digital terrain model	PlasticFinder	F1-score = 0.63	It is a multilayer CNN and uses orthomosaic images, pre-processing with Agisoft PhotoScan software
Fulton et al., 2019	JAMSTEC-J-EDI	RGB images (training: 5,720, testing: 820)	Plastics, ROVs, biota	Image labeling	YOLOv2, Tiny-YOLO, Faster R-CNN, SSD	mAP: Faster R-CNN – 0.83, YOLOv2 – 0.82	Labeling: LabelImg; backbone U-Net architecture: Faster R-CNN with InceptionV2, SSD with MobileNetV2
Kylili et al., 2019	ImageNet	RGB images (total: 12,000)	Bottles, buckets, straws	Augmentation	VGG-16	Accuracy = 0.86	Ridge and Lasso regression regularizes to improve this VGG-16
Hengstmann and Fischer, 2020	UAV	RGB images	Litter samples—red, blue, green, yellow, transparent	Orthoimage pre-processing	k-means clustering	76% of plastics were detected and cigarette buds	Supervised Minimum Distance classifier was trained
Gonçalves et al., 2020b	UAS	RGB images	Beach plastic litter, wood debris, vegetation, dry sand, wet sand	SfM-MVS processing generated 3D point cloud	HoG–Random Forest	F1-score = 0.75	Orthophotos; geomorphic analysis with color descriptor; pre-processing: Agisoft Metashape software
Gonçalves et al., 2020a	UAS	RGB (6 images)	Plastic fragments, fishing strings, foamed buoys, boxes, wood	Orthoimage pre-processing, color assignments	Random forest	F1-score = 0.70	F1-score: DenseNet CNN = 0.60
Jakovljevic et al., 2020	UAV	RGB images	PET, nylon ropes, OPS	SfM, SIFT image feature extraction, 3D sparse unscaled point cloud, densification, building digital terrain model, orthophoto generation.	ResUNet50	F1-score: binary classifier—0.60, multi-class—0.88	Other trained models: ResUNext50, XceptionUNet, InceptionUResNetV2

(Continued)

TABLE 2 Continued

Source	Sensors	Dataset (size)	Pollutants/classes	Pre-processing	AI techniques	Performance analysis	Others
Papachristopoulou et al., 2020	Vessel mounted camera	RGB images	Plastic drink bottles, straws, lolly sticks, pack yokes, plastic bags, plastic food containers, glass, ceramics, metals, rubber, paper, cardboard, clothes, unidentified	Stitching photomosaic images	Linear regression model	Accuracy = 0.50	The split regression model had a lesser error rate of 0.16, and the linear regression model had a 0.29 error rate
Panwar et al., 2020	AquaTrash, TACO, TrashNet	RGB images	Plastic, glass, paper, cardboard, metal, trash debris, litter on land, metal	Labeling	AquaVision	mAP = 0.81	RetinaNet had ResNet50 and FPN as a backbone
deVries et al., 2021	UAV	RGB images (total: 4,000)	Hard plastics, nets, ropes, sea	Augmentation, labeling	YOLOv5	Minimum object size detected: 0.15 m	Labeling: VGG Image Annotator; other trained model: Fast R-CNN
Garcia-Garin et al., 2021	UAV	RGB images (total: 796)	Floating marine macro litter (fmml), no-fmml	Augmentation	CNN	F1-score = 0.86	CNN is a binary model
Kylili et al., 2021	Image library	RGB (1,650 images, train: 1,320, test: 330)	Bottles, bags, straws, food wrappings	Labeling	YOLOv5x	Average accuracy = 0.92	YOLOv5x performed better than YOLOACT++
Marin et al., 2021	JAMSTEC-J-EDI	RGB images (total: 2,395)	Plastic, glass, metal, rubber, other trash, no trash	Labeling	Inception-ResNetV2-SVM	F1-score = 0.92	Feature extractors: VGG16, InceptionV3, ResNet50, Inception-ResNetV2, DenseNet121, MobileNetV2; other trained models: Random Forest, k-NN, Naïve Bayes, Logistic Regression
Martin et al., 2021a	2 UAVs	RGB (750 images)	Containers, bottle caps, drink bottles, drink drums, film (plastic bags), footwear, glass, metal, other liquid containers, ropes, tetra packs, anthropogenic wood	Labeling	Faster R-CNN	Mean F-score = 0.455	1,608 litter objects were found, trained as a binary classifier and multi-class classifier
Pinto et al., 2021	UAV	RGB images	Litter, no-litter, fishing ropes, octopus pots, plastic bottles	Orthoimage pre-processing, color assignments	Neural Network	F1-score = 0.73 (binary classifier)	Average F1-score for all classes = 0.49
Politikos et al., 2021	Towed underwater camera	RGB images (total: 635)	Plastic bags, oversized objects, plastic bottles, cans, caps, cups, fishing nets, plastic sheets, tyres, metal, textile	Augmentation, labeling	Mask R-CNN	mAP = 0.62	Labeling: LabelImg; backbone architecture: MobileNetV1 and RPN

(Continued)

TABLE 2 Continued

| Source	Sensors	Dataset (size)	Pollutants/classes	Pre-processing	AI techniques	Performance analysis	Others
Song et al., 2021	Mobile phone camera	RGB (110 images	Plastics, styrofoam, metal, rubber, glass, fishing gear, unspecified	Image zooming, Labeling	YOLOv5	mAP = 0.87	Accuracy = 0.93 (plastics), 0.80 (unspecified); manual counting had 963 litter items (0.22 error rate), but YOLOv5 predicted 1006 litter items (0.4 error rate)
Xue et al., 2021	JAMSTEC-J-EDI	RGB images (total: 10,000)	Plastic, cloth, fishing net-rope, glass, rubber, natural debris, metal	Labeling	YOLOv3	Overall Kappa coefficient = 0.966	Labeling: LabelImg; feature extractor: ResNet50; other trained models: ResNet50-SSD, ResNet50-Faster R-CNN
Andriolo et al., 2022	UAV	RGB images	Local beached and floating litter	SfM-MVS, digital surface model, orthophoto beach map	CNN	F1-score = 0.86 (pixel-based floating litter classification)	Pre-processing: Agisoft Metashape software; other trained models: Random Forest, SVM, k-NN, NN; random forest F1-scores of local beached litter classification: pixel-based—0.75, object-based—0.72
Armitage et al., 2022	Vessel-mounted camera	Images (total: 10,431)	Plastic shopping bags, bottles, buoys	Augmentation, labeling	YOLOv5s	Overall F1-score = 0.64	Labeling: VIAME software
Hidaka et al., 2022	Digital cameras	RGB images (total: 3,500)	Artificial (plastics, ropes, buoys), living, background, sea, natural (driftwood), sky, sand beach, non-living	Labeling	HRNet	Recall = 0.71 (artificial litter)	Recall = 0.97 for natural litter
Iordache et al., 2022	Multispectral camera	Images, spectral metrics	Plastics, cement, painted surface, oxidated metal, processed wood, grass, tree, soil, water	MAPEO image processing software	Random forest	Overall F1-score = 0.93	Created data artificially; 30 spectral metrics were used as input
Sannigrahi et al., 2022	Sentinel-2	SAR data	Plastic bags, bottles, nets	SNAP software	Random forest	Overall F1-score = 0.86	Other trained model: SVM; incorporated a kNDVI for modeling
Teng et al., 2022	ImageNet, Debris Tracker	RGB images	Plastic bottles, buckets, bags, straws, food wrappings, fishing nets, aluminium cans, cigarette buds	RoI, image centroid counting	YOLOv5	mAP = 0.89	Estimates quantity of debris
Tran et al., 2022	UAV	RGB images	Plastic bottles on the beach, partially buried bottles, overlapped or clustered bottles, deformed bottles	Background removal, segmentation, noise removal	YOLOv2	F1-score = 0.72	Created data artificially; image de-blurring methods in pre-processing could improve performance
Han et al., 2023	Digital camera	RGB images (total: 3,000)	Microplastics: fiber, fragment, rod, pellet	Raman spectroscopy—to eliminate plant and aquatic residue; augmentation, labeling	Mask R-CNN	F1-score = 0.94	Labeling: VGG Image Annotator; backbone architecture: ResNet101
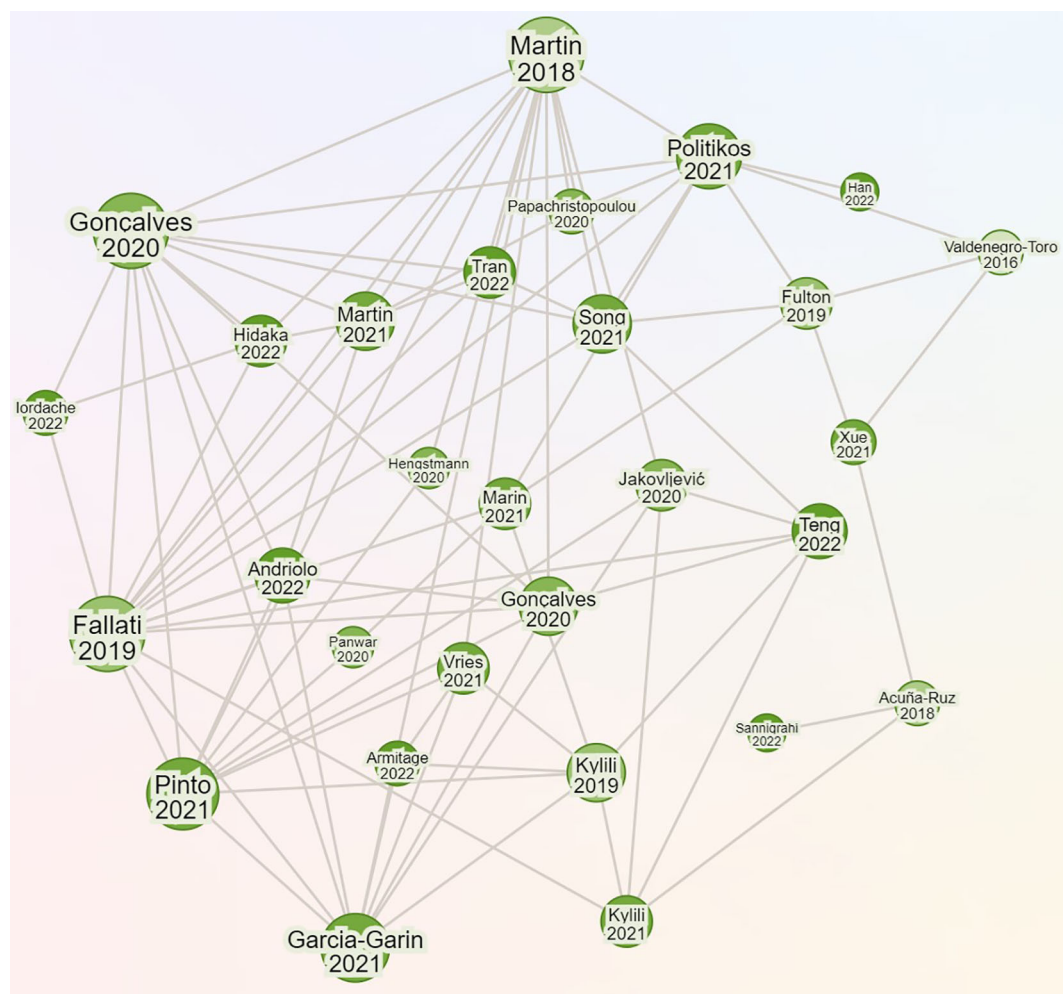
FIGURE 3
Connected graphs for literature of recent AI-based spectral marine litter pollution analysis (2016−2023). The edges represent citations between research articles, the nodes represent research article, and its size represents the number of citations (a large node size has more citations and vice-versa) (graphics from ResearchRabbit.ai).

detect marine litter in various environments. deVries et al. (2021) trained YOLOv5 and Faster R-CNN on UAV images near the Great Pacific Garbage Patch, with YOLOv5 detecting floating macroplastics as small as 0.15 μm, outperforming Faster R-CNN. Similarly, Armitage et al. (2022) used YOLOv5s on vessel-mounted camera videos, achieving an F1-score of 0.64, with better plastic bag detection than YOLOv5m. Teng et al. (2022) trained YOLOv5 on diverse litter images, including plastic bottles, fishing nets, and cigarette butts, achieving a mean average precision (mAP) of 0.89 using centroid tracking for litter quantification. These studies highlight YOLO-based CNNs as real-time marine litter detection tools, emphasizing the importance of high-quality data and model training.

2.2.3 Remote sensing with satellite and stationary or laboratory

Machine learning models, particularly random forest, SVM, and deep learning-based CNNs, have been widely applied for marine litter detection. Sannigrahi et al. (2022) trained random forest and SVM on

Sentinel-2 data, where random forest achieved an F1-score of 0.86 for plastics. In contrast, Acuña-Ruz et al. (2018) found that SVM-linear (accuracy: 0.84) outperformed random forest in AMD classification using spectral data from Chilean beaches. The regression models of Papachristopoulou et al. (2020) predicted beach litter distribution, with the split regression model showing better performance. Deep learning approaches, such as YOLOv5 by Song et al. (2021), achieved a mAP of 0.87 in predicting beach litter in Korea, outperforming manual inspection. HRNet (Guo et al., 2018; Wang et al., 2021) by Hidaka et al. (2022) effectively detected artificial and natural debris in Japan, with recall values of 0.71 and 0.97, respectively. A Mask R-CNN by Han et al. (2023) with ResNet101 backbone classified marine microplastics in Hawaii, achieving an F1-score of 0.94, surpassing U-Net (0.93). These studies highlight the shift from traditional classifiers to deep learning, demonstrating CNNs' superior accuracy and adaptability in detecting marine litter across various environments.

The significant research gaps identified from these 29 research articles in recent AI-based spectral marine litter pollution analysis are as follows:

- Limited multi-sensor and multi-modal data fusion—Most studies rely on single-sensor data (UAV, satellite, or spectral imaging), lacking an integrated approach that combines spectral, spatial, and temporal data for enhanced detection accuracy.
- Challenges in small and overlapping litter detection—While CNN-based models like YOLO and Mask R-CNN show promise, they struggle with small, fragmented, or overlapping litter items, particularly microplastics, requiring improved segmentation and feature extraction techniques.
- Lack of standardized and large-scale datasets—Most models are trained on region-specific, small datasets, limiting their generalizability. A globally standardized, diverse dataset covering different environmental conditions is needed for more robust AI training.
- Limited real-time and autonomous monitoring capabilities—Despite advancements, few models operate in real time or integrate with autonomous systems (e.g., drones, robotic platforms) for continuous large-scale monitoring of marine litter.
- Underexplored spectral signature analysis for litter classification—While some studies use spectral data, many do not fully leverage hyperspectral imaging or advanced spectral decomposition techniques to distinguish between litter materials more effectively.

Future research can address the gaps identified in recent research and significantly advance the effectiveness and reliability of marine litter detection and analysis technologies by implementing the improvements listed below:

- Multi-sensor and multi-modal data integration—Combining UAV, satellite, spectral, and in- situ imaging data can improve detection accuracy by leveraging complementary information across different sensors and wavelengths.
- Enhanced deep learning models for small and overlapping litter—Developing advanced AI models with improved segmentation, feature extraction, and super-resolution techniques can enhance microplastics and overlapping litter detection.
- Creation of large, standardized, and diverse datasets—Establishing global, high-quality datasets with standardized labeling and diverse environmental conditions will improve model generalizability and facilitate study benchmarking.
- Real-time and autonomous monitoring systems—Integrating AI models with real-time UAV and robotic platforms can enable continuous, large-scale marine litter monitoring with minimal human intervention.
- Advanced spectral analysis for material classification—Using hyperspectral and multispectral imaging with machine-learning-based spectral unmixing can enhance the differentiation of marine litter types, including plastics, metals, and organic debris.

3 Discussion

Recent research highlights significant advancements in AI-based marine pollution detection and identifies key challenges requiring further investigation. A primary limitation is the restricted access to high-quality, real-time remote sensing satellite data due to cloud cover, weather conditions, and temporal gaps, which affect AI model performance (Prakash et al., 2021; Ryazanov et al., 2021; Andriolo et al., 2022). To address this, future research should integrate aerial vehicles, offshore sensors, and synthetic datasets to enhance data availability and model training (Wang et al., 2022). The effectiveness of AI models is also hindered by limited and non-diverse training datasets, particularly for detecting deformed or submerged marine litter, necessitating the expansion of multispectral and hyperspectral imaging applications (Prakash et al., 2021). Moreover, developing real-time AI-based monitoring systems using UAVs and offshore spectral sensors can improve the tracking of marine litter and oil spills (Veettil et al., 2022; Rodrigues et al., 2023). Advances in domain adaptation techniques and multi-environment AI models are needed to enhance generalizability across diverse marine conditions (Prakash et al., 2021).

Additionally, by combining automated AI analysis with human verification, hybrid approaches could enhance detection accuracy and minimize false positives (Yang et al., 2022a). Finally, integrating AI with real-time data processing on edge devices, policy-driven pollution management strategies, and multidisciplinary collaborations are crucial to improve marine pollution monitoring and response (Helinski et al., 2021; Ma et al., 2023; Vasconcelos et al., 2023). Addressing these challenges will significantly advance AI-driven marine pollution analysis and contribute to more effective environmental protection efforts.

4 Conclusion

The development and performance of AI models to predict marine pollution are highly influenced by several critical factors: the quality and quantity of training data, which includes images, videos, and spectral data; the pre-processing techniques and feature extraction methods employed; and the architecture of the machine learning models. Current state-of-the-art AI models, such as custom-YOLOv5, have demonstrated superior prediction rates, mainly with spectral sensor data, to detect marine oil spills and litter pollution (Prakash et al., 2021).

Despite these advances, there is significant potential for further improvement. Enhanced results could be achieved by implementing ensembled (Goodfellow et al., 2016; Dietterich, 2020) models and using more extensive, augmented datasets (Prakash et al., 2021). Contrastive learning involves training models with positive (pollution) and negative (clean water) examples, which can enhance training sets and improve future deep learning models for marine pollution detection.

Moreover, data augmentation and transfer learning from pre-trained models can significantly boost the efficiency and accuracy of these AI systems. These strategies will be pivotal in advancing the field of AI-driven spectral analysis for real-time offshore monitoring of marine oil spills and floating litter (Prakash et al., 2021).

By leveraging these advanced techniques, future AI models can become more robust and reliable in predicting and managing marine pollution.

Author's note

The corresponding author conducted this review from 2020 – 2023 while working as a Researcher at DFKI GmbH and a Doctoral Student at ICBM, Carl von Ossietzky University of Oldenburg.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material. Further inquiries can be directed to the corresponding author.

Author contributions

NP: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. OZ: Conceptualization, Funding acquisition, Supervision, Writing – review & editing.

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Authors NP and OZ were employed by DFKI GmbH.

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Supplementary material

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