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Next-gen marine safety: Real-time automated oil spill detection and monitoring with IoT and transfer learning

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ABSTRACT

Marine oil spills pose a severe and persistent threat to ecosystems and coastal economies. Traditional manual or satellite detection is slow, laborious, and error-prone due to sensor limitations, noise, weather interference, small target sizes, and imbalanced datasets. To address these challenges, this paper proposes a novel, integrated framework for the rapid detection and monitoring of oil spills by using the Internet of Things, unmanned vehicles, and transfer learning. The proposed system uses a multi-layered architecture: a physical layer of visual, infrared, and acoustic sensors deployed on a network of Saildrone unmanned surface vehicles for real-time data acquisition; an edge layer for initial processing and low-latency response; and a cloud layer that uses deep transfer learning for accurate spill identification and classification. We fine-tuned pre-trained ResNet models using a Synthetic Aperture Radar oil spill dataset, achieving a peak accuracy of 97.89% with a three-layer transfer learning configuration, outperforming other tested configurations. The efficiency of the system in real-time data handling and leak localization was validated through a controlled experimental prototype. The results demonstrated a robust solution for minimizing response time and environmental impact. Our framework has been proven to gain about 98.3% model accuracy on drone images for oil spill detection.

Keywords: ransfer learning; Deep learning; Internet of Things; Oil spill detection; Continuous monitoring; Sustainable maritime activity

INTRODUCTION

Over 80% of international trade is carried out by sea, making maritime shipping essential for the movement of goods, raw materials, and energy resources [1–3]. Thus, the maritime industry plays a vital role in global development, serving as the foundation of international trade, transportation, and economic growth [4–6]. The maritime sector also creates millions of jobs worldwide, from ship crews and port workers to engineers and logistics specialists [7–9]. Additionally, it plays a key role in national security, environmental protection, and disaster relief efforts. Due to this reason, the maritime sector has been applying advanced and updated technologies, such as hull optimization [10,11], fuel consumption optimization [12,13], application of renewable energy and green fuel [14,15], development of exhaust gas treatment systems [16,17], and the development of advanced materials and equipment to protect the marine environment [18,19], aiming to improve the operation efficiency and enhance environmental protection. Maritime activities include commercial shipping, fishing, offshore oil and gas exploration, shipbuilding, and port operations [20–23]. Maritime activities, while crucial for global trade and transportation, can unfortunately lead to oil spills, posing a significant threat to marine ecosystems [24,25]. These spills often occur due to accidents involving oil tankers, such as collisions or groundings, resulting in the release of large quantities of crude oil into the ocean [26,27]. Operational discharges from vessels, including the illegal dumping of oily waste, also contribute to the problem, albeit often in smaller quantities. Furthermore, offshore drilling operations, though less frequent in causing spills, can have devastating consequences when accidents like well blowouts occur. Therefore, these activities require strict safety and environmental regulations to ensure sustainable development and minimize risks to marine ecosystems [28–30].

Oil spill disasters pose a significant threat to marine ecosystems and coastal communities, causing widespread environmental damage and economic losses [31,32]. Oil spills in the ocean have detrimental effects, causing damage to aquatic organisms, a reduction in sunlight reaching the ocean surface, and decreased oxygen levels [33,34]. Oil-coated birds and marine mammals can suffer from hypothermia, and ingestion of oil is toxic to affected creatures and their habitat [35,36]. Therefore, early detection and monitoring of oil spills are crucial for minimizing their impact and facilitating effective mitigation efforts, as evidenced by the research of Vasconcelos et al. [37]. Traditional methods for oil spill detection, such as visual inspection and radar imaging, are often time-consuming [38], labour-intensive, and limited in their effectiveness [39], especially in vast and remote areas as reviewed by Al-Ruzouq et al. [40]. Computer technology is being used for oil spill monitoring in marine environments [41,42]. Various computational techniques and artificial intelligence-based models have been applied to facilitate decision-making processes in effective marine oil spill management [43,44]. These techniques utilize real-time data, such as satellite and aerial observations, and historical records of oil spill incidents to detect, characterize, and monitor oil spills, as well as to optimize spill management and response [45]. Additionally, the use of IoT and computer systems, such as Raspberry Pi, sensors, and LCD screens, has been proposed to automate oil skimmers and design smart systems for cleaning oil spills in water bodies, as claimed by Abhijith et al. [46]. Furthermore, a ship oil discharge monitoring system has been developed using sensors as a data acquisition technique to calculate the instantaneous discharge rate and total amount of oil discharged from oil tankers [47]. Various advanced methods currently employed to identify oil spills in ocean settings have been significantly improved by the advancements in remote sensing technologies. These enhancements play a crucial role in detecting and monitoring oil spills, offering vital information for effective response and mitigation strategies, as illustrated in Figure 1.

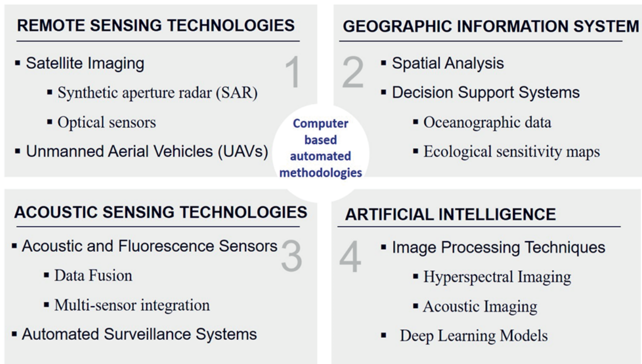


Fig. 1 State-of-the-art techniques used for oil spill detection in marine environments

Emerging technologies like Artificial Intelligence (AI) and Machine Learning (ML) offer promising solutions for environmental concerns, including marine pollution [48,49]. AI serves as the framework for creating intelligent systems, while ML equips them with the ability to analyze vast amounts of historical data and generate informed predictions and decisions [50]. This combination presents significant potential for protecting the marine environment. The applications of AI and ML in marine conservation are diverse, ranging from oceanographic data analysis and shipping monitoring to debris detection, sustainable ocean mining, and preventing illegal fishing, coral bleaching, and marine diseases [51]. These technologies enable the development of specialized tools and applications specifically tailored to address various marine pollution challenges. Furthermore, the integration of Big Data and machine learning technologies into ocean remote sensing evolves into data-driven discoveries while addressing challenges related to data processing, storage, retrieval, and analytics as depicted in Figure 2. Despite advancements, there can still be inaccuracies in data interpretation and limitations in distinguishing between different types of substances on the ocean surface. This article presents the advantages of utilizing IoT data and transfer learning in managing marine pollution through a sustainability lens.

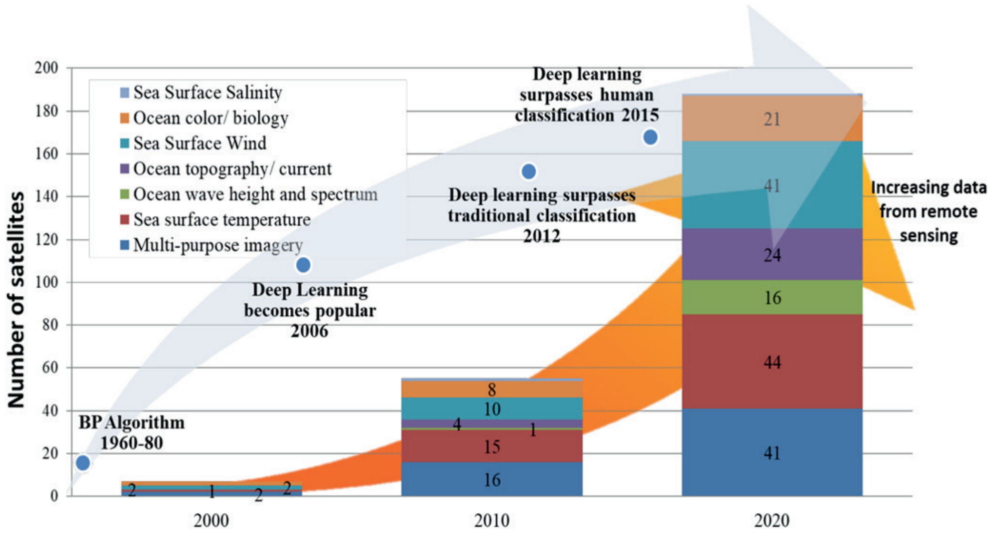


Fig. 2 Paradigm shift in ocean remote sensing transitioning to a big-data environment [52]

The rest of the manuscript continues with Section 2 which discusses relevant research works related to the problem statement. Sections 3 and 4 provide an overview of the system and methodology, respectively. The experimental setup is detailed in Section 5. Section 6 presents the observed effects, while Section 7 summarizes and critiques the findings, leading to the identification of areas for further research.

RELATED WORKS

Hyperspectral remote sensing has been identified as an effective tool for monitoring marine oil spills [42,53], with the development of a spectral-spatial features integrated network (SSFIN) that employs both 1-D and 2-D convolutional neural network (CNN) models to extract spectral and spatial features for oil spill detection Raharjo [54]. Similarly, the use of Synthetic Aperture Radar (SAR) images has been extensively utilized [55], with machine learning models trained on high-resolution satellite and drone imagery to predict oil spill events [56]. The integration of Automatic Identification System (AIS), data of ships into these models further enhances the predictive capabilities. The fusion of deep learning methods with shallow learning methods has been proposed to improve oil spill detection accuracy, especially in cases of limited samples [57]. A decision fusion algorithm based on fuzzy membership degree has been introduced, which integrates multi-scale features after wavelet transform, resulting in higher detection accuracy compared to single detection algorithms as discussed by Murugan et al. [58].

A comprehensive review of remote sensing technologies and ML algorithms for oil spill detection and monitoring has been conducted, analyzing over 100 publications. This review discusses the strengths and weaknesses of different remote sensing data sources, data preprocessing, feature extraction, and the capabilities of various ML techniques [59]. A two-stage deep-learning framework has been introduced for the detection of oil spills from SAR data [60], which includes a novel 23-layer CNN for classification and a five-stage U-Net structure for semantic segmentation [61]. Advances in remote sensing technology, ML, and DL for marine oil

Tab. 1 Characteristics of using AI and ML for oil spill applications in related works

Ref	Learning Model	Learning Task	Data	Disadvantages
[66]	Convolutional Neural Networks	Object detection and U-Net structure for semantic segmentation	SAR images (23 nos.)	• Complex two stage networks • Low training speed
[67]	Convolutional Neural Networks	Patch-based classification	ENVISAT, ALOSPOLSAR, and TERRASAR	• Challenges of accurately labeling the training data • Misclassification due to similar features between oil spills and look-alikes
[58]	Deep Optimized learning	Segmentation and classification	SAR images	Computationally intensive and time-consuming for large datasets.
[68]	Recurrent Neural Network	Classification	SLAR records (12 nos.)	Phase information and other polarimetric information are ignored.
[69]	Convolutional Neural Networks	Semantic segmentation	Sentinel-1 SAR Images	Complexity in integrating Cloude polarimetric decomposition into model
[70]	Generative Adversarial Network	Classification	SONAR images (600 and 300 samples for training and testing)	Higher the training time of the ResNet-ACW model
[71]	Dense-structured network of deep learning (DenseNet)	Classification	Sentinel-1A SAR images	Limitations in detecting smaller or localized oil spills

spill detection, prediction, and vulnerability assessment have been reviewed, highlighting the potential of emerging digital trends in minimizing oil spill hazards [62].

Operational oil spill monitoring using a combination of satellite-based SAR images and aircraft surveillance has been discussed, with recent studies indicating that polarimetric SAR can improve discrimination between oil slicks and biogenic films [51]. A semi-automatic oil spill detection method using texture analysis, machine learning, and adaptive thresholding on X-band marine radar images has been proposed, which allows for accurate and consistent extraction of oil spills [63]. Finally, the development of a new approach to satellite oil spill detection employing two different Artificial Neural Networks (ANNs) has been described in Ghorbani et al. [64]. This approach uses one ANN for segmentation and another for classification, significantly improving the identification of oil spills and reducing the misidentification of look-alike phenomena [65]. In general, characteristics of related works could be given in Table 1.

The motivation behind this work is to segregate the findings documented in this field, contextualized within the framework of autonomic computing, with the ultimate goal of establishing more resilient predictive analytics to ensure a sustainable future. Our paper addresses the research gaps in the existing literature by focusing on several crucial aspects not covered by previous studies. These include concerns regarding the limitations of existing oil spill detection methods, which often rely on manual surveillance or satellite imagery, leading to delayed detection and response. The research gaps identified are follows:

- Assigning a single label to entire satellite images can be problematic when dealing with complex scenarios or when trying to extract detailed information from the content.
- The challenge of distinguishing oil spills from similar-looking natural phenomena in satellite images is a significant limitation of current AI-based detection methods.
- The imbalanced class distribution in datasets, where oil spills are much rarer than non-spill events, poses a problem for machine learning models, potentially leading to biased or inaccurate detection.

However, this vital system is increasingly vulnerable. The UNCTAD Review of Maritime Transport 2024 highlights that critical maritime chokepoint, including the Panama and Suez Canals, face significant risks from geopolitical tensions, climate impacts, and regional conflicts [72]. In 2023, ship transits through these canals declined by over 50%, forcing costly rerouting around longer passages such as the Cape of Good Hope. These disruptions intensify supply chain strain, increase operational costs, and elevate carbon emissions, with disproportionate impacts on vulnerable economies like Small Island Developing States and Least Developed Countries. This emphasizes the urgent need to develop resilient, efficient maritime safety and monitoring systems, such as the integrated multi-sensor and AI-driven framework proposed in this study.

While the threat of oil spills is a global concern, the effectiveness of detection and response systems is highly dependent on local conditions. The factors such as geographic location such as open ocean or congested shipping lanes or icy waters, prevailing meteorological conditions, existing maritime infrastructure, and regional legal and regulatory frameworks, create a diverse set of operational requirements. A solution that is optimal in one context may be impractical or inefficient in another. Therefore, this paper proposes a flexible, modular framework for a next-generation marine safety system. The core technological contributions are presented as a suite of interoperable components, whose specific configuration and deployment must be defined by a set of local boundary conditions and requirements, which we will delineate in the following sections.

To address the limitations, this paper proposes a Next-Gen Marine Safety system that integrates IoT networks, autonomous vehicles, and AI-driven analytics for real-time oil spill detection and response. The primary objective is to develop a modular framework that enables rapid spill detection via multi-sensor fusion, reduces response latency through edge-cloud computing, and ensures high classification accuracy using transfer learning, while remaining adaptable to diverse maritime contexts through defined boundary conditions. Consequently, this research paper significantly advances our comprehension of viable AI-based methods for early detection of marine oil spills. In this paper, we make the following major contributions to oil spill detection using AI technology for safeguarding the marine ecosystem. The proposed Next-Gen Marine Safety system provides real-time detection and response to oil spills through diverse sensors, edge computing, AI-integrated analysis, and adaptable Saildrones to promote a safer marine environment.

- The Next-Gen Marine Safety system leverages a network of diverse sensors (visual, infrared, microwave, underwater) and drones for comprehensive data collection on various marine factors, including oil spill indicators. This real-time data acquisition allows for immediate detection and response to spills.
- Onboard processing and computing capabilities enable initial data analysis and filtering with edge nodes, reducing latency and bandwidth usage compared to solely cloud-based processing. This enables faster decision-making and resource optimization.
- The cloud infrastructure utilizes transfer learning to analyze sensor data and train models for automated oil spill detection, prediction, and classification. This AI-powered approach improves accuracy and efficiency compared to statistical analysis.
- The deployment of tailored Saildrone surface vehicles with the integration of an Acoustic Doppler Current Profiler (ADCP), AIS and advanced sensor designs such as the RBRtridente three-channel fluorescence and backscatter sensor contribute to enhanced oil spill detection and monitoring capabilities and expand the flexibility and adaptability of the system to different scenarios and requirements.

METHODOLOGY

PROBLEM STATEMENTS

Problem 1: Slow Detection and Response: Assume RT to be the response time taken to initiate response after spill detection and environmental damage can be represented as ED as the quantified measure of damage to marine ecosystem. ED = f(RT) where f is a function that increases with increasing RT, indicating higher damage with delayed response.

Problem 2: Limited Assessment and Mitigation: Let SE represent the area covered by the oil spill and the mitigation effectiveness indicates the percentage of oil successfully contained or remediated. The mathematical relationship is indicated by ME = g(SE, Information Availability) where g is a function that decreases with increasing SE and increases with better information about the spill (obtained through real-time monitoring).

Problem 3: Gaps in Surveillance: Surveillance Coverage (SC) refers to the percentage of an area that is effectively monitored, while Detection Probability (DP) represents the likelihood of identifying a spill within a specific timeframe. These two metrics are interconnected through a mathematical relationship, DP = h(SC), where h is a function that demonstrates an increase in DP with expanding SC. This relationship underscores the importance of broader surveillance coverage in enhancing the probability of early detection.

Problem 4: Challenges in Coordinated Response: In the context of the Impact on Ecosystems and Communities (IEC), the relationship between the Resilience of Ecosystems (RCE) and Information Availability can be represented by the function IEC = i(RCE, Information Availability). This function is assumed to decrease as RCE increases and increases with better information availability about the incident. Information Availability refers to the quality and accessibility of information about the environmental incident, and it can significantly impact the effectiveness of response actions.

Problem 5: Risk of Widespread Harm: The cumulative environmental and economic loss EEL=j(1–PIP) where PIP is the probability of promptly discovering a leak and j(*) is an increasing function that quantifies the impact of delaying or missing the spill identification on the total losses incurred. The inverse proportionality $j(*) = \frac{1}{PIP}$ indicates the lower probabilities of proactively identifying a spill leading to greater overall losses.

DEVELOPMENT OF IoT SYSTEM

An IoT network was deployed on main shipping lanes with a multi-sensor array consisting of visual, infrared, and microwave sensors placed at strategic locations in sensitive ecosystems to capture diverse data types. The selection of RF sensors was driven by their demonstrated capability in Abhijith et al. [46] to detect dielectric property changes in oil-contaminated water, while acoustic sensors address the underwater detection gap noted in a study of Dai et al. [70]. Underwater sensors were also horizontally scaled with the IoT network for real-time oil plume tracking and depth measurement. The remote sensing module can be configured to operate various aerial drones, selected based on range, payload, and local airspace regulations, to capture high-resolution images and monitor large areas. The network uses high-speed connectivity for real-time transmission of remote sensing data to an edge node enabling real-time communication between deployed sensors, edge devices, and cloud-based platforms for seamless data transfer. The edge node processes data closer to the source at the edge before transmitting it to cloud servers. It has onboard processing and computing capabilities to perform initial data analysis and filtering, reducing latency in decision-making. Further, as a high-performance computing platform, the cloud infrastructure hosts transfer learning for automated analysis of periodical sensor data and executes raining models to identify, predict, and classify oil spill incidents based on patterns and anomalies detected in the data. Indeed, the overview scheme of Next-Gen marine safety is illustrated in Figure 3.

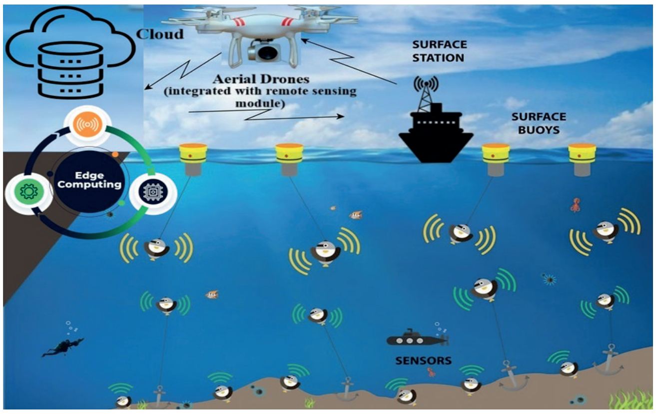


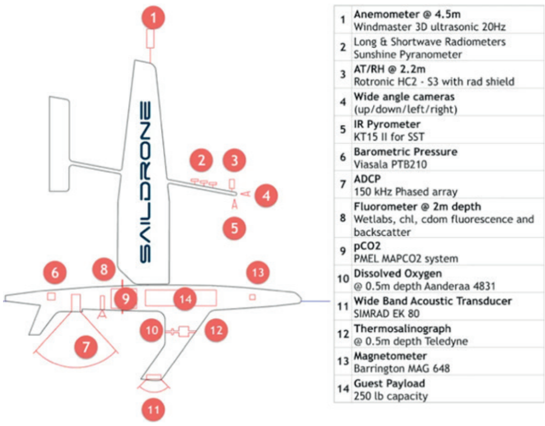
Fig. 3 Next-Gen marine safety: a generic overview [73]

Physical oil recovery system design: The proposed system employs super-hydrophobic polymer-based porous absorbents for physical oil recovery. The advantage of these materials is their high selectivity for oil over water [74]. As per our previous experimentation, these sorbents show a water contact angle >150° and water uptake <1 g/g, an order of magnitude lower than their oil sorption capacity such as >30 g/g for crude oil. This property prevents waterlogging, preserving buoyancy and ensuring full pore volume is available for oil absorption, maintaining high efficiency during spill response. The superhydrophobic surface forms an oil–water–solid interface, allowing oil to penetrate while repelling water through trapped air pockets. This selective wetting keeps sorbent pores available for oil, maintaining high absorption and buoyancy during marine use [75,76]. As detailed in Table 2, these sorbents demonstrate exceptional oil-water selectivity with a 30:1 ratio, ensuring minimal water uptake while maximizing oil recovery capacity.

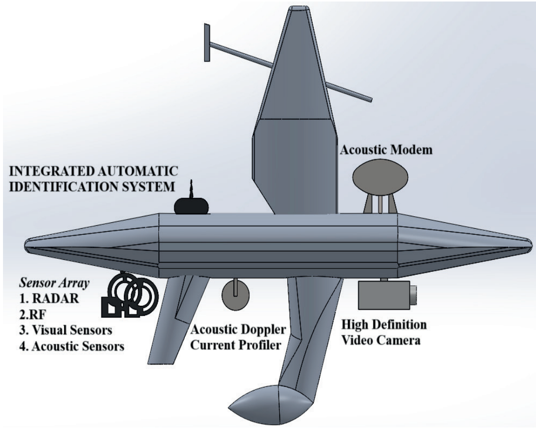
Tab. 2. Sorbent performance characteristics

Parameter	Value	Significance
Water contact angle	>150°	Superhydrophobic behavior
Water uptake capacity	<1.0 g/g	Maintains buoyancy
Oil sorption capacity	>30 g/g	High recovery efficiency
Oil: water selectivity ratio	30:1	Selective absorption
Retention efficiency	>95%	Sustained performance

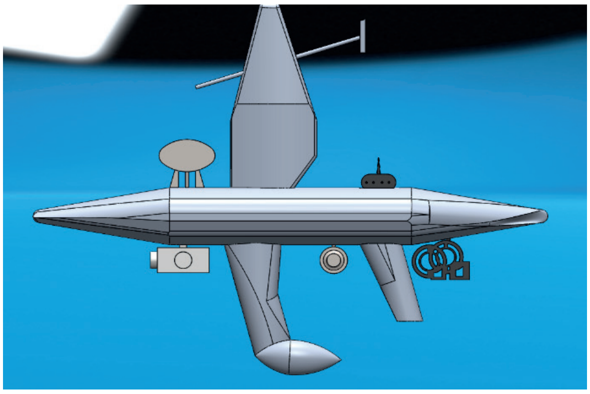
The proposed intelligent seascape platform features a simple design, comprising hardware elements equipped with processing and communication capabilities. These elements encompass a variety of sensors integrated into autonomous platforms like Saildrone USVs. These sensors are tasked with gathering data on diverse marine factors, including indicators of oil spills, and relaying this information in real-time for analysis and appropriate action. The radar sensor is adept at discerning oil spills by detecting alterations in water surface texture resulting from oil presence. Acoustic sensors



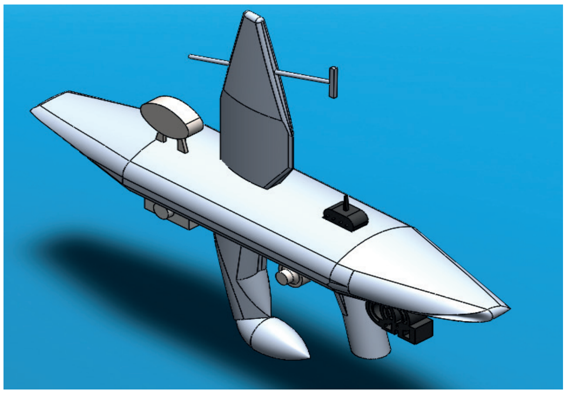
(a) Saildrone configuration



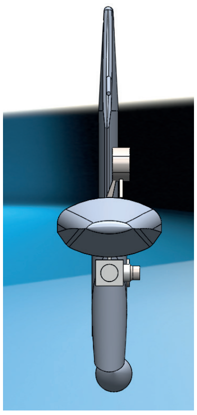
b) Customized Saildrone configuration



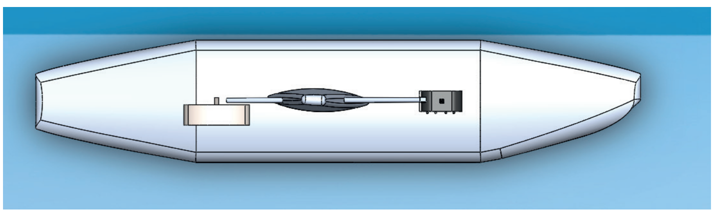
(c) Lateral view of the custom-configured saildrone



d) Skewed view of the custom-configured saildrone



(e) Plan view



(f) Top view

Fig. 4 Tailored Saildrone setup: a) Standard components of a Saildrone [77]; b) Adjustable sensor payloads to suit oil spill monitoring; (c-f) Different angles and views can identify oil spills by gauging alterations in the water's acoustic characteristics due to oil presence. Visual sensors employ image capture of the water surface to detect oil slicks. RF sensors detect oil spills by monitoring changes in water dielectric properties induced by the presence of oil. In general, a Tailored Saildrone setup could be illustrated in Figure 4.

Customized Saildrone configuration: The standard Saildrone components are shown in Figure 4a. The saildrone provides unmanned surface vehicles (USVs) that are equipped with customizable sensor payloads, which can be customized as per our application scenario and requirements and shown in Figure 4b. This customization addresses the geographical flexibility requirement, allowing the system to be adapted to different maritime environments rather than assuming a one-size-fits-all solution.

Acoustic Doppler Current Profiler: An Acoustic Doppler Current Profiler (ADCP) is configured at the underside of the saildrone that uses sound waves to measure the speed and direction of water currents. This active sonar transmits sound waves downward that reflect off particles in the water and are then scattered back to the sonar. By measuring the Doppler shift of the reflected sound waves, the ADCP sonar can determine the speed and direction of the water currents.

Automatic Identification System: It is an infrastructure that transmits data from ships to shore-based stations and other vessels. By utilizing high-resolution images and videos, this system can provide a more comprehensive and timely response to oil spills. Drones equipped with thermal and optical cameras can survey vast areas of the sea, detecting oil slicks and other signs of pollution with unparalleled precision and speed. The combination of AIS and drone data provides a more accurate and detailed picture of the spill, enabling a more targeted and efficient response. By providing real-time data on oil spills, authorities can take immediate action to minimize the damage and prevent further environmental harm.

Sensor design: The RBRtridente three-channel fluorescence and backscatter sensor is used in environmental monitoring, particularly in the detection and characterization of oil spills in marine environments. This sensor is designed to detect and quantify various components in seawater, including hydrocarbons associated with oil spills. In the context of oil spills, certain organic compounds present in crude oil and refined petroleum products exhibit fluorescence when exposed to specific wavelengths of light. By analyzing the fluorescence emitted by these compounds, the sensor can detect the presence of oil in the water column.

Visual sensors: The visual sensor placed in the sensor array is used for object detection and recognition tasks, such as identifying underwater structures or other objects of interest.

Acoustic sensors: The saildrone is equipped with a sensor payload that is designed to support the Vemco VR2C acoustic monitoring receiver. Oil spills produce distinct sounds underwater due to the formation of gas bubbles and interactions with waves. The VR2C, operating at a frequency of 69 kHz, is capable of identifying these unique acoustic patterns within its effective range, usually up to 2 kilometers. By linking the VR2C to an IoT gateway with real-time data transmission capabilities, it enables uninterrupted monitoring and remote retrieval of detected acoustic signals. Furthermore, the payload of the saildrone can be extended to active response.

The mitigation component is the super-hydrophobic sorbent materials. For effective in-situ use, these sorbents are engineered for high mechanical durability, cross-linked porous networks to maintain structural coherence under wave agitation, and to prevent secondary pollution. The operational protocol for these sorbents involves their deployment directly onto oil slicks identified by the sensor network, where their oleophilic and hydrophobic properties enable selective oil absorption. Post-saturation, they are recovered using skimmers or nets. This closed-loop approach ensures the physical mitigation step is both effective and environmentally sound. The scalability of sorbent production is important for system-wide deployment. The polymer-based and functionalized cellulose sorbents discussed are engineered for industrial-scale manufacturing [78,79]. They use abundant precursors and scalable processes such as freeze-drying, cross-linking polymerization, and dip-coating. The super-hydrophobic polyurethane foams are mass-produced in continuous batches and cut into granules, sheets, or booms, enabling flexible, cost-efficient fabrication [80–82]. This ensures a robust supply chain to meet large-scale spill response needs across diverse maritime regions.

Operational modes: The leak detection system operates in three main phases: i). leak detection, ii). leak localization, and iii). leak reporting.

i) Leak detection (default): The sensors continuously monitor for data indicating potential oil spills. The network passes the periodical data to the edge node that performs initial analysis and filters out noise. The transfer learning models in the cloud identify and classify potential spills based on sensor data patterns. The real-time communication between sensors, edge nodes, and cloud platforms enables swift analysis.
ii) Leak localization: Upon confirmation of a spill, drones are automatically dispatched to capture high-resolution images for precise location identification. The underwater sensors provide real-time oil plume tracking and depth measurement, aiding further localization.
iii) Leak reporting: Upon detecting a potential leak, the edge node transmits a dedicated message to the cloud via a narrow-band IoT (NB-IoT) communication link, enabling visualization using real-time data display for monitoring and analysis. Followed by a trigger that activates automated responses like drone deployment. Further analysis with transfer learning models in the cloud performs an in-depth analysis and confirmation of the leak. In areas with no NB-IoT coverage, alternative communication protocols like satellite communications are employed for reliable message transmission.

SORBENT DEPLOYMENT AND RECOVERY PROTOCOL

The integration of super-hydrophobic sorbents into the response strategy is designed to be a targeted, efficient process triggered by the detection and localization phases. The protocol is as follows:

1. Once the spill is detected and its boundaries are precisely mapped, sorbent materials are deployed through a coordinated multi-platform system:
   a. Autonomous Saildrones equipped with on-board dispensers, these units release buoyant sorbent booms or loose granules directly onto the slick for rapid first-line containment.
   b. Large UAVs (Unmanned Aerial Vehicles) with pre-packaged sorbents or pre-formed booms are air-dropped with high positional accuracy, guided by real-time geospatial coordinates.
   c. Utilizing live data streams, manned response vessels deploy extensive sorbent booms along the spill perimeter to maximize containment and facilitate subsequent recovery.
2. There are two complementary application formats employed to optimize oil capture and containment:
   - Loose Granules or Sheets: These are highly porous, lightweight materials whose super-hydrophobic and oleophilic characteristics enable rapid oil uptake into cohesive floating masses while actively repelling water.
   - Integrated Sorbent Booms: These hybrid structures simultaneously act as physical barriers and absorbents, effectively limiting lateral slick spread while capturing surface oil.
3. Post-Saturation Recovery: After oil absorption, the sorbents remain afloat, enabling efficient retrieval. The skimmers or collection nets deployed from Saildrones and vessels recover the sorbent–oil agglomerates, which behave as consolidated masses rather than unstable emulsions. This approach significantly improves recovery efficiency compared to conventional skimming methods.
4. The recovered sorbent–oil mixtures are transported to designated processing facilities, where oil is separated for potential recycling. The sorbents are regenerated for reuse or thermally treated under controlled incineration conditions to eliminate residual contaminants and prevent secondary environmental release.
5. Post-Recovery Processing and Disposal: The handling of oil-saturated sorbents is an important step to ensure an environmentally sound and cost-effective response. We propose a multi-tiered strategy for the post-recovery phase:
   a. Primary pathway - oil recovery and sorbent regeneration: To enhance sustainability and support a circular economy, the primary aim is oil recovery and sorbent regeneration. The recovered sorbent-oil mass can be processed using methods such as mechanical compression or solvent extraction. Mechanical squeezing recovers a large share of crude oil, which can be refined or used as industrial fuel, reducing response costs. For some polymer sorbents, solvent washing with low-boiling solvents efficiently removes oil, enabling its recovery and sorbent reuse. The regenerated sorbent must be tested for structural integrity and sorption capacity retention before redeployment.
   b. Secondary pathway - direct reuse as a fuel source: In remote or logistically challenging scenarios where immediate processing is not feasible, the oil-laden sorbents can be treated as a solid fuel. The high calorific value of the absorbed hydrocarbons makes the material suitable for co-incineration in waste-to-energy plants or in cement kilns under controlled conditions. This process destroys the petroleum hydrocarbons and captures the energy value, providing a disposal route that avoids landfill.
   c. Tertiary pathway - secure final disposal: If the absorbed oil is highly contaminated or regeneration is uneconomical, the final step is secure disposal. The solidified sorbent–oil waste is preferable to liquid oil and can be incinerated in hazardous waste facilities with flue gas treatment. As a last resort, disposal in certified hazardous landfills is safer than marine release.

The choice of pathway is determined by a real-time cost-benefit analysis factoring in the type of oil, the degree of contamination, the volume of waste, and the local waste management infrastructure, as outlined in the boundary conditions.

DEFINING SYSTEM BOUNDARY CONDITIONS AND REQUIREMENTS

The Next-Gen Marine Safety system is built as a flexible, modular framework that clearly recognizes no single system setup fits all maritime operational areas. The design and deployment of system parts must carefully consider specific boundary conditions, which define the operational and contextual limits within which the system operates most effectively. These boundary conditions include physical, infrastructural, economic, and regulatory areas as described below.

Geographical and Environmental Constraints

- **Maritime area classification:** The deployment strategies must differentiate among open ocean, coastal zones, narrow straits, and polar/arctic environments, as these distinct geographies impose varied challenges on sensor coverage, communication infrastructure, and environmental dynamics.
- **Hydrometeorological conditions:** The variations in sea state, including wave height, currents, fog, storms, and ice, significantly impact sensor performance and operational reliability. These factors particularly affect optical/infrared sensors, as well as unmanned aerial vehicles, reducing detection accuracy and slowing system response.
- **Oceanographic parameters:** Water depth, salinity gradients, turbidity, and biological activities determine the performance of acoustic sensor arrays and

fluorescence-based detection methods. These variations require region-specific system calibrations and careful sensor selection to maintain optimal accuracy.

Infrastructural and Economic Constraints

- **Communication infrastructure availability:** The communication networks, such as cellular NB-IoT, satellite links, and maritime broadband, determine the presence, bandwidth, and reliability of data transmission. These factors are vital for enabling real-time monitoring and cloud-based analytics.
- **Existing maritime surveillance assets:** There are integration opportunities with existing maritime monitoring systems such as coastal radar installations, AIS base stations, and prearranged satellite tasking agreements. These factors guide decisions on whether to enhance current systems or create new ones to avoid duplication.
- **Economic Feasibility and Risk Assessment:** The deployment density and the choice of technologies should align with operational risk profiles. The high-risk shipping lanes or ecologically sensitive zones may require dense sensor networks, while low-risk regions might only need sparse drone patrols. A detailed cost-benefit modeling supports these strategic decisions.

Legal and Regulatory Constraints

- **Data Sovereignty and Privacy Regulations:** The cross-jurisdictional data governance issues manage the collection, transmission, storage, and processing of maritime AIS data, drone-captured imagery, and sensor outputs, necessitating compliance with international, national, and regional privacy and security statutes.
- **Airspace and Maritime Operational Regulations:** The autonomous drone operations are subject to nation-specific airspace regulations and maritime policies, particularly within territorial waters, requiring tailored operational protocols and coordination with relevant authorities.
- **Incident Reporting and Response Protocol Integration:** The automated leak reporting modules of the system must be engineered to comply with legally mandated spill notification procedures and coordinate seamlessly with established maritime emergency response frameworks.

The deployments in remote or connectivity-scarce areas prioritize satellite communication links and long-endurance Saildrones. In contrast, high-traffic port areas rely on fixed sensor arrays supported by short-range drone patrols, all managed under strict regulatory and data governance frameworks.

LAYERED APPROACH IN NEXT-GEN MARINE SAFETY

The proposed system transforms the maritime industry by integrating advanced technologies to enhance security, efficiency, and environmental protection. The modern ships are now equipped with AI-powered navigation systems, real-time monitoring, and autonomous operation capabilities, reducing human error and improving situational awareness. Innovations such as smart sensors, predictive maintenance, and automated emergency response systems help prevent accidents and ensure rapid crisis management. Additionally, digital platforms and blockchain technology improve communication and data sharing between vessels, ports, and regulatory agencies. As climate change and global trade present new challenges, next-gen marine safety solutions play a crucial role in protecting lives, assets, and marine ecosystems while ensuring the sustainability of maritime operations. The layered architecture of Next-generation marine safety is depicted in Figure 5.

Physical layer: The physical layer consists of a configurable network of sensors and aerial drones for real-time data acquisition and imaging. The sensor data on reaching a threshold triggers aerial drones equipped with cameras to monitor and image oil spills in real time.The specific mix of sensor types such as the ratio of acoustic to RF sensors is a deployment decision based on the boundary conditions defined in Section 3. In areas with heavy ship traffic, a higher density of AIS receivers and visual sensors might be deployed

Data acquisition with sensor network: A diverse range of sensors are deployed within the system, each serving a specific function in data collection and environmental monitoring. Radiofrequency (RF) sensors facilitate wireless communication within the IoT network, enabling seamless data transmission between devices. Radar sensors contribute to object detection and monitoring, aiding in the identification of oil spills or other anomalies on the sea surface. Visual sensors, such as high-definition video cameras, provide real-time visual data for comprehensive seascape monitoring, further assisting in oil spill detection efforts. Acoustic sensors pick up underwater sounds and vibrations, offering valuable insights into underwater conditions. Microwave sensors monitor the marine environment by providing data on various parameters, including temperature and moisture. Underwater sensors sense the water quality and the detection of subsurface oil spills. Infrared sensors contribute by detecting heat signatures, which can be crucial for identifying temperature changes or anomalies.

Imaging with aerial drones: The drones are equipped with a high-resolution video camera capable of capturing detailed images and videos of the sea surface. This camera has both optical and infrared capabilities to ensure visibility in various lighting conditions. The drones are equipped with the Global Positioning System (GPS) to precisely identify the location of the oil spill. The acoustic data is then linked to geographical coordinates using GPS information and specialized mapping software.

Edge layer: The edge layer has the controller unit that reads periodical sensor data from the IoT network. On hitting the pre-defined threshold, the edge device does local real-time data processing and gets triggered to automatically respond to the detection of an oil spill. In this case, the automated response triggers are used to deploy drones for visual image

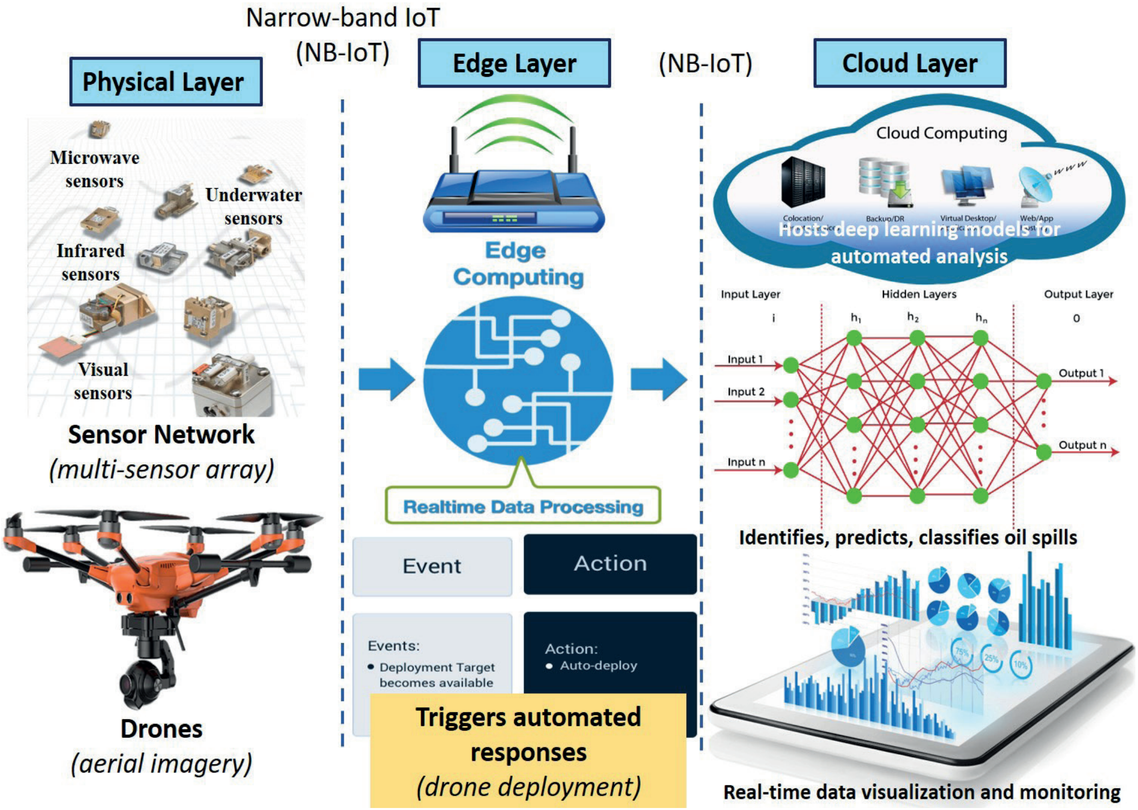


Fig. 5 Next-gen marine safety: Layered architecture

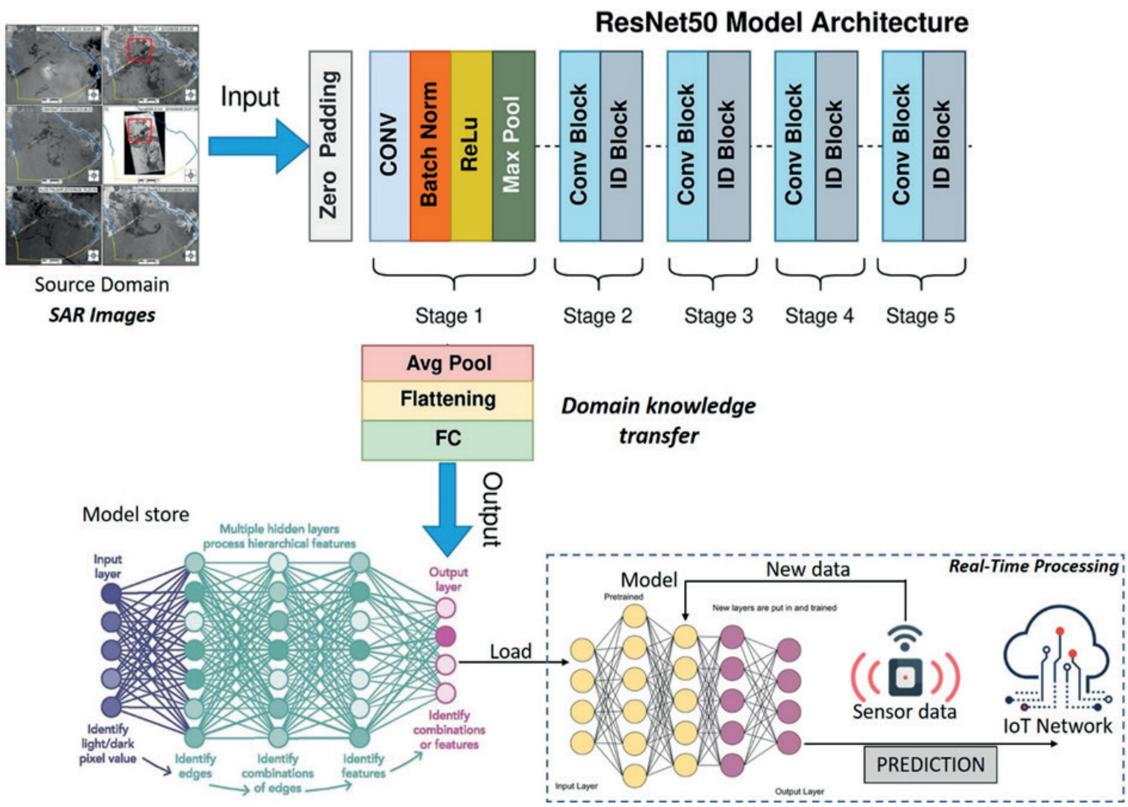


Fig. 6 Transfer learning architecture (Source domain: SOS dataset)

acquisition. the automated response entails the deployment of drones to acquire visual imagery.

Edge processing: The edge nodes located off the shore can remotely control and monitor the drone's flight, camera settings, and data transmission in real time. Additionally, a machine-learning model can be trained using existing acoustic data from known oil spills and other underwater events. This model can then be transferred to the VR2C for real-time classification of incoming acoustic signals, potentially identifying oil spills with high accuracy. The edge-based initial analysis directly responds to the latency issues in cloud-only approaches noted in Murugan et al. [58], enabling the rapid response required for effective spill mitigation.

Intelligent Cloud Processing: The serial and surface images are captured by the saildrone and need to be pre-processed. We employ the Convolutional Neural Networks (CNN) scheme for detecting surface images and their patterns. By implementing the CNN scheme onto the image, the sections are marked out as a region of interest, while all other areas of the picture are specified as the background and dropped out. The transfer learning architecture is shown in Figure 6. The choice of ResNet architectures for transfer learning was informed by their proven performance in similar remote sensing applications [54,64]. Our modification of only the final layers addresses the overfitting concerns raised in a study of Shaban et al. [66] when dealing with limited domain-specific data.

DESIGN RATIONALE AND COMPONENT SELECTION

The system architecture and component selection are directly informed by the critical analysis of existing approaches documented in Section 2. As summarized in Table 3, multi-sensor fusion, edge–cloud hybrid processing, and transfer learning collectively address detection accuracy, latency, and data scarcity challenges. Rather than arbitrary choices, each element addresses specific limitations identified in the literature review:

- Based on the review by Al-Ruzouq et al. [40], which highlights limitations of single-modality detection, we employ a heterogeneous sensor array with visual, infrared, microwave, and acoustic sensors. Hence, the multi-sensor fusion approach overcomes individual sensor weaknesses and reduces false positives from look-alike phenomena.
- Responding to the computational intensity issues noted in studies of Murugan et al. [58] and Shaban et al. [66], our hybrid processing distributes tasks between edge nodes for rapid response and cloud infrastructure for complex analysis optimizing both latency and accuracy.
- Addressing the challenge of imbalanced datasets and limited labeled samples as discussed in Table 1, we use transfer learning from pre-trained CNN ResNet architectures rather than training from scratch, maximizing performance with limited oil-spill-specific data.
- The tailored sensor payload directly addresses the surveillance gap discussed in problem 3. The saildrone integration with custom sensors such as the RBR Tridente fluorescence sensor provides capabilities beyond standard SAR imagery that dominates current literature [42,55,56].
- The three-phase operational mode (detection→localization →reporting) systematically faces the coordinated response challenges identified in Problem 4, ensuring information availability escalates appropriately with incident severity.

Tab. 3 Mapping related work limitations to design solutions and improvements

Limitations from related works	Our approach	Improvement achieved
Single-modality detection [40]	Multi-sensor fusion	Reduced false positives
Computational intensity [58]	Edge-cloud hybrid processing	Reduced latency and optimized system responsiveness
Limited training samples [54]	Transfer learning	Improved detection robustness and accuracy under data scarcity
Poor discrimination of look-alikes [67]	Multi-source data correlation	Enhanced detection precision and minimized misclassification

EXPERIMENT SETUP

Prototyping model: A large tank is selected as a controlled water body at the test location to mimic real-world sea conditions. The setup facilitates the release of various fluids and the generation of acoustic anomalies for detection. The temperature and salinity of the water are monitored and controlled to ensure that the density difference between the fluids is primarily due to salinity. This ensures a small impedance difference for the sonar to detect. Freshwater is released at the dockside to create a freshwater plume in a saltwater environment. Additionally, dispersed oil in water (oil treated with dispersant) is prepared to test dispersant's effectiveness. A high-frequency sonar sensor capable of differentiating between fluids with small impedance differences is deployed. It is connected to a microcontroller unit (MCU), which houses a Raspberry Pi for processing sensor data and initial analysis. A buoy is configured as a floating platform to deploy the sensor and camera for capturing visual data of the water's surface. An IoT gateway transmits data from the MCU to the cloud platform. A custom software application on the MCU collects sonar data, performs pre-processing (e.g., filtering, normalization), and transmits it to the cloud platform.

The sonar system detects and analyses the acoustic anomalies produced by the freshwater plume in salt water and the dispersed oil plume. Data are recorded and analyzed to evaluate the sonar's capabilities in differentiating between fluids and detecting oil spills. The experimentation proceeds by immersing the sonar sensor in the water body on a stationary platform. The sensor is connected to the MCU via a wired connection. A customized Python script continuously collects sonar data, pre-processes it, and transmits it to the cloud platform at regular intervals. Acoustic data collected from the sonar system during the experiments are analyzed to assess the effectiveness of the sonar in differentiating between fluids and detecting oil spills. This analysis helps evaluate the potential for real-time automated oil spill monitoring.

Setting up the cloud platform: The Google Cloud platform has been employed to store data from drones, sonar, and IoT sensors. The Google Cloud AI Platform facilitates the training and deployment of models through TensorFlow Extended (TFX). The Google Cloud Vision API includes pre-trained models for detecting objects such as ships and oil spills that have been fine-tuned. Real-time data processing is enabled through Google Cloud PubSub and Cloud Functions. By integrating these services, the built system responds to newly acquired drone images, triggering the execution of your trained model. BigQuery aids in analyzing vast data sets for real-time anomaly detection, allowing insights to be extracted. The model is trained to distinguish between normal sea conditions and the presence of an oil spill based on distinctive features in the data.

Data Preprocessing: To facilitate the analytical processing of aerial drone imagery, a meticulously designed multistage preprocessing pipeline has been implemented. The acquired images have undergone dimensional standardization by being rescaled to a consistent resolution of 299×299 pixels, thus conforming to the requirements of the chosen deep learning architecture, ResNet, which optimizes efficient model training and predictive capabilities. Aerial imagery is inherently vulnerable to various forms of noise. The sources of this noise include environmental factors such as atmospheric disturbances, hardware constraints such as camera sensors, and dynamic effects such as motion blur. To mitigate the impact of this noise, total variation denoising and median filtering techniques were employed. These techniques were specifically effective in reducing additive white Gaussian noise (AWGN), impulse noise, and salt-and-pepper noise. As a result of these preprocessing techniques, the clarity of the images was enhanced, and the accuracy of subsequent analyses was improved. Geometrical distortions may arise in aerial imagery owing to variables such as camera inclination angles and the spheroidal shape of the Earth. To counteract these deformities, a procedure referred to as orthorectification or geospatial correction was executed. By correcting the image geometry by collecting ground control points, calculating and applying the transformation, this method ensures that the depicted spatial relations and object measurements are accurately represented within the image. In instances requiring extensive coverage of expansive areas through the capture of numerous images from varying perspectives, image stitching techniques were utilized to generate a cohesive panorama. This amalgamated image offers a holistic and integrated perspective of the entire scene.

Feature Extraction: The features to be extracted are the oil spill signatures that encompass various visual cues, including color changes, textures, edges, and shapes. These signatures incorporate variations in spectral response due to the absorption properties of petroleum products, patterns of surface irregularity resulting from the interaction of light with oil films, boundary delineations separating polluted zones from uncontaminated water surfaces, and shape configurations inherently unique to oil spills, such as circular rings or linear streaks, as shown in Figure 7. Due to the restricted amount of training data, the classifier utilizes deep transfer learning, preferring to extract attributes using five pre-trained CNN architectures based on Residual Networks.

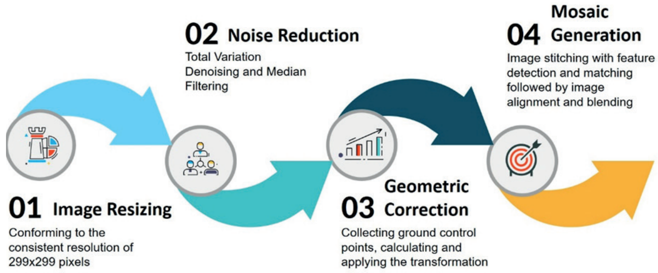


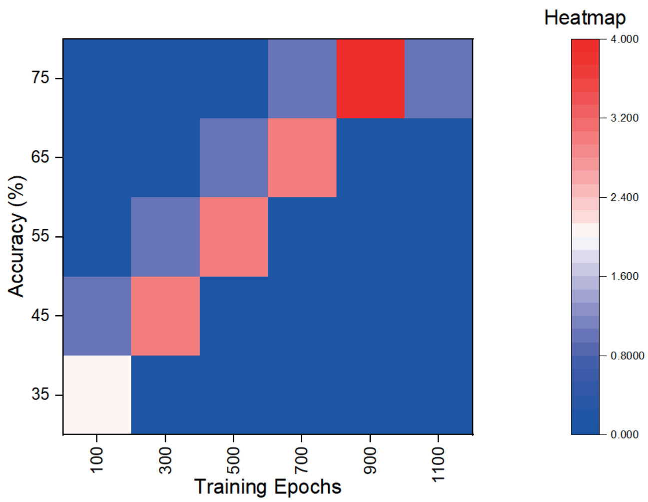
Fig. 7 Feature Extraction from drone images

Deep Learning Model: Due to limited training data, transfer learning is employed using pre-trained ResNet architectures such as ResNet 18, 50, and 101. Only the classification stage of the pre-trained models is modified to suit the task of classifying five types of oil spills in seawater such as non-persistent light oils, persistent light oils, medium oils, heavy oils, and sinking oils. The multi-layered pre-trained model is tailored architecture for specific classification purposes while retaining acquired knowledge. This modification is limited solely to the layers within the classification stage. Instead of inherent fully connected layers found in original pre-trained structures, new fully connected layers are introduced to represent the five types of oil spills. As a result, these fine-tuned pre-trained models are employed for learning using primate imagery data. Notably, the final five fully connected output layers perform classifications on the specified oil spill categories instead of the initial 50 classes from the SOS dataset. This dataset comprises 8070 oil spill images extracted from 21 Synthetic Aperture Radar images, which served as the basis for deriving the weights of the model [52,62]. The improved SOS dataset has also been referenced, which is available at (https://github.com/dongxr2/MOSD_LSAR/tree/main/v1).

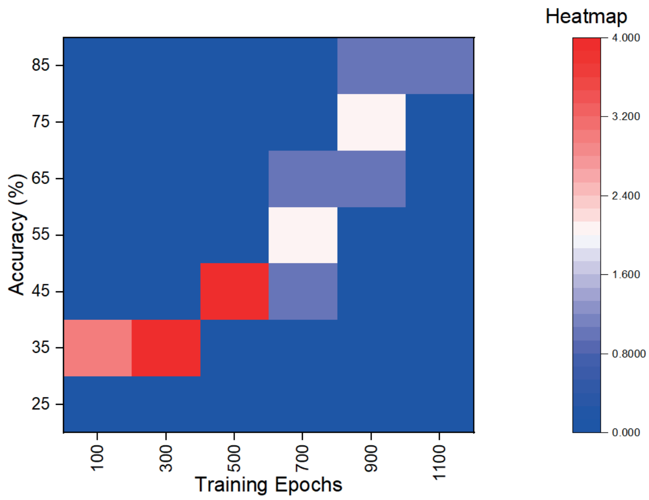
Training Parameters: To mitigate overfitting, a reduced batch size of 32 is implemented. The learning rate is adjusted to 0.001 to prevent divergence during the training process. However, differential learning rates are allocated to distinct layers, with higher rates assigned to newly integrated layers to expedite learning. The model employs the Adam optimizer coupled with categorical cross-entropy loss for tasks involving multi-class classification. Training spans a range of 1000 epochs to ensure robust learning without yielding to overfitting, with validation intervals set at every 10 epochs to monitor progress. Throughout the network, the Rectified Linear Unit (ReLU) activation function is utilized to facilitate efficient training and enhance overall performance.

RESULTS AND DISCUSSION

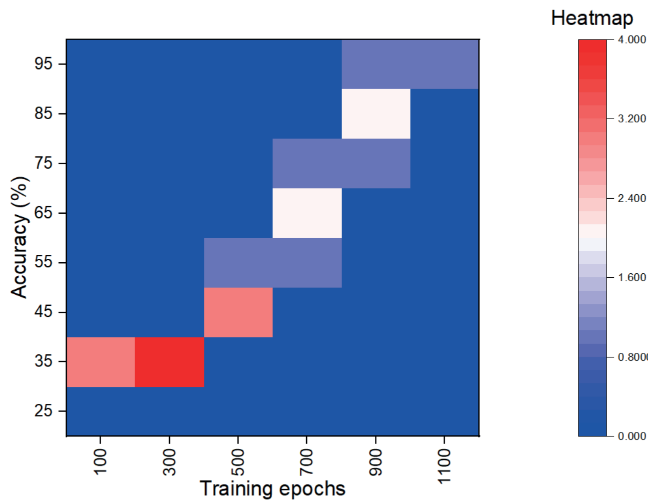
The heat map depicted in Figure 8a represents the correlation between the number of epochs completed during the training process of 1 layer transferred and the accuracy percentage achieved at each epoch. The interpretation of this visualization is facilitated by a color gradient, where darker hues correspond to higher accuracy percentages, while lighter shades denote lower accuracy. Notably, there is an apparent trend indicating an increase in accuracy percentage as the number of epochs progresses. This trend is illustrated by a transition from lighter to darker colors across the heatmap. Initially, with only 50 epochs completed, the accuracy stands at a modest 36.5%, depicted by a lighter color. However, with continued training, the accuracy steadily scales, peaking at approximately 74.9% around the 1000-epoch mark. The highest accuracy achieved was 74% after 900 training iterations. The inference marks the evolution of accuracy with additional training epochs, offering a clear depiction of the performance enhancement over training time. Figures 8b and Figure 8c show the layer transfer of 2 and 3 respectively with a maximum accuracy of 85.72% and 97.89% respectively. However, the transfer of layers 4 and 5 reduces the accuracy drastically to 70.12% and 64.92% respectively.



(a)



(b)



(c)

Fig. 8. a) Accuracy on the test set over training for 1-layer transfer, b) Accuracy on the test set over training for 2-layer transfer, c) Accuracy on the test set over training for 3-layer transfer.

When only one layer is transferred, the model has limited information about the target task, which results in lower accuracy. As more layers are transferred, the model becomes more familiar with the target task, which leads to higher accuracy. However, transferring too many layers can lead to overfitting, which can reduce the accuracy of the model. Therefore, the optimal number of layers to transfer depends on the specific task and dataset. The best network is 3-layer transfer, which performs marginally better than 2-layer transfer. Transferring up to five layers clearly shows that as the number of layers transferred increases, the performance drops. There is around a 9% difference between each layer until the third layer and a drastic drop between the 4th and 5th layer. The best accuracy of each network is given in Table 4, while accuracy metrics for optimized network architecture is depicted in Figure 9.

Tab. 4 Best accuracy of each network

# Layers transferred	Highest accuracy achieved (%)
1	74.90%
2	85.72%
3	97.89%
4	70.12%
5	64.92%

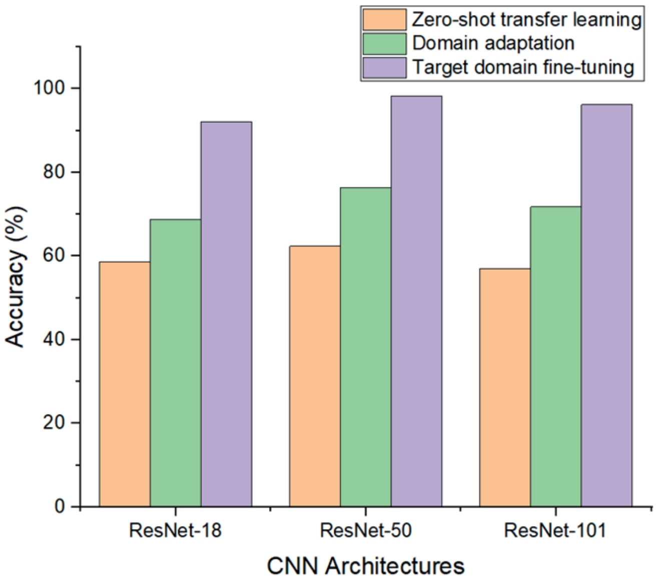


Fig. 9 *Accuracy metrics for optimized network architecture*

The zero-shot transfer learning is the transfer of learning without finetuning the model on the source dataset and the target dataset. Domain adaptation is a transfer learning training process of 3 models performed on unclassified oil pill SAR images that were collected in the source dataset. this step is important for the convergence of the domain between the source and target domains and for reducing the influence of the ImageNet dataset on the performance of the model. This step is important for extracting features that are close to the target task. The target domain fine-tuning is the transfer learning performed on the classified images of the target task that were collected in the target dataset to classify drone images into oil slick and non-oil slick. In the context of these scenarios, the performance of different ResNet architectures has been evaluated based on accuracy metrics. The results given in Table 5 indicate that the performance of ResNet architectures varies across different learning scenarios.

Tab. 5 Comparing the accuracy metric

CNN Architectures	Zero-shot transfer learning	Domain adaptation	Target domain fine-tuning
RESNET-18	58.67	68.76	92.16
RESNET-50	62.36	76.45	98.3
RESNET-101	57.09	71.81	96.23

The experiment is initiated with the creation of an AWS S3 account to initiate a cloud instance and configure three peers with an Intel 4-core i7 processor of 1.30GHz, 8MB cache, 32 GB RAM, and 1TB disk. Figure 10 depicts the correlation between the number of requests and model processing time. As a two-stage architecture (edge-cloud) has been designed, the processing time is twice that of the requests raised per millisecond. This linear dependency is observed due to the two-fold processing time: time to inject local processing with the requested information and time to upload the sensor data to the cloud. However, with the high flooding of requests, edge-to-cloud communication has proven to be superior to cloud request processing. Transmit latency measures the period of a request or response in transit between the networking points.

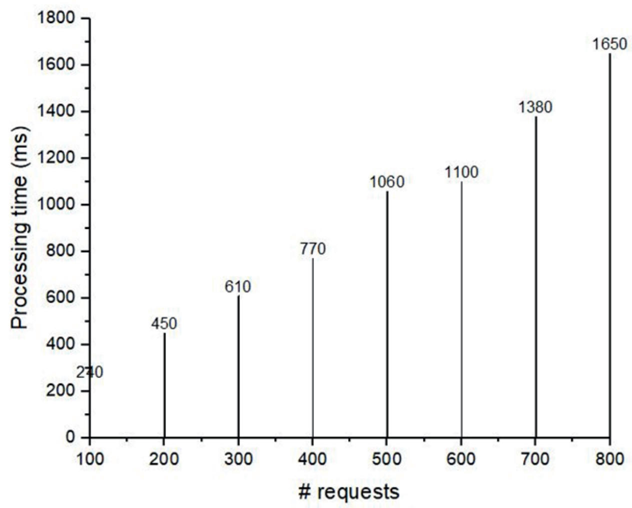


Fig. 10 Number of requests versus model processing time

The experimental progress showed that the performance is increasingly inconsistent with a sparse sample size. The result indicates that the underlying cloud connection has a certain degree of ambiguity. Table 6 illustrates latency, which is defined by the duration it takes for data to traverse between the IoT network as source and the blockchain network as destination. The configured network latency values range in milliseconds for communication among IoT devices (DEV1, DEV2, DEV3), an edge node, and cloud nodes (CLOUD-ID1, CLOUD-ID2). The IoT devices transmit sensor data to the edge node with respective latencies of 20 ms, 22 ms, and 21 ms. Subsequently, the edge node forwards data to CLOUD-ID1 and CLOUD-ID2 with latencies of 51 ms and 55 ms, respectively. CLOUD-ID1 and CLOUD-ID2 engage in communication with each other, incurring a latency of 10 ms.

Tab. 6 Network testbed configuration

Source	Destination	Latency (ms)
IoT Device (DEV1)	Edge node	20

IoT Device (DEV2)	Edge node	22
IoT Device (DEV3)	Edge node	21
Edge node	Cloud node (CLOUD -ID1)	51
Edge node	Cloud node (CLOUD -ID2)	55
Cloud node (CLOUD-ID1)	Cloud node (CLOUD -ID2)	10

With 97.89% accuracy and low-latency edge–cloud processing, the system significantly reduces maritime disruption costs. According to the UNCTAD Review of Maritime Transport [72], the rerouting of container ships around the Cape of Good Hope, for instance, increased ton-mile demand by approximately 12%. Such deviations substantially raise fuel consumption, operational costs, and greenhouse gas emissions. The capability of our system for rapid, accurate oil spill detection and localization contributes directly to maritime operational resilience. By speeding response and enabling targeted containment, the framework avoids costly rerouting, supporting economic and environmental sustainability in global shipping.

CONCLUSION AND FUTURE SCOPE

This work designed and validated a framework that integrates sensor networks, drones, and cloud-based processing to achieve real-time oil spill detection and monitoring. Rather than a monolithic solution, we have proposed a system composed of interoperable technologies whose specific instantiation is guided by a clearly defined set of geographical, infrastructural, and legal boundary conditions. The experimental validation provides strong evidence for the core technical contributions of this approach: (i). Our transfer learning models achieved a peak accuracy of 97.89% for oil spill classification using a 3-layer ResNet configuration, directly supporting the claim of effective analysis of drone and sensor imagery. (ii). The implemented edge-cloud architecture demonstrated its potential for rapid response, with network latency measurements confirming sub-100-ms data transmission between IoT devices and cloud nodes, facilitating the real-time data acquisition and leak localization as designed. (iii). The tank-based experiment served as a successful proof-of-concept, validating the core functionality of the sensor array for fluid detection and differentiation, which underpins the system's operational modes.

This flexible approach ensures that the system can be tailored to provide cost-effective and compliant protection for diverse maritime environments, from ecologically sensitive coastal areas to high-traffic international straits. Furthermore, the societal relevance of this research lies in protecting vulnerable maritime economies. As reported by UNCTAD 2024, Small Island Developing States (SIDS) have seen a 9% decline in shipping connectivity and are hardest hit by rising maritime costs. A rapid oil spill response system is essential for both environmental protection and economic resilience in these regions. The future work aims to integrate data from satellites, weather sources, and coastal monitoring stations to enhance spill prediction and enable full-scale deployment.

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REFERENCES

1. Inal OB. Decarbonization of shipping: Hydrogen and fuel cells legislation in the maritime industry. Brodogradnja 2024;75:1–13. https://doi.org/10.21278/brod75205.

2. Hoang AT, Foley AM, Nižetić S, Huang Z, Ong HC, Ölçer AI, et al. Energy-related approach for reduction of CO2 emissions: A critical strategy on the port-to-ship pathway. J Clean Prod 2022;355:131772. https://doi.org/10.1016/j.jclepro.2022.131772.

3. Hoang AT, Pandey A, Martinez De Osés FJ, Chen W-H, Said Z, Ng KH, et al. Technological solutions for boosting hydrogen role in decarbonization strategies and net-zero goals of world shipping: Challenges and perspectives. Renew Sustain Energy Rev 2023;188:113790. https://doi.org/10.1016/j.rser.2023.113790.

4. Eski Ö, Tavacioglu L. A combined method for the evaluation of contributing factors to maritime dangerous goods transport accidents. Brodogradnja 2024;75:1–20. https://doi.org/10.21278/brod75408.

5. Gao J, Zhang Y. Ship collision avoidance decision-making research in coastal waters considering uncertainty of target ships. Brodogradnja 2024;75:1–16. https://doi.org/10.21278/brod75203.

6. Alamoush AS, Ölçer AI. Harnessing cutting-edge technologies for sustainable future shipping: An overview of innovations, drivers, barriers, and opportunities. Marit Technol Res 2025;7:277313. https://doi.org/10.33175/mtr.2025.277313.

7. Hussein K, Song D-W. Maritime Logistics for the Next Decade: Challenges, Opportunities and Required Skills. Glob. Logist. Supply Chain Strateg. 2020s, Cham: Springer International Publishing; 2023, p. 151–74. https://doi.org/10.1007/978-3-030-95764-3_9.

8. Le TT, Nguyen HP, Rudzki K, Rowiński L, Bui VD, Truong TH, et al. Management Strategy for Seaports Aspiring to Green Logistical Goals of IMO: Technology and Policy Solutions. Polish Marit Res 2023;30:165–87. https://doi.org/10.2478/pomr-2023-0031.

9. Nguyen MD, Yeon KT, Rudzki K, Nguyen HP, Pham NDK. Strategies for developing logistics centers: Technological trends and policy implications. Polish Marit Res 2023;30:129–47. https://doi.org/10.2478/pomr-2023-0066.

10. Karczewski A, Kozak J. A Generative Approach to Hull Design for a Small Watercraft. Polish Marit Res 2023;30:4–12. https://doi.org/doi:10.2478/pomr-2023-0001.

11. Huynh VC, Tran GT. Improving the accuracy of ship resistance prediction using computational fluid dynamics tool. Int J Adv Sci Eng Inf Technol 2020;10:171–7. https://doi.org/10.18517/ijaseit.10.1.10588.

12. Hoang AT, Bui TAE, Nguyen XP, Bui VH, Nguyen QC, Truong TH, et al. Explainable machine learning-based prediction of fuel consumption in ship main engines using operational data. Brodogradnja 2025;76:1–24. https://doi.org/10.21278/brod76405.

13. Nguyen VN, Chung N, Balaji GN, Rudzki K, Hoang AT. Internet of things-driven approach integrated with explainable machine learning models for ship fuel consumption prediction. Alexandria Eng J 2025;118:664–80. https://doi.org/10.1016/j.aej.2025.01.067.

14. Nguyen HP, Pham NDK, Bui VD. Technical-Environmental Assessment of Energy Management Systems in Smart Ports. Int J Renew Energy Dev 2022;11:889–901. https://doi.org/10.14710/ijred.2022.46300.

15. Mallouppas G, Yfantis EA. Decarbonization in Shipping Industry: A Review of Research, Technology Development, and Innovation Proposals. J Mar Sci Eng 2021;9:415. https://doi.org/10.3390/jmse9040415.

16. Suárez de la Fuente S, Cao T, Pujol AG, Romagnoli A. Waste heat recovery on ships. Sustain. Energy Syst. Ships, Elsevier; 2022, p. 123–95. https://doi.org/10.1016/B978-0-12-824471-5.00011-6.

17. Hoang AT. Waste heat recovery from diesel engines based on Organic Rankine Cycle. Appl Energy 2018;231:138–66.

18. Kowalski J, Tarelko W. NOx emission from a two-stroke ship engine: Part 2 - Laboratory test. Appl Therm Eng 2009. https://doi.org/10.1016/j.applthermaleng.2008.06.031.

19. Nguyen VN, Nguyen AX, Nguyen DT, Le HC, Nguyen VP. A Comprehensive Understanding of Bainite Phase Transformation Mechanism in TRIP Bainitic-supported Ferrite Steel. Int J Adv Sci Eng Inf Technol 2024;14:309–25. https://doi.org/10.18517/ijaseit.14.1.19706.

20. Gavalas D. Green finance frameworks for sustainable shipping industry and blue economy: A review. Marit Technol Res 2025;7:Manuscript. https://doi.org/10.33175/mtr.2025.277132.

21. Priya JC, Rudzki K, Nguyen XH, Nguyen HP, Chotechuang N, Pham NDK. Blockchain-Enabled Transfer Learning for Vulnerability Detection and Mitigation in Maritime Logistics. Polish Marit Res 2024;31:135–45. https://doi.org/10.2478/pomr-2024-0014.

22. Genç Y, Kafali M, Çelebi UB. Approximate Estimation of Man-Day in Ship Block Production: A Two-Stage Stochastic Program. Polish Marit Res 2024;31:146–58. https://doi.org/doi:10.2478/pomr-2024-0015.

23. Liang L, Baoji Z, Hao Z, Jiaye G, Zheng T, Shuhui G, et al. Study on numerical simulation and mitigation of parametric rolling in a container ship under head waves. Brodogradnja 2024;75:1–19. https://doi.org/10.21278/brod75305.

24. Wu B, Zhang J, Yip TL, Guedes Soares C. A quantitative decision-making model for emergency response to oil spill from ships. Marit Policy Manag 2021;48:299–315. https://doi.org/10.1080/03088839.2020.1791994.

25. Zhang W, Li C, Chen J, Wan Z, Shu Y, Song L, et al. Governance of global vessel-source marine oil spills: Characteristics and refreshed strategies. Ocean Coast Manag 2021;213:105874. https://doi.org/10.1016/j.ocecoaman.2021.105874.

26. Chen J, Zhang W, Wan Z, Li S, Huang T, Fei Y. Oil spills from global tankers: Status review and future governance. J Clean Prod 2019;227:20–32. https://doi.org/10.1016/j.jclepro.2019.04.020.

27. Le QD, Pham D, Bui TAE, Nguyen LH, Nguyen PQP, Dang TN. Ensemble Machine Learning Model Prediction and Metaheuristic Optimisation of Oil Spills Using Organic Absorbents: Supporting Sustainable Maritime. Polish Marit Res 2025;32:141–55. https://doi.org/10.2478/pomr-2025-0029.

28. Onyena AP, Nwaogbe OR. Assessment of water quality and heavy metal contamination in ballast water: Implications for marine ecosystems and human health. Marit Technol Res 2024;6:270227. https://doi.org/10.33175/mtr.2024.270227.

29. Soria-Rodríguez C. The international regulation for the protection of the environment in the development of marine renewable energy in the EU. Rev Eur Comp Int Environ Law 2021;30:46–60. https://doi.org/10.1111/reel.12337.

30. Podsiadlo A, Tarelko W. Modelling and developing a decision-making process of hazard zone identification in ship power plants. Int J Press Vessel Pip 2006. https://doi.org/10.1016/j.ijpvp.2006.02.017.

31. Negreiros ACSV de, Lins ID, Maior CBS, Moura MJ das C. Oil spills characteristics, detection, and recovery methods: A systematic risk-based view. J Loss Prev Process Ind 2022;80:104912. https://doi.org/10.1016/j.jlp.2022.104912.

32. Anju M, Renuka NK. Magnetically actuated graphene coated polyurethane foam as potential sorbent for oils and organics. Arab J Chem 2020. https://doi.org/10.1016/j.arabjc.2018.01.012.

33. Chau MQ, Truong TT, Hoang AT, Le TH. Oil spill cleanup by raw cellulose-based absorbents: a green and sustainable approach. Energy Sources, Part A Recover Util Environ Eff 2025;47:8269–82. https://doi.org/10.1080/15567036.2021.1928798.

34. Zhao S, Yin L, Zhou Q, Liu C, Zhou K. In situ self-assembly of zeolitic imidazolate frameworks on the surface of flexible polyurethane foam: Towards for highly efficient oil spill cleanup and fire safety. Appl Surf Sci 2020;506:144700.

35. Hoang AT, Pham XD. An investigation of remediation and recovery of oil spill and toxic heavy metal from maritime pollution by a new absorbent material. J Mar Eng Technol 2021;20:159–69. https://doi.org/10.1080/20464177.2018.1544401.

36. Jayarathna MD, Rajapaksha AU, Samarasekara S, Vithanage M. Oil Spill Response: Existing Technologies, Prospects and Perspectives. CleanMat 2024;1:78–96. https://doi.org/10.1002/clem.17.

37. Vasconcelos RN, Lima ATC, Lentini CAD, Miranda JG V., de Mendonça LFF, Lopes JM, et al. Deep Learning-Based Approaches for Oil Spill Detection: A Bibliometric Review of Research Trends and Challenges. J Mar Sci Eng 2023;11:1406. https://doi.org/10.3390/jmse11071406.

38. Liu P, Zhao Y, Liu B, Li Y, Chen P. Oil spill extraction from X-band marine radar images by power fitting of radar echoes. Remote Sens Lett 2021;12:345–52. https://doi.org/10.1080/2150704X.2021.1892852.

39. Ma X, Xu J, Pan J, Yang J, Wu P, Meng X. Detection of marine oil spills from radar satellite images for the coastal ecological risk assessment. J Environ Manage 2023;325:116637. https://doi.org/10.1016/j.jenvman.2022.116637.

40. Al-Ruzouq R, Gibril MBA, Shanableh A, Kais A, Hamed O, Al-Mansoori S, et al. Sensors, Features, and Machine Learning for Oil Spill Detection and Monitoring: A Review. Remote Sens 2020;12:3338. https://doi.org/10.3390/rs12203338.

41. Dong X, Li J, Li B, Jin Y, Miao S. Marine Oil Spill Detection from Low-Quality SAR Remote Sensing Images. J Mar Sci Eng 2023;11:1552. https://doi.org/10.3390/jmse11081552.

42. Wang B, Shao Q, Song D, Li Z, Tang Y, Yang C, et al. A Spectral-Spatial Features Integrated Network for Hyperspectral Detection of Marine Oil Spill. Remote Sens 2021;13:1568. https://doi.org/10.3390/rs13081568.

43. Trujillo-Acatitla R, Tuxpan-Vargas J, Ovando-Vázquez C. Oil spills: Detection and concentration estimation in satellite imagery, a machine learning approach. Mar Pollut Bull 2022;184:114132. https://doi.org/10.1016/j.marpolbul.2022.114132.

44. Shah P, Zaveri T, Kumar R, Sharma S, Patel D. Research oriented foss solution for automatic oil spill detection using risat-1 sar data. 2017 IEEE Int. Geosci. Remote Sens. Symp., IEEE; 2017, p. 3121–4. https://doi.org/10.1109/IGARSS.2017.8127659.

45. Kang S-G, Joung TH, Lee S, Lee J-Y, You Y. The level of oil spill risk in Northwest Pacific and regional cooperation activities of NOWPAP MERRAC on marine pollution preparedness and response. Int Oil Spill Conf Proc 2021;2021. https://doi.org/10.7901/2169-3358-2021.1.1141537.

46. Abhijith A, Rameshbabu H. Secure Data Transmission Framework for Internet of Things based on Oil Spill Detection Application. Int J Adv Comput Sci Appl 2021;12. https://doi.org/10.14569/IJACSA.2021.0120523.

47. Satyanarayana AR, Dhali MA. Oil Spill Segmentation using Deep Encoder-Decoder models. Cornell Univiersity 2023.

48. Liu X, Lu D, Zhang A, Liu Q, Jiang G. Data-Driven Machine Learning in Environmental Pollution: Gains and Problems. Environ Sci Technol 2022;56:2124–33. https://doi.org/10.1021/acs.est.1c06157.

49. seyyedi S reza, Kowsari E, Ramakrishna S, Gheibi M, Chinnappan A. Marine plastics, circular economy, and artificial intelligence: A comprehensive review of challenges, solutions, and policies. J Environ Manage 2023;345:118591. https://doi.org/10.1016/j.jenvman.2023.118591.

50. Li K, Yu H, Xu Y, Luo X. Detection of Marine Oil Spills Based on HOG Feature and SVM Classifier. J Sensors 2022;2022:1–11. https://doi.org/10.1155/2022/3296495.

51. Temitope Yekeen S, Balogun A, Wan Yusof KB. A novel deep learning instance segmentation model for automated marine oil spill detection. ISPRS J Photogramm Remote Sens 2020;167:190–200. https://doi.org/10.1016/j.isprsjprs.2020.07.011.

52. Zhu Q, Zhang Y, Li Z, Yan X, Guan Q, Zhong Y, et al. Oil Spill Contextual and Boundary-Supervised Detection Network Based on Marine SAR Images. IEEE Trans Geosci Remote Sens 2022;60:1–10. https://doi.org/10.1109/TGRS.2021.3115492.

53. Duan P, Kang X, Ghamisi P, Li S. Hyperspectral Remote Sensing Benchmark Database for Oil Spill Detection With an Isolation Forest-Guided Unsupervised Detector. IEEE Trans Geosci Remote Sens 2023;61:1–11. https://doi.org/10.1109/TGRS.2023.3268944.

54. Raharjo D, Solechudin M. Detect oil spill in offshore facility using convolutional neural network and transfer learning. Proceedings, Indones Pet Assoc Forty-Fifth Annu Conv Exhib 2021.

55. Trongtirakul T, Agaian S, Oulefki A, Panetta K. Method for Remote Sensing Oil Spill Applications Over Thermal and Polarimetric Imagery. IEEE J Ocean Eng 2023;48:973–87. https://doi.org/10.1109/JOE.2023.3245759.

56. Wang D, Liu S, Zhang C, Xu M, Yang J, Yasir M, et al. An improved semantic segmentation model based on SVM for marine oil spill detection using SAR image. Mar Pollut Bull 2023;192:114981. https://doi.org/10.1016/j.marpolbul.2023.114981.

57. Ghonaime TW, Farouk Al-Sadek A. OilSpillNet: Deep Learning Model for Synthetic Aperture Radar Imagery Oil Spill Detection. 2023 Intell. Methods, Syst. Appl., IEEE; 2023, p. 412–7. https://doi.org/10.1109/IMSA58542.2023.10217532.

58. J SM, V P. An automatic approach for the detection of oil spill using optimized deep learning in synthetic aperture radar images. Energy Sources, Part A Recover Util Environ Eff 2023;45:6772–87. https://doi.org/10.1080/15567036.2023.2216153.

59. Ozigis MSJ. Detection and Mapping of Terrestrial Oil Spill Impact Using Remote Sensing Data in Combination with Machine Learning Methods. A Case Site within the Niger Delta Region of Nigeria. University of Leicester, 2019.

60. Li C, Wang M, Yang X, Chu D. DS-UNet: Dual-Stream U-Net for Oil Spill Detection of SAR Image. IEEE Geosci Remote Sens Lett 2023;20:1–5. https://doi.org/10.1109/LGRS.2023.3330957.

61. Yang Y-J, Singha S, Mayerle R. A deep learning based oil spill detector using Sentinel-1 SAR imagery. Int J Remote Sens 2022;43:4287–314. https://doi.org/10.1080/01431161.2022.2109445.

62. Zhang Y, Zhu Q, Guan Q. Oil Spill Detection Based on CBD-Net Using Marine SAR Image. 2021 IEEE Int. Geosci. Remote Sens. Symp. IGARSS, IEEE; 2021, p. 3495–8. https://doi.org/10.1109/IGARSS47720.2021.9553884.

63. Ahmed S, ElGharbawi T, Salah M, El-Mewafi M. Deep neural network for oil spill detection using Sentinel-1 data: application to Egyptian coastal regions. Geomatics, Nat Hazards Risk 2023;14:76–94. https://doi.org/10.1080/19475705.2022.2155998.

64. Ghorbani Z, Behzadan AH. Monitoring offshore oil pollution using multi-class convolutional neural networks. Environ Pollut 2021;289:117884. https://doi.org/10.1016/j.envpol.2021.117884.

65. Yang Y-J, Singha S, Mayerle R. Fully Automated Sar Based Oil Spill Detection Using Yolov4. 2021 IEEE Int. Geosci. Remote Sens. Symp. IGARSS, IEEE; 2021, p. 5303–6. https://doi.org/10.1109/IGARSS47720.2021.9553030.

66. Shaban M, Salim R, Abu Khalifeh H, Khelifi A, Shalaby A, El-Mashad S, et al. A Deep-Learning Framework for the Detection of Oil Spills from SAR Data. Sensors 2021;21:2351. https://doi.org/10.3390/s21072351.

67. Bianchi FM, Espeseth MM, Borch N. Large-Scale Detection and Categorization of Oil Spills from SAR Images with Deep Learning. Remote Sens 2020;12:2260. https://doi.org/10.3390/rs12142260.

68. Ma X, Xu J, Wu P, Kong P. Oil Spill Detection Based on Deep Convolutional Neural Networks Using Polarimetric Scattering Information From Sentinel-1 SAR Images. IEEE Trans Geosci Remote Sens 2022;60:1–13. https://doi.org/10.1109/TGRS.2021.3126175.

69. Zhang J, Feng H, Luo Q, Li Y, Zhang Y, Li J, et al. Oil Spill Detection with Dual-Polarimetric Sentinel-1 SAR Using Superpixel-Level Image Stretching and Deep Convolutional Neural Network. Remote Sens 2022;14:3900. https://doi.org/10.3390/rs14163900.

70. Dai Z, Liang H, Duan T. Small-Sample Sonar Image Classification Based on Deep Learning. J Mar Sci Eng 2022;10:1820. https://doi.org/10.3390/jmse10121820.

71. Barzegar F, Seydi ST, Farzaneh S, Sharifi MA. Oil spill detection in the Caspian sea with a SAR image using a densenet model. ISPRS Ann Photogramm Remote Sens Spat Inf Sci 2023;X-4/W1-202:95–100. https://doi.org/10.5194/isprs-annals-X-4-W1-2022-95-2023.

72. UNCTAD. Review of Maritime Transport 2024: Navigating maritime chokepoints 2024.

73. Alghamdi R, Saeed N, Dahrouj H, Al-Naffouri TY, Alouini M-S. On Distributed Routing in Underwater Optical Wireless Sensor Networks. Cornell Univiersity 2018.

74. Zhang Y, Sam EK, Liu J, Lv X. Biomass-Based/Derived Value-Added Porous Absorbents for Oil/Water Separation. Waste and Biomass Valorization 2023;14:3147–68. https://doi.org/10.1007/s12649-023-02112-9.

75. Hoang AT, Nižetić S, Duong XQ, Rowinski L, Nguyen XP. Advanced super-hydrophobic polymer-based porous absorbents for the treatment of oil-polluted water. Chemosphere 2021;277. https://doi.org/10.1016/j.chemosphere.2021.130274.

76. Hoang AT, Nguyen XP, Duong XQ, Huynh TT. Sorbent-based devices for the removal of spilled oil from water: a review. Environ Sci Pollut Res 2021;28:28876–910. https://doi.org/10.1007/s11356-021-13775-z.

77. Saildrone. Saildrone: Defense, Commercial & Science Data Solutions. Saildrone 2024.

78. Cardoso CKM, Moreira ÍTA, de Souza Queiroz AF, de Oliveira OMC, de Carvalho Lima Lobato AK. Bio-Based Sorbents for Marine Oil Spill Response: Advances in Modification, Circularity, and Waste Valorization. Resources 2025;14:140. https://doi.org/10.3390/resources14090140.

79. Haridharan N, Sundar D, Kurrupasamy L, Anandan S, Liu C, Wu JJ. Oil spills adsorption and cleanup by polymeric materials: A review. Polym Adv Technol 2022;33:1353–84. https://doi.org/10.1002/pat.5636.

80. Visco A, Quattrocchi A, Nocita D, Montanini R, Pistone A. Polyurethane Foams Loaded with Carbon Nanofibers for Oil Spill Recovery: Mechanical Properties under Fatigue Conditions and Selective Absorption in Oil/Water Mixtures. Nanomaterials 2021;11:735.

81. Hoang AT, Le VV, Al-Tawaha ARMS, Nguyen DN, Al-Tawaha ARMS, Noor MM, et al. An absorption capacity investigation of new absorbent based on polyurethane foams and rice straw for oil spill cleanup. Pet Sci Technol 2018;36:361–70. https://doi.org/10.1080/10916466.2018.1425722.

82. Li H, Lin S, Feng X, Pan Q. Preparation of superhydrophobic and superoleophilic polyurethane foam for oil spill cleanup. J Macromol Sci Part A 2021;58:758–68. https://doi.org/10.1080/10601325.2021.1934013.