



Deep Learning for Monitoring and Managing Oil Spill in Underwater Sensor Networks: Enabling Technologies

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ARTICLE INFO

Article history:

Received: 4 March 2024

Revised: 25 June 2024

Accepted: 23 August 2024

Online: 31 October 2025

Keywords:

Oil spills

Machine learning

Transfer learning

Deep learning

SAR images

ABSTRACT

Environmental problems can significantly impact people's lives and must be addressed. The oil spill is one of the biggest applications of underwater wireless sensor networks (UWSNs) that threaten aquatic life, so it is essential to focus on it. Oil spill count has risen in recent years because of the rise in shipping and marine transportation industries. Timely and accurate detection of oil spills can improve the response process and get the necessary resources to the affected areas more efficiently. This work was motivated by the fact that oil spill detection is critical to maritime protection. Since oil spill detection is a complex process, it faces various challenges. One of the biggest challenges is similar visual appearance which makes it difficult to identify an oil spill and a similar oil slick in synthetic aperture radar (SAR) imagery. Various radar images are frequently utilized for this purpose. Despite being widely used for earth observation, SAR images have noisy and illegible image quality, which makes classification challenging. Previously, detecting and classifying SAR images required manual involvement, which made the process time-consuming. Therefore, researchers focused on automating such tasks by incorporating deep learning (DL) techniques. Numerous papers proposed the applications of DL in various radar images for oil spill monitoring but faced multiple problems. This study aims to thoroughly investigate oil spills and their detection techniques, utilizing DL techniques applied to various radar images. These studies have originated in diverse nations with distinct environments. However, compared to other types of radar images, synthetic aperture radar (SAR) images are more effective in pinpointing the location of oil spills. However, they are also rather complex.

1. INTRODUCTION

Within the discipline of computer networks and communication systems, the study of underwater wireless sensor networks (UWSNs) is a relatively young and rapidly developing area of research. Due to its development in the real world, it has emerged as one of the most prominent research areas for scientists. The sea is a complex and diverse environment and is an abundant source of food, minerals, oil, and renewable energy. It is also essential to life, weather, climate, and biogeochemical cycles [1]. It is a home to a wide variety of animals and plants. Small sensor nodes located all over make up wireless sensor networks (WSNs). Sensor nodes have components for data processing, communication, and sensing. Node positions do not require engineering and can be flexible. The types of WSNs are chosen based on environmental suitability, including terrestrial, underground, and underwater variants.

UWSNs serve various purposes, from scientific research to disaster prevention. They are also increasingly utilized in ocean monitoring, deep sea surveillance, and aquatic creature tracking. Underwater sensor technology is applied in various settings, from the oil industry to aquaculture, including instrument monitoring, pollution management, climate sensing, natural disturbance prediction, search, and marine life research. Research and development of new technologies and procedures are necessary since the oil industry still poses hazards and problems. Unwanted oil spills, or the leakage of hydrocarbons from crude oil, are a severe hazard [2]. They may happen unintentionally or on purpose.

Oil transportation in tankers, pipeline breaches, oil exploration, oil transfer onto ships, and illegal activity. Interference with oil wellheads and vandalism are a few examples of how it could be related [3]. Early detection of oil spills is crucial to prevent any form of damage. Crude oil or refined petroleum discharge into bodies of water due to

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accidents, sabotage, or illegal disposal, causing severe environmental catastrophes and affecting wildlife and human populations. Oil spills vary in scale and severity, with the amount and kind of oil, the spill's location, and cleaning efforts impacting the environment. The rapid spread of oil forms slicks that threaten marine life and coastal habitats. Both minor and large oil spills occur globally, with large spills often resulting from broken pipelines, sinking tankers, and drilling issues, leading to long-lasting effects on ecosystems and economies.

The tremendous adaptability of UWSNs in a variety of fields is depicted in Figure 1. UWSNs are essential to environmental monitoring because they gather information on pollution levels, water quality, and the health of marine life. They are necessary for disaster prevention systems because they can identify early warning indicators of tsunamis or undersea earthquakes. UWSNs greatly aid resource exploitation by exploring the ocean floor for profitable minerals and assisting with oil and gas development. They are also necessary to ensure submerged infrastructure integrity, such as pipelines and offshore platforms. UWSNs collect real-time data in submerged environments, crucial in disaster management and aided

navigation. UWSNs are responsible for monitoring environmental changes and evaluating the harm caused by incidents such as oil spills.

Additionally, UWSNs provide localization services, underwater mapping, and assistance to emergency responders and maritime operators in handling challenging underwater scenarios, all contributing to assisted navigation. Additionally, Figure 1 illustrates the use of UWSNs in military (security and defence) applications such as anti-submarine warfare, maritime border protection, and underwater surveillance. UWSNs facilitate the real-time monitoring of underwater activities and improve situational awareness in naval environments. UWSNs optimize swimming and diving techniques by monitoring the underwater movements of athletes through the use of sensors. This enhances performance monitoring. Real-time competition analysis is facilitated in sports such as underwater hockey by using UWSNs to monitor player positions underwater, offering instructors and spectators valuable insights. Furthermore, UWSNs prioritize the safety of athletes and spectators by monitoring environmental conditions, including water temperature and quality, during aquatic events.

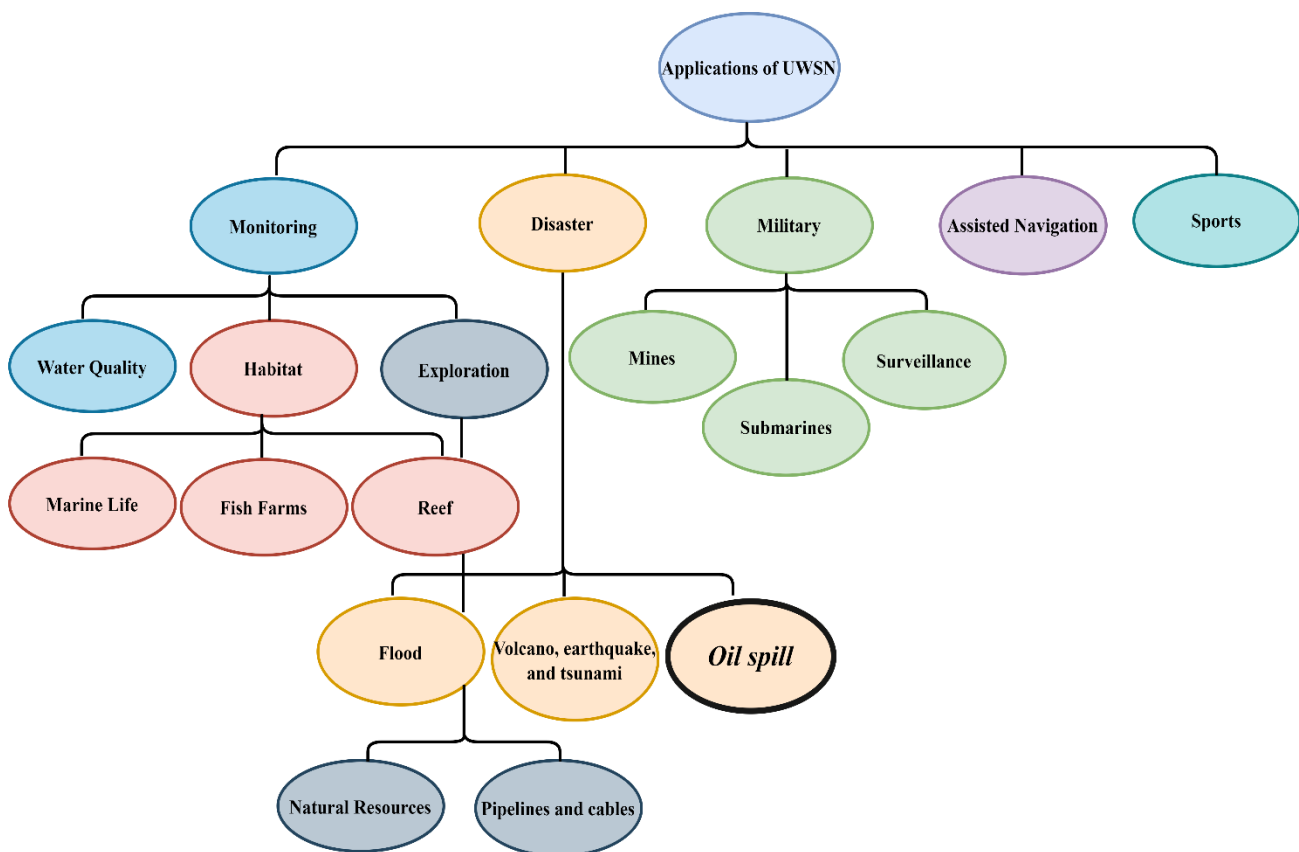


Fig. 1. Diverse Applications of UWSNs [4].

1.1 Motivation and Significance

Some deadly disasters, such as oil spills and their leakage, are caused by oil transportation through ships and pipelines. Prior and timely knowledge can save human life, the environment, and marine life, even though it cannot be entirely stopped. This motivates us to identify these challenges so that proactive, efficient actions can be implemented. The availability of modern technologies like DL and the rapid growth of UWSNs underlined the crucial need for awareness to rise frequently due to their adaptability and wide range of applications in many fields. DL models are quite helpful in automating the detection of these problems.

1.2 Organization

This study aims to offer readers detailed insights into one of the biggest applications of UWSNs, i.e. oil spill detection. Because DL models can handle large, complicated datasets like multispectral, SAR, and satellite imaging. These are increasingly employed for oil spill detection. The main advantageous techniques are CNNs and RNNs, as well as their variations. While RNNs perform better at sequential data analysis and interpreting temporal trends in meteorological and oceanic data, CNNs are better at extracting spatial features. DL architectures' versatility enables ongoing improvement, guaranteeing resilience and scalability in detecting and monitoring oil spills in various

environmental scenarios. This improves the accuracy and dependability of systems that detect oil spills, enabling prompt and efficient response actions. DL has shown to be a formidable instrument for detecting oil spills, with great promise for early identification. The problem in the current scenario is data scarcity about oil spills and the problem of patterns similar to oil spills, which in turn don't show promising results. This paper's contributions are as follows:

1. It provides the readers with a sequential and coherent understanding of UWSNs and oil spills and motivates the researchers to work in this direction using DL.
2. A detailed analysis of oil spill detection using different DL models was discussed.
3. Provide the reasoning behind the selected DL model architecture (e.g., CNN, RNN).
4. Give the potential future visions for identifying oil spills.

The structure of the rest of the content is as follows. This study consists of a total of five sections. The oil spill and its consequences are discussed in detail in section II. Related work is provided in Section III. The datasets used by existing models, types of images to detect oil spills, performance of existing DL techniques, and their findings are discussed in Section IV. In the end, Section V presents the conclusion and future vision.

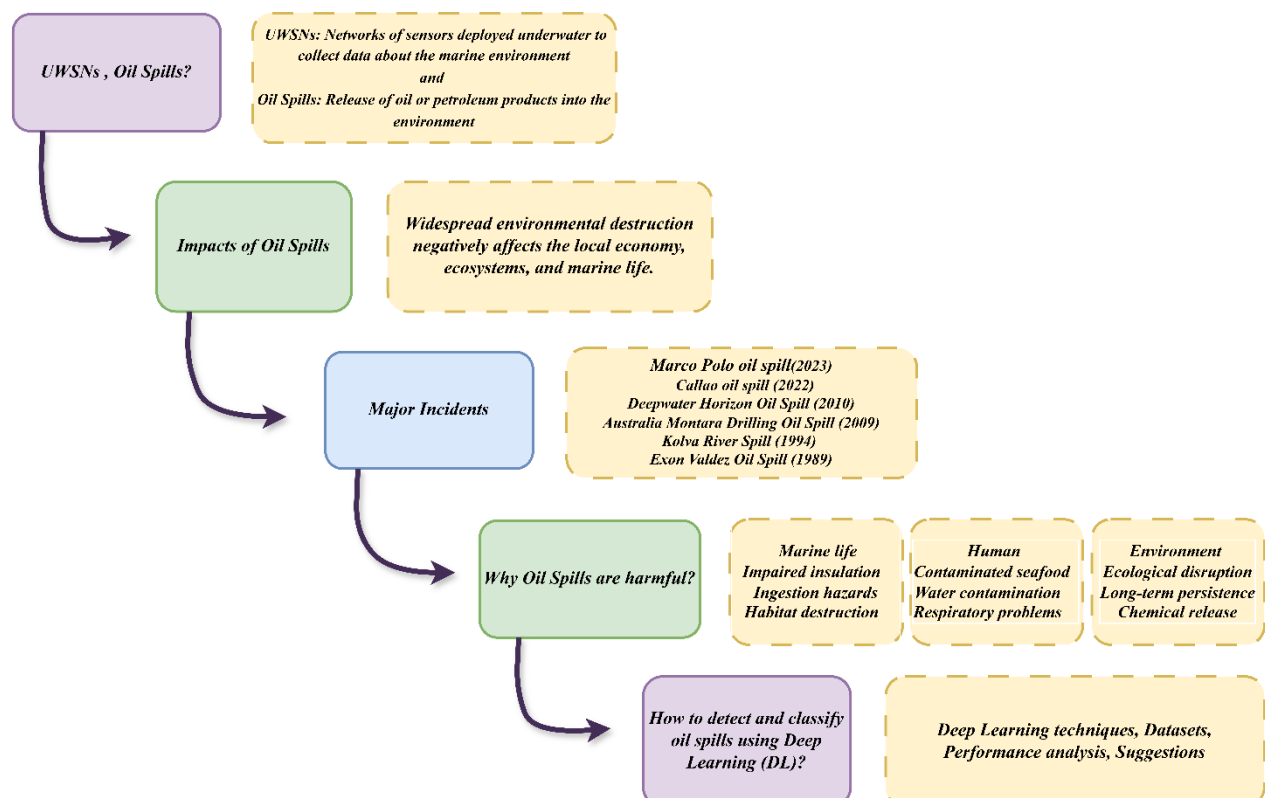


Fig. 2. Systematic View of Oil Spills.

2. OIL SPILL AND ITS CONSEQUENCES

Rapid overlaying of Open-water oil spills has a detrimental impact on the marine ecosystem and raises environmental issues. There are numerous reasons why oil spills happen, and there are numerous techniques to clean them up. However, we should also work towards preventing leaks in the future [5]. Figure 2 presents an orderly perspective on oil spills in this work.

2.1 Oil spill and its properties

An oil spill is the uncontrolled discharge of liquid petroleum hydrocarbons into the environment in oceans, seas, rivers, or lakes. Tanker crashes, pipeline ruptures, well blowouts, equipment failures, and illegal vessel discharges can cause this leak.

Oil spills may coat surfaces, kill wildlife, alter ecosystems, and contaminate water sources, posing environmental and economic dangers. Government authorities, industrial players, and environmental organizations must coordinate complicated, costly cleanup and repair initiatives.

DL excels at complicated data pattern recognition. It makes use of the following characteristics to detect oil spills:

- **Spectral Features:** Oil spills exhibit diverse properties in visible and infrared light. DL algorithms can distinguish oil from water and other things using these spectral fingerprints.
- **Water Surface Texture:** Oil has a smoother texture, whereas pure water has ripples.
- **DL models can analyze the shape and size of oil slicks.**
- **Analyzing temporal features in satellite or aerial pictures helps follow oil spill movement and spread.**

DL models may use these characteristics to identify oil spills more accurately and efficiently than older approaches.

Figure 3 displays the incidence of the oil spill and its cleaning process. There is a growing hazard of oil pollution worldwide due to the exploration, production, and use of oil and petroleum products. Up to ten to fifteen transfers are required to transport petroleum from the oil fields to the customer, including tankers, pipelines, railcars, and tank trucks. The fastest, safest, most affordable, and most reliable way to constantly transfer oil and gas is through a submarine pipeline [6].



(a)



(b)



(c)

Fig. 3. (a) Oil spill (b), (c) Oil spill cleaning process [7].

2.2 Impacts of Oil Spills

Remote sensing has become vital for locating oil spills [8], [9]. Sea surface oil spills are primary hazards to the marine natural environment; hence, early warning systems and efficient monitoring are required. Nevertheless, finding oil spills is difficult due to how complicated the environment is around us [10]. The fact that marine pollution is a long-term problem rather than a temporary one makes it a national and worldwide concern. The spills persist for many years and will not go away until the proper steps are implemented to reduce, eliminate, and avoid the risk.

Oil spills also make the seafood unsafe to eat. Oil spills and leaks are among the most significant environmental catastrophes. Oil is the most trafficked commodity worldwide, and due to its chemical makeup, it is transported mainly by water. When two ships carrying oil cargo collide, spills like this happen. Oil spills contaminate the entire ecosystem in addition to the sea. Because it is an unnatural activity and a form of pollution, it directly affects the marine ecosystem. Economically, environmentally, and socially, oil spills impact society. The spills have occurred in volumes ranging from several thousand tones to several lakhs. Beaches, marine creatures, fish, and birds are all harmed by oil spills, as seen in Figure 4 [11].

Weathering and transport are the two critical components of oil behavior under ice conditions following an oil spill. Weathering, which includes evaporation, emulsification, biodegradation, dissolution, and photo-oxidation, is used to modify oil's chemical and physical arrangement. Transport is the term used to describe oil flow, including encapsulation, advection, spreading, and dispersion. Various models have been created to assess how oil behaves when there is ice. Oil spills have been the subject of

extensive research [12]. When this occurs, individuals must accept responsibility and act to reduce the harmful impacts on marine life by cleaning up the water. Oil spill clean-ups could be costly. Additionally, removing oil from the ocean may take plenty of time.



Fig. 4. Impact of oil spills [11].

2.3 Major Incidents

The 2023 Marco Polo oil disaster occurred off China when the MV Felicity Ace caught fire and sunk while transporting thousands of Porsches and Audis and hazardous chemicals. Oil and chemicals spilled from this incident raised environmental concerns. A Petroperú-owned underwater pipeline rupture caused the 2022 Callao oil disaster in Peru's El Callao area. The spill contaminated local beaches and marine habitats, requiring cleanup and environmental monitoring. One of the worst ecological disasters in U.S.

history was the 2010 Gulf of Mexico Deepwater Horizon Oil Spill. It was caused by the Deepwater Horizon offshore drilling rig explosion, which released millions of barrels of crude oil over months. The disaster devastated marine life, coastal towns, and the Gulf Coast economy. The Montara Wellhead Platform blowout in 2009 caused the Montara Drilling Oil Spill off Western Australia. Tens of thousands of barrels of oil were released into the Timor Sea, causing massive environmental damage and cleaning activities. A pipeline breach in Russia released 2 million barrels of oil into the Kolva River in 1994. The spill damaged wildlife and ecosystems by polluting streams and the environment. In 1989, the Exxon Valdez oil ship went aground in Alaska's Prince William Sound, releasing approximately 11 million gallons of crude oil into the pristine seas. The spill devastated the region's marine life, fisheries, and towns, causing environmental devastation and legal disputes.

2.4 Why Oil spills are harmful?

Oil spills severely harm humans, the environment, and marine life. Fish and other sea life, such as birds, are covered with oil, which makes it harder for them to live. The oil damages plant life and the food chain by upsetting ecosystems. If humans consume contaminated seafood, it can cause health issues and severely damage coastal economies that depend on fishing and tourism.

2.5 Why oil spill detection and classification using DL?

DL's use in remote sensing picture classification has garnered much interest. DL has a robust representational learning capacity to enhance classification performance and the ability to mine knowledge spontaneously [13], [14]. DL is a potent instrument for identifying and categorizing oil spills from remote sensing images, especially SAR images. DL models can extract and learn complex patterns from SAR data, effectively detecting oil spills even in difficult situations like cloud cover or choppy seas. Its ability to easily handle large, complex information makes it a potent tool for oil spill detection. A DL can handle large-scale datasets, capture the most complicated patterns and features from raw data, hierarchical identification of patterns, non-linearity, and adaptability. Also, DL can model complex relationships between input attributes and output, adapting to different surface types and environmental conditions. Figure 5 shows the process used to study the literature. It includes how the manuscripts were searched and found, and only journal research articles incorporating DL techniques were approved.

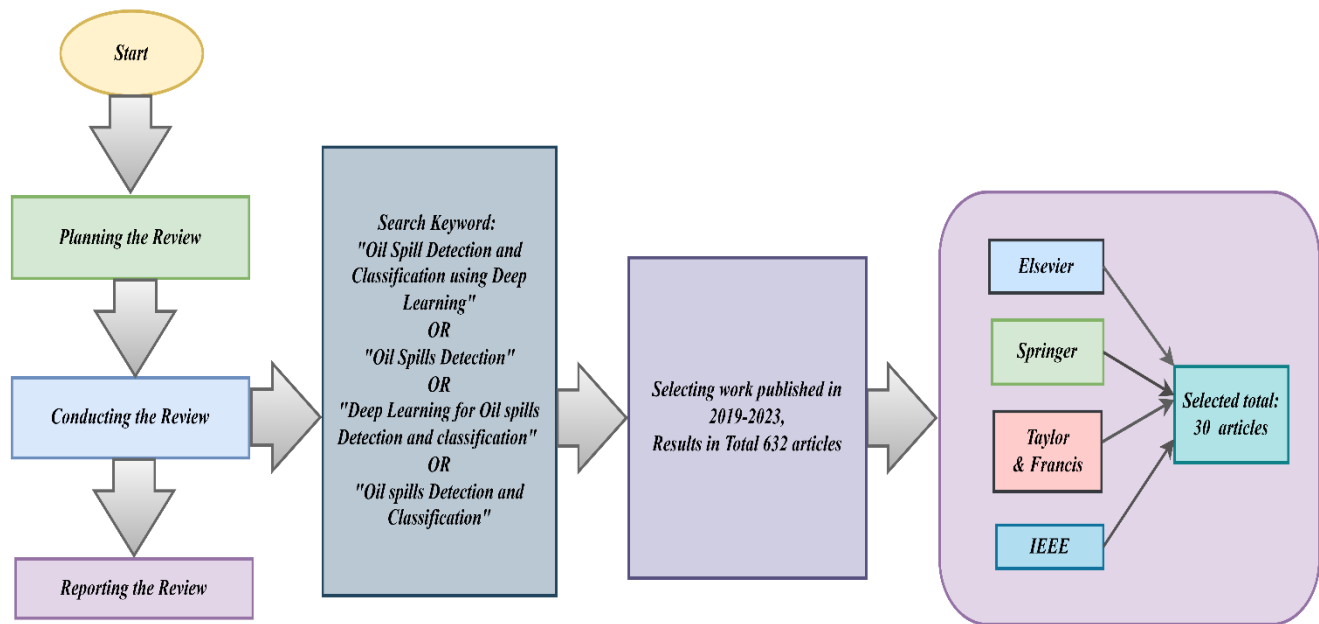


Fig. 5. Review process

There are two categories for object detection and identification using CNN. Two stages are involved in the first category: locating and recognizing the target. The first method within this category is region-convolutional neural network (R-CNN). To overcome its drawback, subsequent innovations like Faster R-CNN and Fast R-CNN were introduced [15]-[17]. The second category encompasses one-stage detection methods. "You Only Look Once" (YOLO) and the single shot multi-box detector (SSD) series are well-known examples of this methodology. Advancements in CNN designs and attention mechanisms can enhance performance in challenging detection tasks, particularly in detecting oil spills using large sets of SAR images with annotations. It can then be identified and categorized using these models on fresh SAR photos. DL has shown to be a valuable technique for classifying and detecting oil spills, providing a viable means of enhancing environmental surveillance and response activities. SAR imaging is an excellent alternative for quick oil detection since it covers a large area, gathers data at frequent intervals, and enables daytime and nighttime imaging in all-weather situations. DL significantly improves segmentation accuracy.

3. RELATED WORK

With the fewest images and maximum accuracy possible, U-NET and DeeplabV3 neural networks in [18] separate the oil spills from SAR images. Due to the benefits of automatic extraction of features and high-precision identification, DL neural networks have been utilized to detect oil spills in recent years [19-20]. Due to a shortage of hardware, such as GPUs, to train hundreds of neural networks, two precise CNNs for oil spill segmentation have been discovered.

Decomposition algorithm and other slick detection methods for MODIS/Terra satellite image RISAT-1 image [21]. Results are compared visually and shown only for a smaller number of images. Number of images tested is not known. An improved reconstruction algorithm for CP SAR data is developed. The study says there is a correlation between the incidence angle and the appropriate values in the statistical model, so further exploration can increase the accuracy [22]. A standard procedure provided in the SNAP software was used to process the SAR images, and the Lagrangian transport model contained in the GNOME package was used to create the numerical simulation [23]. Combining these technologies made it able to distinguish between natural oil slicks and their imitators.

Five free Sentinel-1A sensor photos are picked out of the GEE collection. It is giving an accuracy of 96.37%. The approach developed was crucial for improving the grasp of the parameter space for oil spill detection using SAR images. Review studies conducted up to this point have used images collected between 2006 and 2010 and reported that C-band radar has been heavily utilized in detecting oil spills. Since environmental wind speed condition measurements are essential for detecting oil spills, the measurement was used in about 68% of the articles the authors analyzed. From a methodology perspective, only a few have used DL algorithms, with the majority choosing various conventional classification, segmentation, and statistical methods [24]. There isn't a thorough analysis of oil spill-detecting techniques in the literature. A reasonably accurate MDNN segmentation model was created [25] using a database of sixteen ENVISAT-ASAR images taken over various sea locations. Additional multispectral data is

utilized to determine the type and thickness of oil. Additionally, data augmentation is employed.

A fast and accurate ML method was developed to detect hydrocarbon leaks in a Sentinel-1A satellite's SAR image captured in the Caspian Sea [26]. The required image is fed into a densely structured network, which separates as non-oil spill and oil spill. Compared to the traditional CNN approach, this dense network performs better. According to [27], a novel network architecture based on texture superpixel is named SSWT-UNet++. SAR images often show several similar oil spill areas that are hard to differentiate, and DL networks need help training properly due to the lack of accurate oil spill data. An oil spill detection model using MTGANs has been given in [28] to discriminate oil spills from look-alikes in a single framework to address the issues above. The first GAN discriminator is redesigned into a classifier that can distinguish between actual and synthetic oil spills. The second GAN model's generator combines several convolution blocks with a fully convolutional symmetric structure.

To overcome the problems of pixel annotations and the lack of labels generated by domain experts within HSI, a self-supervised SSTNet is presented in this research [29] for hyperspectral oil spill mapping. A new DL model based on the DAM can automatically identify oil spills in a body of water, as proposed in [30]. To emphasize only specific significant and discriminative properties of oil spills in SAR data, a DAM is integrated into a traditional UNet segmentation network. DAM comprises two stacked Channel Attention and Position Attention Maps in the UNet decoder network. The research offers fresh perspectives on how attention modules could be integrated into other DL applications, such as speech recognition, action detection, image-based analysis, and machine translation. Developed and contrasted the effectiveness of machine learning models [31] with varying degrees of complexity to identify the source, scope, and movement of oil spills on a broad scale. The Persian Gulf CNN's performance is superior to that of Random Forest and SVM.

Because there is so little information on oil spill events accessible, developing an oil spill segmentation model is extremely difficult. Consequently, a unique data generator based on the Seg-Net model implemented in the CGAN was proposed in the study [34]. This approach improves the final oil segmentation results. This paper [35] suggests creating fake datasets of oil spills using a CGAN model, namely Pix2Pix, as a data augmentation technique. This method can improve data when detecting or segmenting formless items like mildew, oil spills, cracks, and water seepage. This study [36] has exploited the sensitivity of THz radiation to polar molecules and the data processing power of the DL to generate a set of hybrid experimental computations. This type of predictive analysis provides detailed curves for the length and depth of pollution. It can be applied to the live-

tracking of crude oil spills and the study of polluted sand particles. CNN also Gives better results in colorization [37].

Using publicly available Sentinel-1 SAR images, the author of this study [38] has created a DL-based object detector to automatically identify oil pollution from both marine accidents and intentional discharges in this region. This paper [39] proposed an offshore oil leak detection technique using remote sensing data based on the Monte Carlo DQTN. As a primary feature extraction module, a novel DeeplabV3+based network using ODGghostNetV2 is built, and an ATA module is simultaneously included in the encoder and decoder [44]. By doing this, the network model's receptive fields are expanded, and the richness of the semantic characteristics is enhanced. A DaNet DL model was trained for identifying and categorizing oil spills using a dataset that included patrol recordings from EOIR cameras installed on Korean Coast Guard helicopters and data gathered from the internet [46]. A maritime oil spill on the surface is regularly monitored using data from remote sensing.

The origin of the marine oil leak is then ascertained using the deep-Q-network that utilizes offline transferred knowledge. A two-stage DL architecture based on a wildly imbalanced dataset for identifying oil spill occurrences is presented in [50]. The first stage uses a unique 23-layer CNN to classify patches according to the percentage of pixels with oil spills. In contrast, a five-step U-Net structure is used in the second stage to carry out semantic segmentation. Their main drawbacks are the complex design of the algorithms used in current SAR oil spill detection techniques, unbalanced data sets, uncertainty in feature selection, and comparatively lagging detection speeds. To overcome these limitations, a unique DL model, the Faster R-CNN, is presented in [57] for quick and efficient SAR oil spill detection.

A unique lightweight bilateral segmentation network for spotting oil spills on the sea surface is presented in the paper [58]. First, a novel DL semantic-segmentation algorithm is developed to examine the features. Next, a BiSeNetV2 is chosen as the fundamental network design. Additionally, the traditional network's semantic branch's GE layer is modified, and the parameter complexity is decreased. The types of oil involved in the accident, their respective masses, and other pertinent facts must be disclosed. In [59], a DaNet DL model was trained for oil spill detection and classification using a dataset that included patrol recordings from EOIR cameras installed on Korean Coast Guard helicopters as well as data gathered from the internet. The results show that the DaNet model finds an average intersection over the union of 72.54% and an average accuracy of 83.48% in spotting oil. Furthermore, the model's macro-average F1-score of 83.91% lets it correctly classify four distinct types of oil. This investigation also reveals that the DaNet decoder achieves 6.14% more accuracy than PsPnet.

Table 1: Oil Spill detection from 2019 to 2024, reference, Technology used, datasets, performance analysis, and suggestions

Sr. No.	Reference	Technology used	Dataset	Performance analysis	Suggestions
1	Saeid Dehghani-Dehcheshmeh et al. (2023) [5]	A combination of CNN and ViT	C-band SAR visuals from Sentinel-1 satellite	The F1-score obtained is 78.48.	High capacity to identify borders of oil spills even in noisy visuals. The largest obstacle is the low proportion of oil spill pixels compared to the image's total pixel count.
2	Huajun Song et al. (2023) [27]	SSWT-UNet++ network	The datasets utilized in the image are generated from the network-sourced video of the submerged oil pipeline leak.	Mean intersection over union 0.906 and superpixel accuracy 0.977. The average precision is 0.985.	Improves the detection timeliness and accuracy. Capable of realizing the real-time monitoring function. The results shown are quite low. No repository was mentioned.
3	Jianchao Fan et al. (2023) [28]	GAN	Sentinel-1 ERS- $\frac{1}{2}$ GF-3	Oil spills and look-alikes classification accuracy can reach 97.22%. The average precision is 86.69%.	Suitable for small datasets.
4	Xudong Kang et al. (2023) [29]	SSTN	HOSD	Four objective metrics have an average value above 90%: F1 score, Kappa coefficient, Average Accuracy, and Overall accuracy.	The degree of transferability for practical use is constrained.
5	Amira S. Mahmoud et al. (2023) [30]	DAM-UNet	The EG Oil Spill dataset consists of 3000 SAR imagery.	Obtained 94.2% overall accuracy.	It is contrasted with four baselines: the conventional UNet, PSPNet, LinkNet, and fully convolutional network models. Further improvements can be made, for the identification of oil spills more accurately and efficiently.
6	Sahand Najafizadegan et al. (2023) [31]	SVM, RF, CNN models	Sentinel-1 SAR data	CNN-95.8 % RF-86.0 % SVM-78.9 %	Used statistical, geometrical, and textural features.
7	Yu Li et al. (2023) [32]	CVCNN	C-band SAR data from Radarsat-2	The classification accuracy of clean seawater and oil is 97.69% overall and for crude oil and biogenic oil classification accuracy is 96.33%, which is 0.86% higher than that of RVCNN.	A few manually derived real-valued polarimetric SAR features, like co-polarized phase difference and H/A/ α decomposition parameters, can be considered in conjunction with the classification of oil spills.
8	Rodrigo N. Vasconcelos et al. (2022) [33]	The feature's importance is determined using the Gini index. Random forest for image classification.	GEE is providing five complimentary Sentinel-1A sensor images.	Angola (0.9960), Italy (0.9506), Kuwait (0.9547), Trinidad & Tobago (0.9829), and Dubai (0.9344). On average, 96%.	Only five images of different areas were used to create more images. More focused on using independent features of the evaluated images, still need to investigate this issue.
9	Samira Ahmed et al. (2022) [34]	The seg-Net model implemented in CGAN	Sentinel-1 SAR images	99.04% accuracy on average, 96.59% is the IoU index, and a precision of 85.24%	Only 50 images are used for training, quite less in number.
10	Fatemeh	U-NET and	SAR images from	Oil spill detection	Accuracy is quite low.

	Mahmoudi Ghara et al. (2022) [18]	DeeplabV3 neural networks	different sources like Sentinel-1, EnviSat, etc.	accuracy using U-NET is 78.8%, which is more than the Deeplabv3 network (54%).	To increase the quantity of images, data augmentation is used.
11	Zhan, Honglei et al. (2022) [36]	1D CNN	SEM images	F1 score 97.90% AUC .99 indicates high consistency and robustness.	1D CNN was used to demonstrate the effects of sand and crude oil mixtures on THz waves. It can be used for detecting oil spills.
12	Yi-Jie Yang et al. (2022) [38]	A DL-based oil spill detector and YOLOv4 for object detection	Sentinel-1 SAR imagery	69.10% and 68.69% AP on the test and validation sets, respectively.	Not every time could the lookalikes be easily identified. Transfer learning can be used to identify oil spills in different areas.
13	Yuewei Wang et al. (2022) [39]	A Monte Carlo-based DQTN	Oil spill images of Penglai region of the Bohai Sea occurred on June 4, 2011	Up to 98.97% of the targeted oil spill points are accurate.	The average time was 184.5 minutes, which is quite consuming.
14	Ana Cláudia Souza Vidal Negreiros et al. (2022) [40]	q-EFE-based feature extraction technique paired with MLmodels	Public dataset with 1112 SAR	SVM and XGB performed best for the imbalanced original dataset Bac is 69.79%.	Due to the sensitive nature of this type of data, there are no readily available data sets about oil spills. Multiclass study can be done by using q-EFE to distinguish between oil spills and lookalikes. This work can be evaluated for other applications.
15	Dawei Wang et al. (2022) [41]	BO-DRNet.	SAR images	The mean accuracy is 74.69%. Mean dice of 0.8551.	Highlights the potential use of a polarisation
16	Kai Li et al. (2022) [42]	HOG features combined with an SVM	Utilized the DJI ROYAL 2 UAV to gather images of the spill.	The recognition accuracy in the context of tiny infrared oil film samples was 91.3%. It requires less time to train.	Weather and sea conditions have a big impact on UAV monitoring of offshore oil spills. Flying UAVs in windy and very rainy weather is not recommended. For all weather monitoring, many UAVs must work together. There are fewer samples available.
17	Nastaran Aghaei et al. (2022) [43]	Efficient ShuffleNet	Images from the European satellite Sentinel-1, showing oil spills between September 28, 2015, and October 31, 2017.	Compared to the best outcomes of several earlier techniques, the mean IoU was improved by 7.1%.	Results can be enhanced or improved by making use of pre-trained networks with shuffle architecture.
18	Xiaoshuang Ma et al. (2022) [10]	Improved DeepLabv3+	Sentinel-1 data from the ESA data distribution	Achieved superior performance, in terms of both, overall accuracy is 98.92% and inference time is 0.19 sec.	The model's capabilities are built in difficult circumstances, such as strong and low winds. Boost the network's performance to further increase the model's ability to detect oil spills from PolSAR images.
19	Kai Du et al. (2022) [45]	Built the CBF-CNN using the CBF loss function	An image taken in the Andaman Sea by the CZI of the HY-1C satellite	For the detection of oil emulsions, the F1-Score of CBF-CNN is 0.88. Oil slick detection results have an F1-Score of 0.96–0.97.	could train the model using a lot of data from oil spills and achieve successful remote-sensing oil leak detection. The model works well for spotting oil spills in places with little sunglint.
20	NVA de Moura et al. (2022) [46]	Semantic segmentation architectures with four	Sentinel-1B images	With the Efficient-net-B3 backbone, U-net's results were somewhat improved	The majority of errors happen around the boundaries of the oil spill, and they get worse in long, narrow features.

		backbones			Consequently, for supervised DL tasks, image annotation is crucial.
21	Zahra Ghorbani et al. (2021) [47]	Segmentation is done using the Mask R-CNN and PSPNet models after the VGG16 model for detection.	Nafta dataset	Detection of an oil spill in an image with an accuracy of 92%. Segmentation with an MIoU of 49% (Mask R-CNN) and 68% (PSPNet).	Detection accuracy and IOU can be enhanced.
22	Xinzhe Wang et al. (2021) [48]	CNN AlexNet Model	GF-3 and Radarsat-2 SAR images	On average, the accuracy is 97.03.	AlexNet is slow but provides better accuracy than OTSU, FCM, and SVM.
23	Seyd Teymo or Seydi et al. (2021) [49]	Multi-scale multidimensional residual kernel CNN	Images from the Gulf of Mexico captured by the Landsat-5 satellite.	Less than 5% of false alarms and miss detections occurred, while accuracy exceeded 95%.	Patch size affects performance.
24	Mohamed Shaban et al. (2021) [50]	A two-stage DL framework	Sentinel-1 satellite distributed by ESA	A maximum of 40 training epochs can be employed, with a learning rate of 0.00005. The precision achieved was 84%.	When dealing with a multiclass problem that includes additional targets like ships and lookalikes, it is useless. Unsupervised learning has been studied and may be used to classify oil spill pixels more effectively. Further, accuracy could be enhanced.
25	Thomas De Kerf et al. (2020) [51]	An FCN network and a mobile feature extractor	The dataset was constructed by automatically labeling RGB images	The accuracy achieved is 89%	More sophisticated RGB preprocessing methods could be used for better outcomes. Primarily used to find minor oil spills that the port authority would miss. The results shown are for a smaller number of images.
26	Dongmei Song et al. (2020) [52]	CNN	Full polarimetric SAR data from RADARSAT-2	Approximately 98% accuracy and loss of 0.05%.	Research on feature-level fusion and decision-level fusion can be done for various datasets to increase accuracy. Other models like FCN can be considered.
27	Shamsudeen Temitope Yekeen et al. (2020) [53]	Mask-Region-based Mask R-CNN	COCO Dataset	The accuracy rate for look-alike and oil spill detection is 96.6%.	Necessary to avoid overfitting and fluctuations in training and validation losses by using a sizable oil spill data set for model training.
28	Hui Huang et al. (2020) [54]	Faster R-CNN	Spectral dataset	On average giving an accuracy of 92.886%.	The suggested method's quickness and precision can be improved by incorporating more images.
29	Ramoni Reus Barros Negreiros et al. (2020) [55]	pre-trained CNN (resnet34)	ImageNet Dataset	Best case accuracy is 91%	Lack of images labeled. Increasing the dataset size, then it is going to enhance the accuracy. Classification of images only not detection.
30	Zeyu Jiao et al. (2019) [56]	Deep CNN, Otsu algorithm	Dataset acquired by UAVs	Comparing the cost of oil spill detection to the conventional manual inspection process and reducing it by 57.2%. Detects and evaluates oil spills automatically and accurately.	To enhance the model's functionality, more aerial photos of oil spills must be gathered over an extended period. Use of pre-trained networks to build a DCNN model that could outperform the existing one. To support patrolling at night, need to make use of some infrared devices on AUV.

The framework presented in [60] has a spectral model that figures out the type of oil and how much there is, as well as a 2-step DL model (F1-score = 0.88) that uses the spectral, spatial, and geometrical properties of optical images to find out if oil is present or not.

For semantic segmentation of SAR pictures, this study [61] applies and contrasts three algorithms: PSPNET, DeepLapV3, and FCN with U-Net. The findings showed that U-Net and FCN can identify and classify areas affected by oil spills, with U-Net showing somewhat better IoU scores and a 95% accuracy rate. For previously encountered SAR pictures, the DL models generalize effectively. This research [62] provides a concise overview of the categorization of contemporary methods used to identify oil spills, as well as the use of machine learning techniques to address this issue. Only a few studies have been taken into consideration.

Figure 6 shows the articles used in this study, year-wise, from 2019 to 2024. Various DL models (Standard CNN or pretrained) were used to detect oil spills. More research took place in 2022.

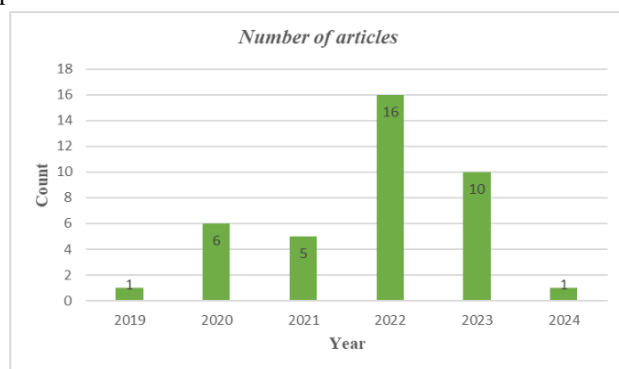


Fig. 6. Distribution of Research Articles by Publication Year.

4. DATASET, RESULTS, AND DISCUSSION

4.1 Dataset

Various kinds of images have the potential to be utilized for identifying oil leaks. These are shown in Figure 7. A brief overview of the many categories of optical photography describes images captured using visible light. This most popular category of images includes a large number of satellite images. Infrared pictures use longer wavelengths of invisible light than visible light. They come in particularly handy while trying to see through fog or at night. Radar uses radio waves to produce images. Radar can produce photographs of the Earth's surface, even through clouds. Synthetic aperture radar, or SAR, is a type of radar that can produce high-resolution pictures. LIDAR (light detection and ranging) uses light pulses to produce imagery. LIDAR's applications include the creation of three-dimensional terrain maps. Images that are hyperspectral or multispectral collect information from several electromagnetic spectrum bands. This data can identify the many materials that make

up the Earth's surface. Images from the air are captured from aircraft or other aerial vehicles. Specialized cameras are used to capture underwater imagery.

SAR imagery is the most suitable type of image for DL-based oil spill identification and categorization. Because SAR imagery can see through clouds and darkness, it is especially well adapted for this kind of work and allows oil spill monitoring even under challenging situations. Moreover, SAR images may be acquired under all circumstances, and DL algorithms can successfully analyse the unique texture of these images to detect oil spills.

- Oil spills may now be continuously monitored, regardless of the weather.
- The texture of SAR images is distinct from that of water and other natural characteristics. DL algorithms can identify oil spills by properly analyzing this material.
- Up to one meter of spatial resolution in SAR photos allows for detecting even tiny oil spills.

Apart from SAR imaging, optical and hyperspectral imagery are other forms of remote sensing imagery that can be employed for oil spill identification and categorization.

Other phenomena include sea ice, wind shadows, and organic surfactants on the water's surface that produce similar-looking dark patches in SAR data. This can lead to false positives in SAR-based oil slick identification, enhancing the precision of oil slick detection using SAR [63].

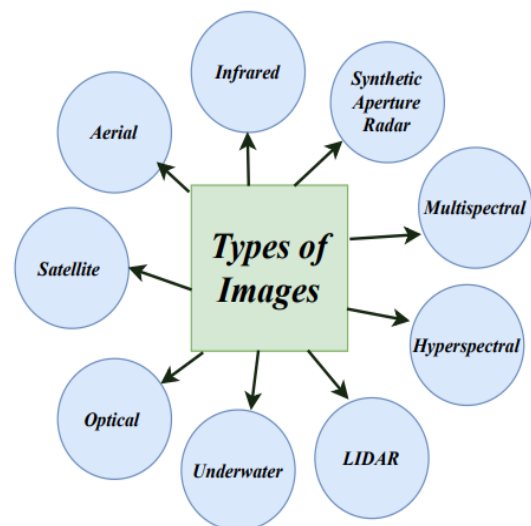


Fig. 7: Kinds of images that can be utilized to find oil spills.

Notable CNN designs are widely used in various computer vision applications, including VGGNet, ResNet, LeNet-5, AlexNet, and InceptionV1. These architectures have demonstrated significant processing power in optical and medical image processing and invited researchers to investigate the models in various fields of study. As such, the merging and incorporation of models in SAR applications is limited, creating opportunities for further

research. These datasets, which cover many platforms and sensors, provide a variety of viewpoints on oil spills in varied environments.

Table 2: Datasets utilised for 2019–2024 research

Satellite Data	• Sentinel-1 and Sentinel-1B: These constellations offer C-band SAR images with wide coverage and frequent revisits, ideal for large-scale monitoring. • ERS-2, EnviSat, Radarsat-2: These historical datasets provide valuable long-term insights into spill behavior and environmental changes. • GF-3: This Chinese satellite offers high-resolution C-band SAR data for regional studies. • Landsat-5: Optical imagery from this satellite can complement SAR data for contextual information.
UAV Data	• EG-Oil Spill dataset: This curated collection features images captured by 2 UAVs, offering close-up views of spills. • Network-sourced videos: Extracting images from videos of submerged leaks.
Public Datasets	• HOSD: This public dataset contains SAR images of various environmental events, including oil spills. • Penglai oil spill images: This regional dataset. • COCO, Spectral, and ImageNet datasets: These general-purpose datasets can be leveraged for pre-training or transfer learning tasks related to oil spill detection.

This wide variety of datasets from satellites, UAVs, and other sensor types opens the door to creating reliable and broadly applicable oil spill detection systems. UAVs have become quite famous in agriculture, UWSNs, and other industries [64]. Researchers may develop solutions that work well in various settings and circumstances by integrating the advantages of each dataset, eventually leading to safer and cleaner oceans.

4.2 Results

This section also discusses the results achieved by DL models employed from 2019-2024. Various measures were used to measure the accuracy of the DL models. Figure 8 depicts the performance of various DL models used in 2020 for oil spill detection. Among all, CNN is showing 98% accuracy but at the expense of limited data.

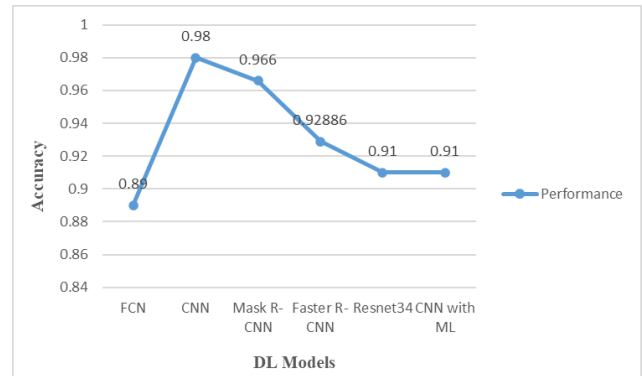


Fig. 8. Performance achieved by DL models in 2020 in terms of Accuracy.

The performance of several DL models employed in 2021 for oil spill detection is displayed in Figure 9. CNN, Alexnet is the most accurate of all. It performs quite well but at a slower pace.

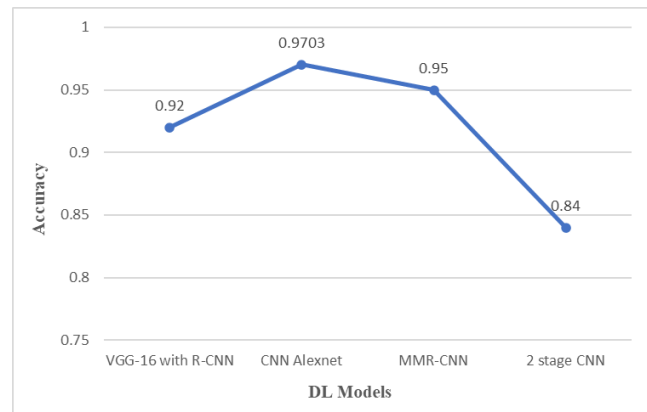


Fig. 9. Performance achieved by DL models in 2021 in terms of Accuracy.

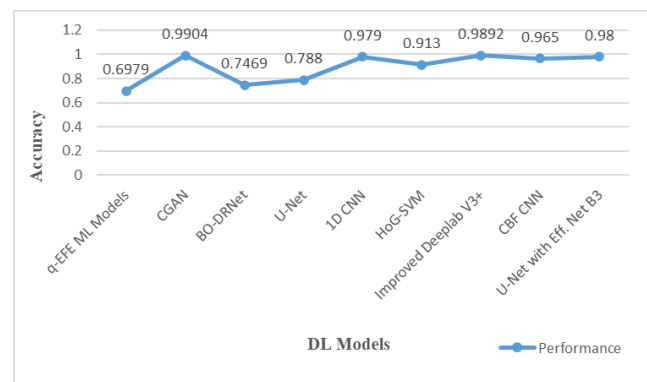


Fig. 10. Performance achieved by DL models in 2022 in terms of Accuracy.

The result of different DL networks used for the identification of oil spills in 2022 is displayed in Figure 10. Improved Deeplabv3 has the highest accuracy rate of all, at 98%, but needs to strengthen the network, to increase the

model's effectiveness in detecting oil spills using PolSAR images.

Figure 11 shows the effectiveness of multiple DL models for detecting oil leaks in 2023. Out of all, SSWT UNET++ is exhibiting excellent performance. The average precision is .985, the superpixel accuracy is .977, and the MIoU is .906 at 98%. It enhances the precision and timeliness of detections and can carry out real-time monitoring functions. But the displayed findings are quite less. This is carried out with the use of datasets whose images are produced from network-sourced footage of an oil pipeline breach underwater.

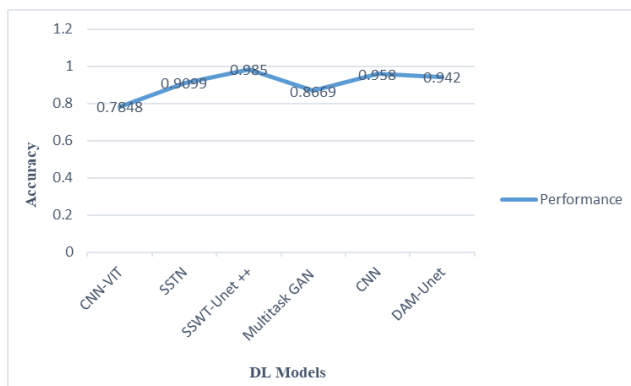


Fig. 11. Performance achieved by DL models in 2023 in terms of Accuracy.

4.3 Discussion

Various DL models have been seen for the same purpose. Each has its problems, still, there is a need to work on the problem of data scarcity, efficiency, and actual and look-alike oil spill detection. Data shortage can hinder DL oil spill detection.

Few Annotated Data: Oil spill detection data is limited. High-performing DL models require a lot of labeled data, which oil spills may not have.

Pre-training and Domain Adaptation: We could pre-train the model on medical photos and then fine-tune it on oil spill images. This method uses transfer learning to reduce scarcity [65].

Researchers investigate dataset amplification methods to improve model performance. Horizontal and vertical flips and random rotations are non-learning picture transformations. These methods increase model generalization and data availability [66].

Oil spill detection using DL architectures like V-Net is promising despite data scarcity. These models abstract, forecast, and generalize data by employing multiple hidden layers.

Addressing data scarcity is essential for achieving reliable oil spill detection using DL models. Scientists persist in investigating novel methodologies to surmount this obstacle and enhance environmental surveillance [50, 67].

4.3.1 DL Techniques Barriers

DL is an effective technology for detecting oil spills, but it encounters several obstacles:

- **Data scarcity** is a significant challenge when it comes to training DL models, particularly for oil spill detection. Obtaining a sufficient amount of high-quality images of oil spills, especially under different environmental circumstances, might be somewhat limiting.

- **False Positives:** Oil spills may exhibit visual similarities to other phenomena such as shadows or algae blooms DL algorithms may encounter difficulty in distinguishing them from real spills.

- **Cost of Computation:** DL model training can be computationally costly, using a large amount of computing power and resources. For businesses with a limited computing infrastructure, this might be a challenge.

- **Explainability:** DL models can occasionally be like "black boxes," with little explanation provided for the predictions they produce. In essential applications where comprehending the reasons behind a detection is crucial, such as oil leak detection, this lack of explainability might be problematic.

- **Variations in the Real World:** DL models that were trained on certain datasets may not be able to adapt adequately to real-world scenarios involving various types of weather, bodies of water, and oil spills. When used in the field, this may result in errors.

4.3.2 Advantages of DL Networks for Detecting Oil Spills

DL neural networks have emerged as a powerful tool for oil spill detection in recent years, offering several advantages:

- **Automated feature extraction:** Without the requirement for human feature engineering, DL algorithms can automatically discover and extract pertinent features from SAR images. In comparison to conventional techniques, this may result in more reliable and precise detection.

- **High detection precision:** New research has shown that DL models can identify oil spills with astounding accuracy rates, more than 90% in some scenarios. The efficiency of attempts to respond to an oil spill can be greatly increased using this.

- **Versatility:** DL models can be modified to tackle a range of issues in finding oil spills, including the need to distinguish oil spills from their lookalikes and deal with noisy SAR data.

- The reviewed studies showcase various promising advancements in DL-based oil spill detection

- **Multi-channel data fusion:** Combining SAR images with additional information like wind field maps can improve feature extraction and accuracy.

- Attention mechanisms: Integrating attention modules into DL models can help focus on relevant features of oil spills for better detection.
- Domain-specific designs for improved performance.
- Solutions for data limitations using GANs and CBF loss functions.
- Need for further study to address unresolved issues even with current developments.
- Need for efficient, lightweight network architectures for real-time oil spill detection on UAVs.
- Combination of environmental data analysis and DL algorithms for environmental impact assessment.
- Continuous improvement: Exploring newer DL architectures and techniques can increase the accuracy, robustness, and generalizability of several models for detecting oil spills.

The ultimate goal of this study is to encourage readers to contribute towards a cleaner and safer future for our oceans.

5. CONCLUSION AND FUTURE VISION

DL offers exciting solutions for automatic oil spill detection in SAR images. This ability is essential for protecting the environment and responding promptly to oil spills threatening aquatic life and ecosystems. Although SAR pictures offer better detection than other forms of radar, their intrinsic complexity demands more complicated models. This paper emphasizes the necessity for models that can reliably and effectively identify and segment oil spills based on shape and texture parameters. It also shows the research advancements in DL-based oil spill recognition from 2019 to 2024. Further developments in DL algorithms and the addition of domain expertise could greatly enhance the accuracy and practicality of oil leak detection. The evaluated studies suggest several intriguing directions for future research on oil spill detection. We are addressing issues such as data imbalance and shortage, improving model architectures and feature extraction, boosting the ability to differentiate between real and fake oil spills, addressing environmental concerns, and implementing real-time monitoring and response. The included literature review is quite insightful. Future improvements and proactive contributions to this vital field of study can guarantee our seas' safety and cleanliness. This study aims to thoroughly investigate oil spills and develop techniques for detecting them using DL on various radar images. These studies are from a variety of nations with diverse environments. However, SAR images can detect oil spills more accurately than other types of radar scanning. However, they're also rather complex.

ABBREVIATIONS

UWSNs	Underwater Wireless Sensor Networks
WSNs	Wireless Sensor Networks
SAR	Synthetic Aperture Radar
DL	Deep Learning
ML	Machine Learning
ESA	European Space Agency
RNNs	Recurrent Neural Networks
R-CNN	Region-Convolutional Neural Network
YOLO	You Only Look Once
SSD	Single Shot Multi-Box Detector
ViT	Vision Transformers
MioU	Mean Intersection Over Union
UAVs	Unmanned Aerial Vehicle
IoU	Intersection over Union
AP	Average Precision
HOSD	Hyperspectral Oil Spill Database
CNN	Convolutional Neural Network
CVCNN	Complex Valued Convolutional Neural Network
Mask R-CNN	Mask-Region-based Convolutional Neural Network
GEE	Google Earth Engine
Seg-Net	Segmentation Network
DQTN	Deep Q-Transfer-Learning Network
XGB	Extreme Gradient Boosting
q-EFE	q-Exponential distribution
HOG	Histogram Of Gradient
SVM	Support Vector Machine
ESA	European Space Agency
CZI	Coastal Zone Imager
HY-1C	Haiyang-1C
CBF loss function	Class-Balanced F loss function
CBF-CNN	Class-Balanced F loss function -Convolutional Neural Networks
SSWT-UNet++	Suitable Superpixel With Texture network
THz	Terahertz
BiSeNetV2	Bilateral Segmentation Network
MDNN	Multi-Channel Deep Neural Network
GE	Gather-and-Expansion
GAN	Generative Adversarial Network
MTGANs	Multitask Generative Adversarial Networks
HSI	Hyperspectral Image
SSTNet	Spectral-Spatial Transformer Network
DAM	Dual Attention Model
ATA	Adaptive Triplet Attention
FCN	Fully Convolutional Networks
CGAN	Conditional-GAN
RF	Random Forest

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