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Review of Applications of Artificial Intelligence and Drones in Oil Pollution in Seawater

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Abstract

An ancient fossil fuel, oil is a crucial energy source for various daily activities, such as electricity generation and vehicle operation. However, its ship transportation poses a significant threat to the marine ecosystem. Oil spills into seawater, harming sea creatures and endangering human life in the event of an accident. The frequency of such oil pollution incidents in seawater is a persistent concern that demands immediate attention. Oil spills quickly spread to multiple areas, though they originate in a particular location, posing a threat to numerous species. During adverse weather conditions, detecting and mitigating these oil pollution incidents is complex. In this review, we would like to highlight the potential usage of drone technology as a solution to this challenge. In this paper, we discuss the current developments in the detection of oil pollution using various drone Techniques based on Scientific and Technological Concepts. We concentrate on the applications of drone techniques in seawater oil pollution and discuss the contribution of artificial intelligence techniques to the oil spilling problem in seawater. The Insights presented in this review article are informative and highly valuable to researchers dedicated to detecting and removing oil pollution in seawater. Their work is integral to the advancement of this field, and this research is a testament to that. The applications of drones and artificial intelligence techniques are very useful to society in detecting oil pollution in seawater. The methods used in artificial Intelligence techniques are highlighted, and the new challenges to be addressed in the future are elaborately discussed. This Research article elaborately listed and Discussed the Different kinds of drones normally available for detecting oil pollution in seawater. It also discussed the challenges in drone techniques for detecting oil pollution in seawater. New Research openings are suggested for detecting oil pollution in seawater using drones and artificial intelligence techniques. Researchers must read this paper to determine new solutions and do additional Research in this field. This research article paved the way to clearly understand the problems, solutions, and deficiencies.

Keywords

Types of Oils, Sensors, Artificial Intelligence Techniques, Drone Techniques, Supervised Learning

1. Introduction

The utilisation of oil is essential for energy transportation, production, and several industrial processes in this era [1]. The oil is predominantly located in a few countries. It is transported across oceans by Ships as the oil extraction and transportation are done through sea water and face significant risks, particularly in the event of spills, as shown in **Figure 1**. The oil spill is in one place but spread to different places through seawater because of tides. The oil spreading affects the in and around sea area and the adjacent coastal area land within less time; since it spreads on the broader region, it involves human beings and creatures. The disaster of oil pollution detection is very difficult because the ships are not near the shore. The effects of oil pollution are hazardous for creatures because of the contaminated seawater.

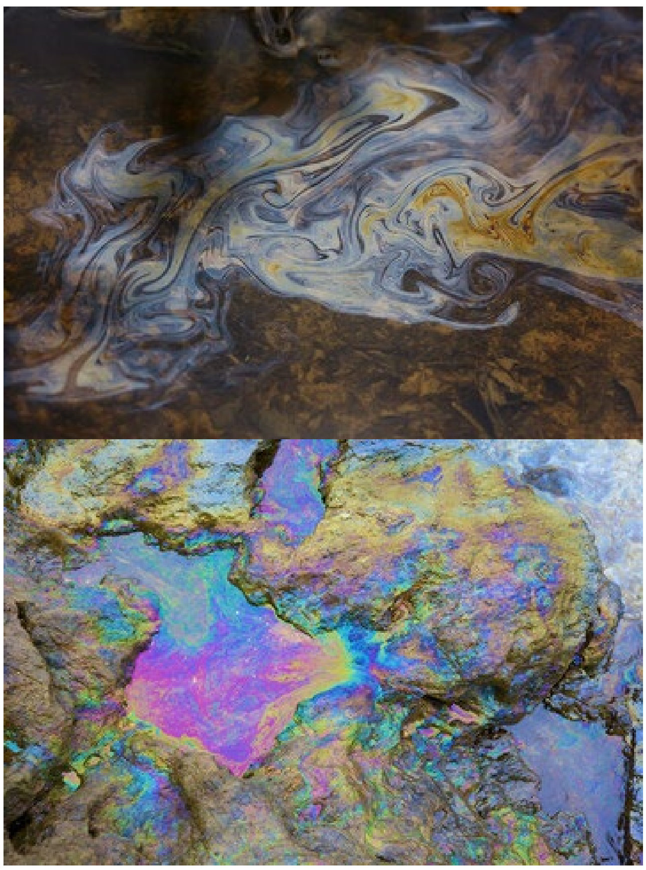

Figure 1. Example images with oil spill incidence in marine environment.

The detection of oil spills using standard methods is very difficult [2]. Hence, using drones and artificial intelligence to detect oil spills in seawater is very useful for solving this problem. The technologies belonging to Artificial Intelligence and Drones are reducing the cost of solving this natural disaster. By applying the latest techniques, the working cost of this process can also be reduced. The different types of oil and their properties are discussed in this paper so one can understand the significance of the disaster.

This Research article enlightens the several types of drone technologies and artificial intelligence. This Research article briefly discusses the different types of oils and their properties. A better understanding of the types of oil transported in seawater is essential for effectively detecting oil spills in seawater [3]. Capturing images of seawater pollution through the cameras helps to get some good information about the disaster. These recorded data are essential for detecting oil spills in the sea water.

2. Materials and Methods

2.1. Types of Oils and Their Properties

Crude oils are the highest-pollution oil content in seawater. Ship accidents cause spills in millions of tons of sea water every year. The various types of crude oils are given below:

2.1.1. Class A (Light Volatile Oils): [4]

These oils are highly fluid and spread over a short time on a solid surface and surface of the water. These oils are spread across impervious surfaces. Class A oils are characterized by a strong odour and tend to evaporate quickly due to their high evaporation rate.

The challenges and priorities in cleaning up oil spills in seawater are numerous and varied. These include the spilt oil's toxicity, possible environmental damage, and difficulty removing the oil from surfaces. The oils in this category include Gasoline, Kerosene, Petroleum Ether, Petroleum Spirit, Petroleum Naphtha and Jet Fuel, each presenting its own challenges for cleanup and recovery.

Light Volatile Oils release chemical elements with low boiling points, such as hydrogen, nitrogen, and carbon dioxide. These elements, prominent in Class A oils, harm society, humans, wildlife, and seawater creatures. The oils also have a high penetrating power on porous surfaces, such as sands and earth.

Class A oils are very harmful to living organisms. These oils, being transparent, are sometimes difficult to detect on the water surface. Gasoline is under the class A crude oil. These oils are highly in-flammable. They are the most refined oil, also very costly and highest quality. They used Flushing with water to remove them on surfaces hard like tiles, rocks, etc.

2.1.2. Class B (Non-Sticky Oils): [4]

This Class B oil, with its unique characteristic of feeling like wax when touched, piques our interest. These oils adhere more to surfaces with less toxicity than Class

A oils. It has little impact on the environment as they have a lower penetration property on porous substances. However, it enhances the penetration power with the increase in temperature, adding an intriguing aspect to their behaviour.

These oils soak into surfaces very well. These oils are hard to remove from the soaked surfaces. The class B oils are evaporated, and then the oils become class C or class D oils. When Class B oils are volatile, they will be converted into heavy oils. This class contains Moderate to Dense Paraffinic oils. The residue is deposited at the vessel's bottom when these oils are evaporated.

2.1.3. Class C (Heavy, Sticky Oils): [4]

The Class C oils are viscous, sticky (or) tarry in nature. The Class C oil is brown or black. Compared with class B oils, these oils are not highly absorbent by surfaces. The class B Oils density is almost equal to the water density. This oil sinks into the water easily and is less toxic than the Class B type. Evaporation of class C oils generates class D oils. It is a residual oil and a medium crude oil. These oils spill into the water and drown the wildlife.

2.1.4. Class D (Non-Fluid Oils): [4]

These oils are comparatively nontoxic and do not penetrate porous surfaces. They are usually black or dark brown. Class D oils are heated, then dissolve and cover the complete surface. They are very difficult to remove if they spill on the floor. Heavy crude oil, such as bitumen, is found in tar sands. While heating the class D oil, it will turn to class C oils. High paraffin oils fall under this category, and weathered-type oils fall in this category.

3. Artificial Intelligence Techniques

3.1. Unsupervised Learning

Unsupervised learning applies ML—Machine Learning algorithms to study and cluster unlabelled data sets, also known as unsupervised Machine Learning. These algorithms detect the sequence or clustering of information without human involvement. Unsupervised learning is the skill to find differences and similarities in the said information. It gives the perfect solution for data analysis and provides cross-selling approaches. It provides a solution for customer segmentation and image recognition.

Unsupervised learning methods or models are utilised in three critical tasks; they are

- **Clustering Algorithm**
- **Association Algorithm**
- **Dimensionality Reduction Algorithm**

3.1.1. Clustering Algorithm (CA): [5]

CA is a machine learning and data mining technique that groups similar data points into clusters or groups based on certain patterns and variances. Clustering algorithms analyse raw data and unclassified data into groups that contain data in the form of structures or patterns. Clustering algorithms are beneficial for detecting oil pollution in seawater.

a. K-Means Algorithm: K-Means unsupervised machine learning algorithm that divides data points into groups based on similarities to identify the invisible patterns among them. K refers to the number of centroids (clusters) and calculates the distance from each group's centroid. The data points adjoining the specified cluster will be grouped under a similar class. K-means extracts oil spill regions effectively and is used to classify texture features of preprocessing images.

A lesser k value will have larger clusters and less granularity, whereas a larger k value will indicate smaller groupings with more granularity. It is widely used in data classification. It analyses the images that belong to oil pollution images and gives the results accurately.

b. Probabilistic Clustering Algorithm: A probabilistic clustering model is an unsupervised technique for solving density estimation or soft clustering difficulties. Data points are grouped into specific clusters depending upon the possibility that they belong to each cluster. This approach detects dark formations caused by oil spills into seawater, and look-alike oils are also detected using this approach.

c. Gaussian Mixtures Model Algorithm: It is another clustering technique which offers more flexibility than traditional models. Unlike relying on the mean values of data points, GMM allocates data points into different clusters based on possibility distribution. Mean and variance are not known in Gaussian mixture models. Here, assume the latent or hidden variables exist to cluster data points. It is commonly applied to estimate the assignment possibilities of a given data point belonging to a specific cluster. This algorithm is used in the classification of oils in oil spill detection.

3.1.2. Association Algorithm

An Association algorithm is a rule-based technique used to identify connections between variables in each data set. These approaches are used to understand relationships between different products for market basket analysis.

1) Apriori Algorithms: Apriori algorithms were popularised with market basket analysis. They lead to different recommendation engines. They are used within transactional data sets to detect frequent item sets or collections of items.

3.1.3. Dimensionality Reduction Algorithm

Dimensionality reduction is a technique for reducing the number of data inputs. It also preserves the integrity of the data sets. Processing more data can achieve more accurate results. Dimensionality reduction can also effect the machine learning algorithms performance. In this algorithm, it can be challenging to visualise data sets.

1) Principal Component Analysis (PCA): PCA is a dimensionality reduction algorithm. It is used to decrease the redundancies and to club data sets. It reduces the data sets through feature extraction. This approach uses a linear transformation concept. This method gives the set of principal components. The first and second principal components are to find the maximum variance of the data set, and the second component is entirely uncorrelated to the first principal component. It gives a perpendicular or orthogonal direction to the first component, and the method reoccurs based on the number of dimensions.

4. Applications of Unsupervised Learning

4.1. News Sections

Google News covers similar stories from various online news mediums by using unsupervised learning and classifies the articles.

4.2. Computer Vision

Unsupervised learning algorithms utilised for pictorial perception tasks.

4.3. Medical Imaging

An unsupervised machine learning algorithm is essential in medical imaging, where it extracts key features to aid in Image Detection, Segmentation, and Classification. These techniques are used while performing Radiology and Pathology to analyzes medical images and to assist in diagnosing patients quickly and accurately.

4.4. Anomaly Detection

Unsupervised learning models can handle and analyse vast amounts of data and are used to identify typical patterns or data points within the data. The potential issues such as faulty equipment, human errors, or security breaches can be alerted by these irregularities.

4.5. Customer Personas (CP)

CP enable understanding common behaviours and business clients' buying traits easier.

5. Supervised Learning Techniques for Oil Spill Detection

Supervised learning utilises training data set containing inputs and correct outputs that enable educating models and producing the desired output. There are two different types of supervised learning.

- **Classification Algorithms**
- **Regression Algorithms**

5.1. Classification Algorithms

a) Neural Networks Algorithm(NN): [6] NN algorithm is a Deep Learning(DL) algorithm. In NN the training data extracted by combining the human brain using layers of nodes. Each node contains all the basic parameter values. The value of output exceeds the fixed threshold, then that data sends to the next layer in the network. This mapping is learn by neural network using supervised learning. Oil spill detection by this algorithm to distinguish crude oil, plant oil, and oil emulsion.

b) Naive Bayes Algorithm(NBA): [5] NBA is a categorisation method that applies the Bayes theorem. One's feature presence does not affect another feature's presence in determining the possibility of an outcome. There will be equal impact on the outcome for each predictor. There are three types of Classification Algorithms available in the Naive Bayes technique. Naive Bayes theorem creates predictions and uses training data to estimate probabilities. This algorithm is used to classify the oil spills in seawater and identify oil spills in seawater. Naive Bayes is achieving the best accuracy algorithm.

c) Support Vector Machine (SVM): [5] Vladimir Vapnik developed a popular supervised learning method SVM. This method is applied for classification and regression and is typically used for classification problems and to construct the hyperplane. The hyperplane is built at a point where the distance between two class sets of data points is at the maximum. This hyperplane is called the decision boundary, which separates the classes of data points on both sides of the plane. SVM projects the data points into a higher dimension space through kernel function. It separates the data points into two parts using a hyperplane. A support vector machine algorithm is applied to analyse the characteristics of oil based on their visibility. Using this algorithm, we shall classify the types of oils.

d) K Nearest Neighbour (KNN) Algorithm: The KNN algorithm is a non-parametric algorithm. The data points are classified by considering the distance of the data. It also calculates the Euclidean distance and assigns a category based on average or frequent category. It has a low calculation time, and because of this reason, the data scientists preferred this algorithm for many of their data classification work. Its numerous benefits include its non-parametric nature, simplicity, and ability to record decision boundaries. This algorithm is applied to classify oil spills in seawater with the help of image data.

5.2. Regression Algorithms

Regression algorithms are also essential for supervised learning, particularly for forecasting continuous variables. The focus here has been on classification algorithms. However, classification techniques are typically more relevant due to the unconditional nature of the problem in identifying and categorising different oil spills.

Regression is a statistical process. Regression analyses the relation between variables. Regression algorithms solve regression problems. The regression algorithm has some characteristics like regression coefficients, regression lines, residuals, and loss functions. A regression algorithm is used to detect the pollution level of water. A regression algorithm is used to detect the oil spilling in sea water using SAR images.

Different types of regression algorithms

5.2.1. Logistic Regression Algorithm (LRA): [7]

The LRA used for diverse classification problems. It is applied to pixels. This algorithm's input and output values are the intensity values of specific pixels. The probability estimation of the specific pixel belongs to a possible oil slick—automatic Adjustment of the probability differences between classes for oil background.

5.2.2. Convolutional Neural Networks Algorithms (CNNA): [7]

CNNA have a function that gives the input data set and gets the desired output. Such techniques and neural networks are used to detect oil spill images. In a convolutional neural network, the input and output are an image. That output generated using this convolutional is also an image with similar dimensions as the input image. Convolutional neural networks learn automatically for a task. Normally, the convolutional filter has a feature to respond to what it has learned. This feature is very useful in oil spill detection.

5.2.3. Decision Tree Algorithm (DTA): [8]

A decision tree is a regression model. The DTA is well-suited for oil spill detection. The decision forest model is to identify oil slick and lookalike oil slick with an accuracy of 84.4%. The DTA has high accuracy in oil spill detection for spectroscopic images. The DTA has high accuracy because the training data set is divided into smaller subsets.

5.2.4. Genetic Algorithms (GA): [9]

A GA is an evolutionary algorithm. It imitates the process of natural selection. A GA is also an optimal search algorithm. The GA solves optimization problems using natural evolution techniques, including inheritance, mutation, selection, and crossover. It is used for the automatic oil spill detection. GA differs from classification algorithms. This algorithm implements probabilistic transition rules.

5.2.5. Artificial Neural Network Algorithms: [10]

The spread and advection of oil under diverse hydrodynamic conditions are predicted using Artificial neural networks that have been designed and trained to forecast. The neurons in the human brain have inspired an artificial neuron model. Artificial neural networks process data from the input layer through one or more hidden layers and finally to the output layer. Artificial neural networks use a backpropagation algorithm. The oil slick transportation in coastal environments can be managed with the ANN model, which offers a critical tool for quick oil slick trajectory prediction.

6. Applications of Supervised Learning Algorithm

a) Recommendation Engines: KNN method is recommended for engines and image recognition.

b) Object Detection: Logistic regression is used for spam identification.

c) Spam Identification: The Naive Bayes Algorithm is used for text classification, spam identification, and recommendation systems.

d) Image Recognition: Supervised learning is used to detect the image and object detection.

7. Different Types of Drone Technologies for Oil Spill Detection in Seawater

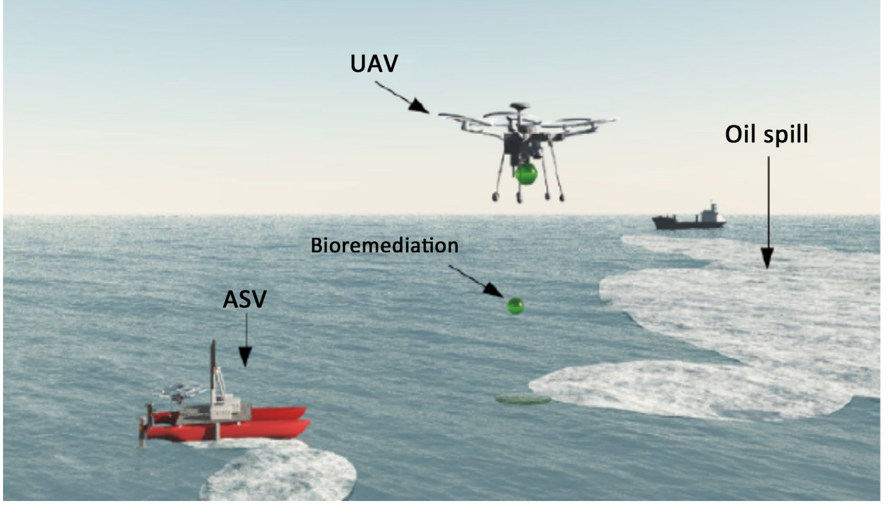

Figure 2. Conceptual approach for multi-robot oil spill mitigation with a team of heterogeneous autonomous vehicles, particularly an ASV and a UAV.

7.1. Drones Using Optical Technology (As Shown in Table 1 for Understand)

a) Optical Sensors(OS): [11] Oil has a reflection when light is projected on it. The reflection of oil is sensed with OS. Oil has appeared in different colours. The colours are black, brown, or grey. The oil has appeared in limited colours. Drones use optical sensors to detect oil spills in seawater. Oils are in the visible range (400 nm to 700 nm); oil does not have many spectral features in this band. As shown in **Figure 2** oil spill detection and mitigation process.

b) Infrared Sensors (IRS): [11] Using IRS, drones are the better option to detect oil spills in seawater. Using infrared rays' detection of oil spills in seawater in night mode can also be effectively detected. Different density-based oils appear in the infra-red images and are Detectable. But thin oil or sheen oil are not detectable in infrared images. In night mode, it appears in reverse. The wavelength of infrared rays is 8 μm to 12 μm. The IRS are also very useful for detecting seawater oil spills in night mode.

c) Ultraviolet Sensors (UVS): [11] Drones use UVS to detect thin oil slicks in the seawater. Sheen oil slicks are also mapped with ultraviolet sensors. The relative thickness map of oil slicks is formed by often combining Ultraviolet and infrared images. However, Ultraviolet data often results in many false positives, which is why UVS are rarely used in an operational response mode in detecting Oil Spelling in seawater.

7.2. Drones Using Laser FluoroSensors

When light is reflected on oil, laser fluorosensors have some properties in the visible spectrum region [12]. Different types of oils give different types of fluorescent signatures and intensities. Floor sensors are used to detect oil in seawater.

7.3. Drones Using Microwaves

It uses radar and passive sensors for detecting oil spills [12]. Radar is advantageous in oil spill detection as it can operate at night and see through fog or clouds. The emissivity factor for water is 0.4 and for the oil is 0.8; the passive sensor detects this difference. Real-time streaming of area surveillance and data gathering through these devices. Multi sensors are used to detect the oil spilling sea water. As shown in **Figure 3**, UAV based oil spill detection.

Table 1. Different types of drone technologies

s.no.	Technology	Sensors	Reference
1.	Optical technology	Optical sensors	[11]
2.	Optical technology	Infrared sensors	[11]
3	Optical technology	Ultraviolet sensors	[11]
4.	Laser technology	Laserfluoro sensors	[12]
5.	Microwave technology	Radar sensors	[12]

Different types of drone technologies

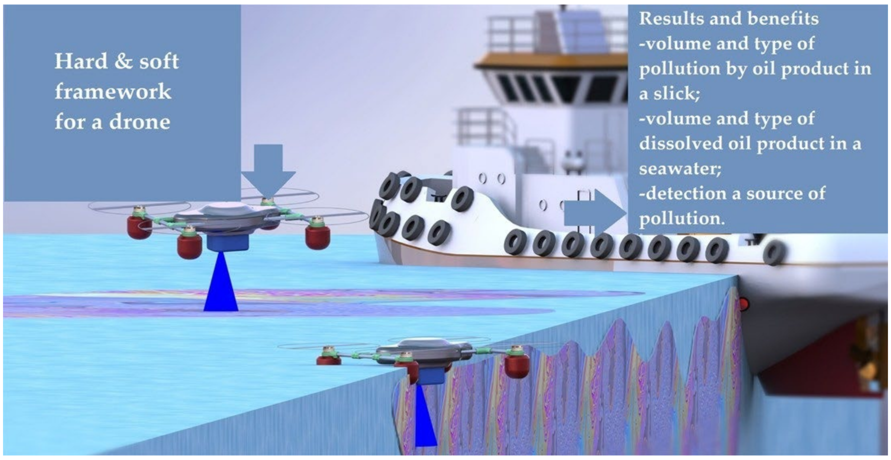

Figure 3. UAV based system for oil spill detection.

8. Applications of Artificial Intelligence Techniques in Oil Spill Detection and Management in Seawater: [13] (Table 2)

8.1. Oil Spill Mapping and Detection: [6]

- Applying a SVM Algorithm to retrieve ocean surface chlorophyll concentration in the sea or polluted water.
- Using Support Vector Regression (SVR) Algorithm to detect oil pollution in

seawater.

8.2. Detection and Classification: [7]

- Using the CNN Algorithm detection of oil pollution in seawater.
- Region-based Convolutional Neural Networks (R-CNN) are used to detect oil spills in seawater.

8.3. Image-Based Analysis: [13]

The Machine Learning(ML) model can be trained by using high-resolution satellite and drone images labelled with oil spills water and clean water.

8.4. Complex and Large-Scale Analysis: [13]

- Various Complex ML Models will be used to detect the spill's origin, the oil's extension, and the movement of a large area.
- ML Algorithms given the complex relationships between oil slicks' spectral, geometrical, and textual properties.
- DL Algorithms are used for the detection of wave modelling.
- DL Algorithms are utilised to surveil the coastal water.
- DL Algorithms are utilised to surveil the prediction ofcoastal morphological properties.

8.5. Environmental and Ecological Analysis: [7] [8]

- The SVM Algorithm is utilised for habitat modelling.
- Random Forest Algorithm is used utilised for mapping marine substrates.
- K-Means Algorithm used for clustering ocean biomes.

8.6. Advanced Techniques: [13]

Advanced Deep Learning Techniques attained high precision in oil spill detection.

Table 2. Applications of artificial intelligence techniques in oil spill detection.

S.no.	Technique	Research Concentrations	Reference
1	Support Vector Machine algorithm	Oil spill mapping and detection	[5]
2	Convolutional Neural Network (CNN)	Detection of oil pollution in sea water	[7]
3	Support Vector Machine algorithm	To retrieve ocean surface chlorophyll concentration in seawater or polluted water	[6]
4	Support Vector Machine algorithm	Habitat modelling	[5]
5	Region-based Convolutional Neural Networks (RCNN)	Detection of oil spill in seawater	[7]
6	Various-complexity Machine Learning models	Detect the origin of the oil spill, Extension of oil and movement of a large area.	[14]
7	Random forest algorithm	Mapping of marine substrates	[8]
8	K-means algorithm	Clustering Ocean biomes	[7]

Continued

9	Machine Learning algorithms	Given the complex relationships between the spectral, geometrical, and textual properties of oil slicks	[13]
10	Deep Learning algorithms	Detection of wave modelling	[13]
11	Deep Learning algorithms	To monitor the coastal water	[13]
12	Deep Learning algorithms	Monitor prediction of coastal morphological properties	[13]
13	The ML model	Images labelled with clean water and oil spills water were collected from high-resolution satellite and drone images	[13]
14	Support Vector Regression algorithm	Detection of oil pollution in sea water	[5]
15	Deep Learning techniques	High accuracy in oil spill detection	[13]

Applications of Artificial Intelligence Techniques in Oil Spill Detection.

9. Drone Applications in Oil Spill Detection and Management (Table 3)

9.1. Monitoring and Imaging

Drones monitor the sea water and capture images [15].

9.2. Oil Type Detection and Classification

Drones detect the different types of oils when light is projected on them, capture images, and classify the oils [15].

9.3. Oil Movement Simulation

Robotic drones use used GNOME simulation system. This GNOME simulates oil movement due to winds, currents, tides, and spreading [16].

9.4. Laser-Induced Fluorescence Lidar Detection (LIFLD)

It is an Unmanned Aerial Vehicles design. LIFLD system uses fluorescence remote sensing to measure seawater [15].

9.5. Detection of Pollution Sources

LIF lidar water detects seawater pollution disorder and small-scale abnormalities [15].

9.6. Thermal Infrared (IR) Detection

Drones are equipped with thermal infrared (IR) cameras to identify oil spills within the port environment. These cameras can detect oil spills at night as well [14].

9.7. Radar Systems

Radar systems are used by drones to detect oil pollution in seawater [17].

9.8. Airborne and Satellite-Borne Detection

Oil detection methods are mainly designed for airborne or satellite-borne applications. Synthetic Aperture Radars (SAR) and advanced synthetic aperture radars (ASAR) are used to monitor Oil pollution from space [12].

9.9. Spreading Area and Perimeter Calculation

Drones detect and monitor oil pollutants and calculate their spreading area and perimeter [16].

9.10. Unstructured Environment Exploration

Drones are used to explore the unstructured environment of oil pollution in sea water detection [16].

9.11. Swarm Drone Technology

The origin of oil spilling into the sea water is detected by swarm drone [7].

Table 3. Drone applications for oil spills in seawater.

S.NO.	Technologies	Research Concentrations	Reference
1	Drones	Monitoring the sea water and capturing images	[15]
2	Drones	Detect the different types of oils when the light is projected on the oil and, capture the images, and classify the oils.	[15]
3	Robotic Drones	GNOME simulation system	[16]
4	Laser Induced fluorescence (LIF) lidar	LIF lidar system uses fluorescence remote sensing to measure the seawater	[15]
5	LIF lidar	Detect sea water pollution disorders caused by small incidents.	[15]
6	Drones are using with thermal infrared (IR) camera	Detecting the oil spills inside the port environment	[14]
7	Drones are used the radar system	Detect the oil pollution in seawater	[17]
8	Airborne or satellite-borne	Detection methods for oil spills	[12]
9	SAR and ASAR	Monitoring of oil pollution from space	[18]
10	Drones	Monitoring of oil pollutants and also calculating the spreading area and perimeter of oil pollutants	[16]
11	Drones	Exploring unstructured environment of oil pollution in seawater detection	[16]
12	Swarm Drone's	Detection of the origin of spilling of oil into the seawater	[7]

Drone applications for oil spills in seawater.

10. Future Enhancement

Future Challenges in Artificial Intelligence and Drone Technologies in Oil Spilling Detection in Seawater. As shown in the Table 4.

10.1. GNSS Signal Interference

GNSS signals are used for Drone navigation; it is a challenge to use this signal promptly in the oil spelling region due to oil pollution [15].

10.2. Distinguishing Oil Types and Look-Alikes

Drones face challenges in detecting exact and look-alike oil spills [19].

10.3. Semantic Segmentation Model Improvement

Semantic segmentation model using different algorithms for recognition of images. This area has many challenges to improve recognition quality and the algorithm's ability to recognise images, particularly in oil spilling problems [7].

10.4. Fuzzy Logic in Object-Oriented Analysis(FLOOA)

Object-oriented analysis with fuzzy logic methodology is used to detect oil spills in shipping channels. To improve the accuracy in fuzzy logic methodology [20].

10.5. Multi-Source Data Extraction

It is difficult to extract marine oil spill information from multiple data sources with various temporal perspectives [20].

10.6. 3D Motion-Planning Algorithms

A novel goal-updating algorithm is recommended. The proposed method is 98.5% accurate. In future research, they aim to extend the current 2D motion-planning method to 3D motion for oil spills in seawater, which is challenging [21].

10.7. Cognitive Radio for UAV Communication

The cognitive radio method could be a valuable tool in developing MAC protocols for UAV's-assisted networks, particularly in managing the challenging task of oil spilling in seawater [22].

10.8. Optimal Trajectory Detection

The CPO algorithm detects the optimal trajectory. The success rate of this algorithm is 90%. It is improved a challenging task [23].

10.9. Wind Disturbance Mitigation

UAVs improve flight against wind disturbance, which is also challenging in the oil spill in seawater detection problem. The best solution is still pending [24].

10.10. Oil Type Detection and Fire Detection

Detecting the oil type using images captured by the drone is crucial and challenging in identifying fire accidents occurring in seawater [25].

Table 4. Future challenges in drones and artificial intelligence in oil spilling in seawater.

S.no	Technology	Research Concentrations	References
1	GNSS signals	Drone navigation is a challenge to use this signal promptly in oil spelling regions due to oil pollution.	[15]
2	Drones	Detection of the exact oil spilling and look alike oil spilling is a challenge.	[19]

Continued

3	Semantic segmentation model	This area has many challenges to improve recognition quality and the algorithm's ability to recognise images, particularly in oil spilling problems.	[7]
4	Object-oriented analysis with fuzzy logic methodology	For detecting oil spills in shipping channels	[20]
5	Extract marine oil spill information	It's a challenge to extract information from multiple data sources	[20]
6	Novel goal-updating algorithm	2D motion-planning approach to 3D motion in an oil spill in sea water is a challenging task	[21]
7	Cognitive radio approach	A potential collaborator in developing MAC protocols for UAVs-assisted networks for a challenging task for oil spilling in sea water	[22]
8	CPO algorithm	Detect the optimal trajectory	[23]
9	UAV	Fighting against wind disturbance is also challenging in the oil spill in seawater detection problem.	[24]
10	Drones	Images captured by the drone are essential and challenging for detecting fire accidents in seawater.	[25]

Future challenges in drones and artificial intelligence in oil spilling in seawater.

11. Future Work in AI and Drone Technologies for Oil Spill Detection

11.1. Hybrid Collision-Avoidance for UAV Navigation

A hybrid collision-avoidance method [21] has been developed for the UAV's real-time navigation in challenging environments with volatile interruptions. In future research, they aim to extend the current 2D motion-planning method to 3D motion.

11.2. Fuzzy Rule-Based Models and Deep Learning (FRBMDL)

This technology [26], by installing a synthesised FRBMDL, will resolve using its understandability and efficiency. Non-transparent, Black-Box modelling paradigms characterise a wide range of AI/ML algorithms are not acceptable in the present case. The result is 70% achievement. In subsequent studies, we consider several types of UAVs as each has different fulfilments for safe separation distances because of their unique flight characteristics, including speed, endurance, altitude capabilities, and weather resilience.

11.3. Safe Reinforcement Learning (SRL) for UAV Mode Transitions

This study [23] emphasises advancing a SRL method for managing back-transition between level flight and hover mode. They showcase the CPO algorithm is the best approach for SRL. This transition trajectory created by the CPO algorithm is very similar to the optimal trajectory using the popular GPOPS-II software with the SNOPT solver with a success rate of 90%. Future research should focus on helping UAVs to perform multi-tasks (*i.e.*, from hover to level flight, hovering in windy conditions and maintaining level flight, but still need further development to address the challenges involved.

11.4. Advanced UAV Control Algorithms

In this [27], three different algorithms are used. distance maintenance, automatic yaw rotation, and potentially dangerous object avoidance, are used to operate the drone, and all 3 algorithms are enhanced by a PID controller. The results are very accurate and claimed 89.11%.

11.5. Neural Control Techniques

In future work to develop the system more accurately than this by concentrating on various parameters, This paper uses a neural control technique [28]. The online learning algorithm uses a neural correlation principle, which uses predictive and reflexive sensory information. It needs more precise sensor systems with automatic sensor range adaptation. Additionally, it has further system requirements, for instance, system states and dynamic models of the UAV.

11.6. Human-Centered AI (HCAI)

In this paper [29], human-centred AI (HCAI) is a mix of "Artificial Intelligence" and "Natural Intelligence". Future developments in this technology will progressively provide real-time data and insights across the entire value chain with location accuracy for oil spill detection.

11.7. Machine Learning in UAV Communications: [30]

In this paper, ML techniques have been used in UAV-based communications. Additional improvements in uncrewed aerial vehicle communication networks are based on the machine learning application.

12. Conclusion

In this paper, we attempt to discuss the various types of drone technologies and artificial intelligence techniques involved in this oil spilling challenge in seawater. This paper elaborately discussed the applications of artificial intelligence techniques in seawater pollution and the drone Technological contributions in this field. This paper reviewed the application challenges of drones and artificial intelligence technologies in its future challenges in this field are also discussed very clearly.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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