Chapter 08

Advanced Materials, Artificial Intelligence, and Sustainable Technologies for Energy and Environmental Engineering
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Waste Oil Monitoring and Water Informatics Using AI and IoT

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ABSTRACT

The paper addresses one of the major issues of modern technogenic society, that is the pollution of water areas by oil and petroleum products. It is noted that timely and accurate detection of oil spills along with trajectory prediction allows for their prompt localization, subsequent collection, and minimization of environmental damage. The aim of the present review is to assess the efficiency of modern technologies for detecting oil pollution in various conditions, particularly focusing on the application of sensor networks and the Internet of Things (IoT) technologies, as well as artificial intelligence methods. The paper provides a description and comparative analysis of various technologies, ranging from visual identification, technology of scattered light, fluorescence, and microscopy, to remote, optical, and wireless sensing techniques. The characteristics of devices for detecting oil spills have been presented. The potential of applying Visible Sensors, Infrared Sensors (TIR), Ultraviolet Sensors (UV sensors), Synthetic Aperture Radars (SAR), Side-Looking Airborne Radars (SLARs), Microwave Scatterometers, and Microwave Radiometers is described. Advanced systems capable of accurately measuring the thickness of an oil slick have been described, such as Laser Ultrasonic Remote Sensing of Oil Thickness (LURSOT), Effective Oil Thickness (EOT), and others. A review of multiphase sensors for crude oil facilities and transportation pipelines has been presented. It has been established that this type of sensors is unsuitable for operation under natural aquatic conditions. A potential solution to this problem is the deployment of systems comprising multispectral sensors, radiometers, sorbent materials, dip plates, imaging devices, tube samplers, acoustic detectors, and photometric sensors – so-called hybrid and remotely operated systems. The study describes the following modern systems: Multi-modality Systems, Remotely Operated Systems, and Microwave Sensors. A substantial paragraph is devoted to oil spill detection and monitoring using artificial intelligence, particularly Traditional Machine Learning Techniques. The possibility of using the following algorithms for classifying oil spills and their analogues has been considered: artificial neural network (ANN), support vector machine (SVM), decision tree (DT), K-nearest neighbor (KNN), genetic algorithm, random forest (RF), maximum likelihood, and linear discriminant analysis. The potentialities of monitoring oil spills using Artificial Neural Networks, Support Vector Machines, and Deep Learning Techniques have been outlined.

Keywords: Synthetic Aperture Radar (SAR); Optical Sensors; Internet of Things (IoT); Deep Learning; Remotely Operated Systems.

INTRODUCTION

Water and oil: the former is a source of life on the planet, without which the development of modern post-industrial society is impossible. The latter represents one of the key pillars

of energy sector (accounting for 36 % of global demand for primary energy); it is also used as raw material in the oil refining and chemical industries for the production of fuels, plastics, synthetic rubber and synthetic fibers, ethyl alcohol, detergents, and a wide range of other products. However, the processes of extraction, transportation, and processing of oil, given oil's toxic impact on the environment, are associated with certain risks. Particularly dangerous are leaks from offshore drilling platforms, discharge of ballast water from ships, pipeline ruptures, and sudden emergency discharges from wastewater treatment systems at oil refineries.

The difference between marine and terrestrial oil spills lies in the rate at which oil moves or disperses and in the corresponding size of the affected area. Oil spills in water are carried by wind and currents and often over long distances. However, oil movement on land is typically slower, it follows a downslope path, and tends to accumulate in natural lowlands, making it generally easier to predict.

Annually, 2,4 million tons of oil enter marine waters, forming a surface film with an area of about 48 000 000 km^2. Under the influence of several factors, such as temperature, ultraviolet rays, wind and wave currents, as well as the processes of diffusion, sedimentation, emulsification, evaporation, and biological decomposition, physical and chemical parameters of oil slicks gradually change. Toxic light oils evaporate quickly. Heavy oils are less toxic but persist in the environment for much longer periods. Heavy oils can bind with pebbles and sandy shorelines, where they can remain for years. Over time, oil slicks thin out, forming what is visually recognized as "oil sheen" caused by the difference in the refractive indices of oil and water, as well as the thickness of the film. According to the Bonn Agreement[1], the codes for the visual appearance of oil are presented in table 1.

Table 1. Appearance of oil on a calm water surface[1]

Code	Description Appearance	Layer Thickness Interval (μm)	Litres per km^2
1	Silvery sheen	0,04 to 0,30	40 – 300
2	Rainbow sheen	0,30 to 5,0	300 - 5000
3	Metallic	5,0 to 50	5000 to 50 000
4	Discontinuous true oil color	50 to 200	50 000 – 200 000
5	Continuous true oil color	200 to more then 200	200 000 to more then 200 000

The data from the above-mentioned table are used both to determine the degree of sheen formed by the oil slick layer on the surface and to estimate its thickness and volume.

All fractions of oil cause irreparable harm to the environment by altering the parameters of the water surface, reducing oxygen levels, and worsening living conditions for plants and animals. Therefore, monitoring and detection of oil slicks are essential components of emergency response planning in the event of oil spills. Accurate detection of oil spills with trajectory prediction is necessary for their timely containment, they are beneficial for fisheries, wildlife protection, resolution of liability disputes, and resource management for monitoring and preservation of the marine ecosystem. However, visual detection of oil spills (table 1) is unreliable, since during daylight hours it can be mistaken for marine algae, and in the evening or at night, as well as in foggy conditions, visual detection is simply impossible.

The aim of this paper is to assess the efficiency of modern technologies for detecting oil pollution in water under various conditions, particularly focusing on application of sensor networks and the Internet of Things (IoT) technologies, as well as artificial intelligence methods.

METHOD

Methods and Technologies for Monitoring Oil Pollution in Aquatic Areas

Traditionally, oil monitoring in water has been carried out manually. For example, to detect bilge water discharges, technologies such as that of scattered light, fluorescence, and microscopy have been applied.

Scattered light technology is a popular choice onboard ships due to its relatively low cost and insensitivity to water color. On the other hand, an excessive amount of suspended particles may affect instrument readings. It is also necessary to take into account the influence of external factors that alter the properties of oil and thereby lead to errors in classifying oil types. This technology allows determining oil concentration based on the results of measuring the intensity of light passing through the water column. Oil particles present in the sample "refract" light depending on the level of oil concentration in the water. The higher is the oil content in the water, the greater is observed light diffusion. It should be noted that solid particles are also capable of scattering light. However, unlike the spherical molecules of oil, the irregular shape of solid particles affects the refraction of a light beam in a different way. The use of multiple sensors installed at different angles highlights the shape of the molecules and allows solid particles to be disregarded.

The quantitative assessment technology involves determining oil content by infrared absorption of the sample extract. At the first stage, after sampling, the samples are acidified to a low pH level and then extracted using chemical reagents. At the second stage, an infrared quantitative assessment is conducted, determining the oil content based on the infrared absorption of the extract and the total methylene (CH_2) content.

Fluorescence is a phenomenon in which a substance absorbs light energy and then emits it as light of a different wavelength. Oil particles are known to possess the ability to fluoresce under ultraviolet (UV) radiation. Since each type of oil responds to a specific light wavelength, the use of waves of known ranges makes it possible to determine the corresponding type of oil. However, the simultaneous presence of several types, especially in the presence of accompanying pollutants, may lead to measurement inaccuracies.

Microscopy is the determination of oil concentration by measuring the size of its droplets in bilge water using image processing and recognition software. A high-speed camera takes pictures of a sample at the speed of several shots per second. These images are analyzed using an existing database of components that can identify visible differences between oil, gas, and solid particles.

All the methods mentioned above relate to direct—stationary determination of oil products under laboratory conditions. It should be noted that this type of sampling has a number of limitations. Firstly, point samples, unlike continuous ones, are taken only at a specific moment in a specific location, which does not allow researchers to obtain a complete real-time picture of environmental pollution. Secondly, when using some methods, there may be potential confusion regarding the concentrations of "dissolved" and "dispersed" oil, since both are extracted using solvent extraction. As a result, fractions of dissolved oil may be included in the dispersed state, making it difficult for operators to accurately determine the ratio of fractions in accordance

with environmental requirements.

Based on the above, it can be concluded that current conditions urgently demand the application of innovative methods and technologies, including those based on artificial intelligence (AI), for tracking oil discharges, resource management, and environmental risk assessment.

Such methods include remote, optical, and wireless sensing techniques (table 2). Information required to model the spread of an oil spill can be obtained from multi-temporal imaging captured by remote sensing sensors. Devices of remote sensing include infrared video and photography, thermal infrared imaging, airborne laser fluorescent sensors, airborne and satellite optical sensors, as well as airborne and satellite SAR. Although satellite remote sensing provides a synoptic view, it suffers from low spatial and temporal resolution. The following information can be provided by sensors for an oil spill: location, area, and movement of oil slicks on the water surface; thickness of the film and the volume of spilled oil; and the classification of oil type for assessing environmental damage.

The information can be collected trhough remote sensing by both active and passive methods. Active sensors emit radiation directed toward the target, collecting reflected radiation from it. Passive sensors, on the other hand, collect and measure naturally available energy, such as solar radiation.[2] The characterisics of major remote sensing technologies for detecting oil spills over marine wathers are presented in table 3.

Table 2. The main methods for oil slicks detection[3]

Categories	Methods/Techniques	Description of the Methods
Remote sensing	Camera in visible and infrared spectrum[4]	Include passive observation, optical techniques, visible spectrum, infrared sensors, radar, satellite radar systems, laser fuorosensors, and slick thickness measurements using ultrasonics and chemical analysis
	Underwater acoustic method[5]	Detection feasibility of Hazardous and Noxious Substances (HNS) using two methods. Firstly, a tank experiment with 200-kHz active sonar utilized castor oil as a chloroform alternative to examine underwater acoustic detection, and secondly, a computer simulation evaluated the potential of side scan sonar for detecting chloroform and tetrachloride randomly distributed on different seabed types.
	Multi-temporal approach[6]	Change Vector Analysis (CVA) was employed to examine the present image of the region and compare it to a reference image dataset that had undergone statistical analysis to lessen sea spectral variability across time to develop an automatic detection algorithm.
Optical sensing	Light Emitting Diode (LED) and Light Dependent Resistor (LDR)[7]	The study proposes an optical sensor system using LEDs to monitor oil concentration in irrigation ditches. The sensor differentiates between the presences of diesel engine oil, ideates the gasoline engine oil source, and estimates the concentration of oil from 0 to 0,20 mL/cm^2 range. The algorithm combines signals from white, blue, and red LEDs for comprehensive oil monitoring in the irrigation system.

	Light Detection and Ranging (LIDAR) sensor[8]	A 905 nm laser LiDAR system, with 3 channels and 3 Hz scanning, distinguishes seawater from oil. It detects various oil thickness, presenting thick oil as brighter pink on the seawater surface. Key parameters include sensed area, spill thickness, detection Field-of-View (FoV), and time.
	Laser-induced fluorescence (LIF) sensor	Discuss LIF spectral features for different states of oil products in seawater and thin slicks. It introduces a calibrated LIF method for identifying and measuring ocean pollution from bilge water disposal, along with a small-sized LIF sensor for unmanned aerial vehicles (UAVs) to monitor oil pollution at sea.
	Optical reflectance[9]	The proposed method effectively estimated the thickness of oil samples in laboratory conditions and accurately determined the volume of thicker oil samples in outdoor settings using RGB images.
Wireless sensor	Wireless Sensor Networks (WSNs)[10]	The method involves incorporating intelligence at multiple aggregation levels, transforming sensor nodes into active, intelligent observers, thus enhancing the efficiency of the network and contributing to the improvement of oil spill detection in oceanographic research.
	Internet-of-Things (IoT)[11]	The study describes the creation of an autonomous oil—water separator that is Internet of Things (IoT)-based and supports water ecosystems' oil pollution monitoring system. The water-oil separation was carried out by applying semi-permeable membrane nanotechnology.
	Satellite Aperture Radar (SAR) An MPRI Technical Report	This study introduces a novel method for detecting oil spills using satellite synthetic aperture radar (SAR) systems. The technique employs convolutional neural networks (CNNs) trained with an adversarial loss function for image-to-image translation, demonstrating promising results in discriminating between real oil spills and lookalikes in SAR data from Radarsat-2 and Sentinel-1 over the Mediterranean Sea, Atlantic Ocean, and the North Sea.

Table 3. RS technologies for detecting oil spill over marine water[12]

RS Technique	Sensor	Principle of detections	Results
Optical Remote Sensing	Visible	Color, absorption of sun-glint on water surface, optical properties differences.	Easy distinguishing the oil spill due to color contrast[13,14]
	Infrared	Absorption of light at specific wavelengths	Identification of oil slicks[15]
	Thermal Infrared	Detection of oil spill on the bases of Thermal characteristics difference between oil and marine water	Thickness of oil spill over water surface[16]
RADAR (SAR)	Microwave	The dampening action of the spilled oil causes a change in surface roughness.	Oil spills can be easily distinguished from other ocean features[17,18]

The studies by Goodman[19] contain the characteristics of remote sensing bands and related instruments used for oil spill detection (table 4).

Table 4. Remote sensing bands and related instruments used for oil spill detection[19]

Band	Wavelength	Type of Instruments
Radar	1-30 cm	SLAR/SAR
Passive microwave	2-8 mm	Radiometers
Thermal infrared (TIR)	8-14 μm	Video cameras and line scanners
Mid-band infrared (MIR)	3-5 μm	
Near infrared	1-3 μm	Film and video cameras
Visual	350-750 nm	Film, video cameras and spectrometers
Ultraviolet	250-350 nm	Film, Video cameras and line scanners

Visible Sensors: despite a number of disadvantages that hinder the accurate identification of the exact location of spills (such as sun glint and surface ripples creating the illusion of oil sheen; presence of marine algae and darker shorelines mistakenly interpreted as oil spills), Visible Sensors continue to be widely used in remote sensing. The advantages of Visible Sensors include their wide availability and ease of installation on aircraft. A number of recent innovations in the development of this technology should be noted. Drones are equipped with both visible and infrared cameras. Recent advancements in sensor technology have enabled the creation of hyperspectral sensors like the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) and the Airborne Imaging Spectrometer for Applications (AISA). Hyperspectral imagery captures data across dozens or even hundreds of spectral bands, allowing for the identification of an object's unique spectral signature.[20]

Infrared sensors: in the studies[21,22] the authors discuss the use of infrared sensors for determining the properties of oil spills. Oil absorbs solar radiation and re-emits a portion of it as thermal energy, primarily in the thermal infrared spectrum (8-14 μm). In the study by Salisbury et al.[23] the authors noted that since oil has lower emissivity, its spectral signature in the thermal infrared range (TIR) is clearly visible against the water background. Thicker layers of oil absorb more radiation and therefore appear warmer in thermal infrared (TIR) imagery. Oil with medium thickness tends to appear cooler in this region, while thin sheens are generally undetectable in TIR. The minimum detectable oil thickness ranges from 20 to 70 μm, and the transition from a warm to a cool appearance occurs within the 50 to 150 μm thickness range.[24] At night, the reverse pattern is observed: heat loss in oil is faster than in water and therefore, thick oil appears cooler than water. The drawback of infrared sensors is their inability to detect oil emulsions, since emulsions contain up to 70 % water and their thermal properties are similar to those of background water.[24]

Ultraviolet Sensors make use of reflected sunlight in the ultraviolet region (0,32-0,38 micron) for oil spills detection. A UV sensor can detect thin sheens (less than 0,1 micron thick), whereas oil spills of thickness more than 10 micron are not generally detected by this type of sensors. UV images are only capable of providing information concerning the relative thickness of oil slicks.[25] Additionally, there are a number of interferences that hinder accurate detection, such as wind-driven ripples, sun glint, and algae accumulation. As these interferences differ from those that affect infrared measurements, the combination of IR and UV sensing can provide a more accurate indication of the presence of oil than using either method alone.

Radar: the radar functions as an active sensor, operating within the radio wave region, and is used for detecting oil in a large area. Ocean water is imaged brightly as a result of radar waves

being reflected by capillary waves.[26] The presence of oil in the ocean reduces reflectance by diminishing capillary waves. Therefore, oil can be detected as a dark area in a bright image of the ocean.[27]

There are two main types of radars used for remote sensing of oil spills: Synthetic Aperture Radars (SAR) and Side-Looking Airborne Radars (SLARs). The latter is an older and less expensive technology that achieves spatial resolution using a long antenna. The synthetic aperture radar uses the aircraft's forward motion to create a very long antenna, achieving excellent spatial resolution (independent of range) but requiring sophisticated electronic processing.[24] Compared to SLAR, SAR radars, although more expensive, offer a wider range and better resolution.[28]

The radars are characterized by a number of serious flaws because of numerous deception targets. Fresh water slicks, wind slicks (calms), shadows cast by waves, land or structures, weed beds, which calm the water just above them; glacial flour, biogenic oils and the sea state are all factors to be considered.[24] A number of studies highlight the impact of wind speed on radar readings.[29,30] Indications are that wind speeds of at least 1,5 m/s (3 knots) are required for detection, and speeds of 6 m/s will remove the effect again. Shipborne radars suffer from similar limitations and have the additional drawback of low installation height, which limits their range to 8–30 km depending on the antenna height.[31]

Microwave Scatterometers: a microwave scatterometer is a device that measures how a target scatters microwave or radar energy. Just as it does for radar sensors, the presence of oil reduces the scattering of microwave signals. However, this is subject to a large number of interfering factors, as mentioned above.[24] Microwave scatterometers are characterised by two main disadvantages: the inability to discriminate between oil and the lack of imaging capability.

Microwave Radiometers: both seawater and oil are sources of microwave radiation. However, oil is a stronger emitter, as evidenced by a comparison of their emissivity coefficients: for seawater the emissivity coefficient is 0,4, while for oil it is 0,8.[32,33] Microwave Radiometers detect this difference and thereby enable detection of pollution by oil. Additionally, there is a signal change in thickness, which, in theory, means the device could measure it. Having analyzed the studies,[24,34,35] it can be concluded that passive microwave radiometers can be used as all-weather oil detection sensors. However, their potential as a reliable device for measuring the thickness of an oil slick is questionable.

Slick Thickness Sensors: accurate measurement of the thickness of an oil slick would enable more effective response actions, including dispersant application and in-situ burning. As early as the late 1980s and early 1990s, a number of laboratories conducted research on thermal remote sensing methods. The first results were described in the study,[36] and the method was later named accordingly – «thermal mapping». In this technique, an infrared camera is used to examine the temperature profiles created over a small region near the heated oil. These profiles are the result of a laser being used to heat the oil. The thickness of the oil determines the temperature profiles that are created.

Another, more advanced method—Laser Ultrasonic Remote Sensing of Oil Thickness (LURSOT)—was first described in the works.[37,38] This system consists of three lasers, one of which is connected to a Fabry–Pérot interferometer for precise measurement of oil layer thickness.[38] The sensing process is initiated by a thermal pulse generated in the oil layer by the absorption of a powerful CO_2 laser pulse. Rapid thermal expansion of the oil layer occurs near the surface, where the laser beam was absorbed.

This results in a step-like increase in the surface of the sample, as well as a high-frequency, large-bandwidth acoustic pulse (~15 MHz for oil). The acoustic pulse moves through the oil until it hits the oil-water interface. At this point, it is partly transmitted and partly reflected back towards the oil-air interface. This causes a small movement of the oil surface. The time taken for an acoustic pulse to travel through the oil and back to the surface again depends on the oil's thickness and acoustic velocity. A second laser probe beam is used to measure the displacement of the surface. This beam is aimed at the surface.[24,27] Surface motion causes a phase or frequency shift (Doppler shift) in the reflected probing beam. This phase or frequency modulation of the probing radiation can then be demodulated using a confocal Fabry–Pérot interferometer).[39] The thickness can be determined by measuring the propagation time of the acoustic wave between the upper and lower surfaces of the oil slick. This method is considered to be well-established and reliable for assessing the thickness of oil layers.

Thermal remote sensing methods have been capable of estimating the Effective Oil Thickness (EOT) from image pixels with a significant oil presence, regardless of the type of oil emulsion. [40] Daniel Leifer et al.[41] applied thermal infrared (TIR) remote sensing to estimate the thickness of oil slicks using a numerical three-layer heat transfer model based on thermal contrast. It was found out that the thermal profile decreased linearly through optically thin oil both with and without illumination, and through thick oil without illumination. Thus, this method is dependent on the type of oil, varying environmental conditions, and surface illumination. More recent developments include multiphase sensors and measurement systems for separation tanks in crude oil facilities and transportation pipelines.[42,43] The systems in question include floaters (displacers) based on density, differential pressure transmitters, ultrasonic transducers, gamma-ray sensors and multi-electrode capacitive sensors.[4,5]

In the studies [6,8] sensors specialized in detecting emulsion layers in oil tanks are described. Furthermore, the work of S. Chakraborty et al.[11], presents sensor characteristics capable of detecting contamination levels in air–oil–water systems in industrial facilities, oil tanks, and transportation pipelines. However, all the aforementioned multiphase sensors were developed for operation under controlled industrial conditions and are not suitable for measuring oil slicks on open water. This is due to the continuous variation of the physical properties of oil mixtures in open water conditions, influenced by weather and sea dynamics. Moreover, oil spills create complex and sometimes unpredictable properties of oil–water mixture, which in certain cases cannot be identified using traditional autonomous calibration methods. These complications make the measurement of oil slick thickness one of the most challenging tasks during oil spill events.

A potential solution to this problem is the deployment of systems comprising multispectral sensors, radiometers, sorbent materials, dip plates, imaging devices, tube samplers, acoustic detectors, and photometric sensors (table 5).[44]

Multi-modality Systems: these systems integrate several techniques, such as capacitive, inductive, conductive, ultrasonic, and optical methods to measure the oil thickness collaboratively.

Inductive monitoring systems are widely used for multi-interface contamination level measurements at industrial processing plants. They typically consist of several inductive coils distributed vertically along a guiding rod. Their operating principle is based on detecting changes in induced current in each coil, which correlates with the conductivity of the surrounding

medium. Therefore, they are limited to differentiating between conducting and non-conducting materials—such as oil and water—but cannot distinguish between non-conducting substances like air and oil. One advantage of these systems lies in their reduced susceptibility to contamination issues due to the magnetic nature of their measurements. This principle was employed in the inductive-capacitive dual-mode sensor, which has combined arrays of flat electrodes and coils to achieve multiphase level measurement.

Table 5. Hybrid & remotely operated systems properties[44]

Modality	Structure	Target Application	Resolution (mm)	Range (mm)
Capacitive and inductive[45]	Capacitive array for non-conductive - inductive array for conductive materials	Multiphase gravity separators	Not reported	< 200
Capacitance and resistance[46]	Combining tomograms from commercial ECT (M3C) and ERT (V5R) systems	Visualizes gas-oil-water multiphase flow in horizontal pipelines	Pixel dimension of 1x1	Tomogram (60x60 pixels)
Capacitive and ultrasonic[47]	Capacitive sensor array to detect the oil-water interface - ultrasonic sensor to detect the air-oil interface	Measures the oil slick thickness	2 (handheld), 12 (skimmer)	< 92 (handheld), < 552 (skimmer)
Acoustic[48]	Acoustic sensors mounted on ROVs and AUVs	Measures the oil slick thickness	Not reported	< 6
Multispectral[49]	Multispectral sensors mounted on UASs	Classification of oil slick thickness from thin sheens to actionable oil	0,01	0,0005 to 20
Ultrasonic[50]	Ultrasonic sensors (2,25 MHz and 5 MHz central frequencies) mounted on an ROV	Measures oil slick thickness	0,5	1 and 4,5
Ultrasonic and Vision[51]	ROV with ultrasonic sensors combined – an airborne drone with an optical camera	Measure thick oil slick thickness and estimate the oil volume	Not reported	> 0,5 (< 7,5 tested)

Remotely-operated Systems: the method for measuring the thickness of an oil slick involves the use of acoustic sensors positioned beneath the slick. This technique is used for real-time quantification of the rate and efficiency of in-situ burning. Experimental results demonstrated its capability to measure oil slick thickness within the range of 1 mm to 10 mm.Unmanned aerial vehicles (UAVs) have been employed to measure oil slick thickness using multispectral sensors. [49] Experimental evaluation has shown that this method could classify oil thickness ranging from thin rainbow-colored sheens (a few micrometers thick) to dark oil patches (several millimeters to centimeters thick).

The study [51] presents research on measuring oil slick thickness using two ultrasonic sensors (2,25 MHz and 5 MHz) mounted on an ROV. Ultrasonic reflections were collected from beneath the oil slicks while the ROV was either stationary or in motion. Oil layer thickness was estimated

based on the analysis of ultrasonic transit time within the oil slick. As a result of the conducted experiments, the minimum measurable layer thickness was determined to be 0,8 mm and 0,45 mm for the 2,25 MHz and 5 MHz transducers, respectively. The two transducers were able to measure oil slick thickness in the range of 1 mm to 4,5 mm with a maximum absolute error of approximately 0,3 mm when the ROV was stationary.

Microwave (MWR): the microwave (MWR) is a passive sensor. It is used for oil spill detection. It can also be used for oil thickness measurements. Microwave radiation is stronger from oil than from water, and it looks brighter too. The measurement of oil thickness using MWR is affected by the presence of radiation from the upper and lower boundaries of the oil film. However, microwave sensors are favored over optical ones because they are capable of acquiring data at any time, regardless of lighting conditions. Microwaves are emitted by satellites, which then use reflected waves to identify the presence of oil spills on the water surface. The dissipation of waves is accelerated and their growth is slowed down by oil due to its viscoelastic properties. There are a number of ways to detect oil spills using satellite images. These include image segmentation, dark spot detection and feature extraction. The methods are based on the idea that isolated image sections are easier to investigate.[52,53] Additional Requirements – MWR (Microwave Radiometry) requires a specialized antenna to receive the emitted microwave radiation, as well as extensive information on numerous environmental characteristics and oil properties. All of these factors indicate both the complexity of system operation and its high cost.

Oil Spill Detection and Monitoring Using Artificial Intelligence. Studies on remote sensing of oil spills[54,55,56,57] have primarily focused on the advantages of utilizing different sources of remotely sensed data and various techniques for oil spill detection and delineation. However, they have not considered applying modern machine learning (ML) techniques for identifying oil spills/slicks. A wide range of studies have examined and adopted the use of RS technologies and ML algorithms for detecting and monitoring oil spill slicks, with these technologies being used in a synergistic way.[58,59,60,61] The analysis of remote sensing data has demonstrated the efficiency of using ML techniques for detecting oil spills in an automated mode.

Figure 1 illustrates the process of developing and adopting machine learning (ML) models for oil spill detection.[62]

Traditional Machine Learning Techniques: the main stages of oil spill detection using this technology include: preprocessing of remote sensing data; image segmentation to identify dark spots; determination of distinguishing features and classification of objects in the image for distinguishing oil spills and their look-alikes. The method is based on the results of recursive and iterative analysis of possible solutions from a predefined database of sample inputs and features, without explicit programming.[63] The following algorithms may be used for classifying oil spills and their look-alikes: artificial neural network (ANN),[64,65,66] SVM,[67] decision tree (DT),[68] K-nearest neighbor,[69,70] genetic algorithm[71] random forest (RF),[72] fuzzy logic,[73] maximum likelihood, linear discriminant analysis,[74] k-means,[75] ensemble learning.[76]

Artificial Neural Network: the basic topological structure of Artificial Neural Networks (ANNs) consists of three layers: input, hidden, and output. The training process of artificial neural networks (ANNs) consists of three key stages: feeding the input data forward through the network, computing the error between the predicted output and the actual output, and updating the connection weights accordingly.).[77] After completing training and validation, the neural network model can accurately identify oil spills in new data with similar features. A key

issue in using ANNs for oil spill classification is determining the optimal combination of ANNs hyperparameters, such as the number of hidden units, the size of batches, training iterations, learning rate, and momentum, since poor choices may negatively impact its accuracy and computing performance. The accuracy of the ANN method in oil spill studies ranges from 72 % to 99 %.

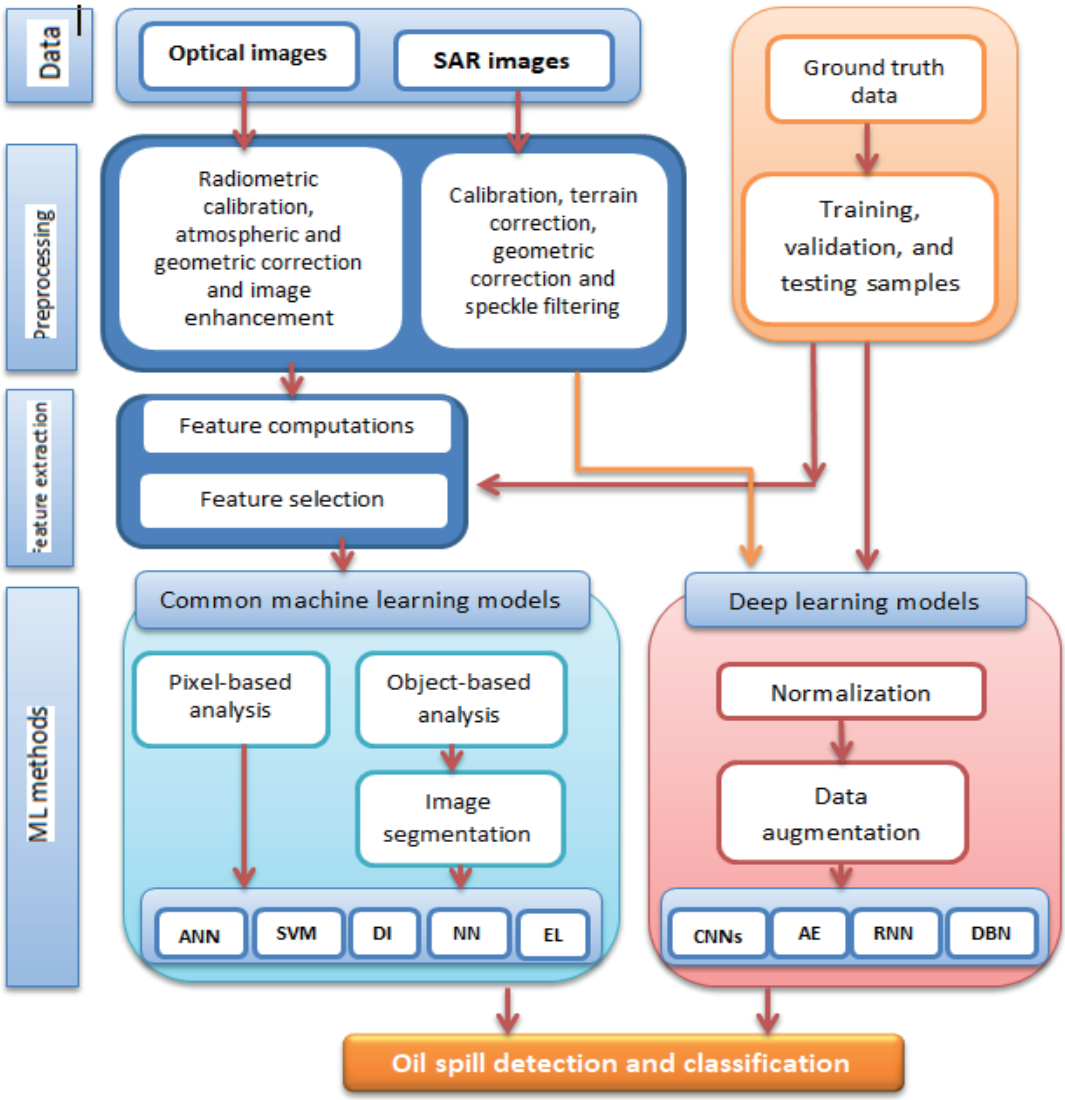

Figure 1. Framework of oil spill detection[62]

Support Vector Machine: SVM,[78] a non-parametric controlled machine learning technique, based on the principle of minimization of statistical learning theory, has been successful in a large number of remote sensing applications. The SVM method allows processing of a multidimensional feature space and provides achieving satisfactory classification results with a limited number of training samples. SVM focuses on samples that lie close to the class boundaries in the feature space, referred to as support vectors. The SVM method aims to determine the location of a separating hyperplane (decision boundary) that provides optimal class separation to minimize

classification errors and achieve satisfactory generalization capability. The accuracy of SVM in oil spill studies ranges from 71 % to 97 %.

Decision Tree: DT is a simple non-parametric machine learning classifier that recursively divides the input dataset into branches of data subsets; each subset is described by a set of features, threshold values, and class labels.[79] DT is widely used to assist in developing rule sets for classifying remote sensing data using an object-based image analysis (OBIA) approach, due to its ability to handle non-linear relationships between features and feature values from different scales or value ranges and classes. Tree-based classifiers are highly sensitive to even minor variations in the training data. Therefore, it is essential to carefully develop a training dataset that can successfully distinguish between oil spills and lookalikes.[68] The accuracy of DT in oil spill research ranges from 80 % to 96 %.

Deep Learning Techniques: Deep Learning (DL) algorithms represent a series of distinct deep neural networks (DNNs) that automatically learn complex discriminative features from significantly larger volumes of data in a hierarchical manner, extracting information through multiple high-level abstraction layers.[80] Unlike traditional machine learning methods, deep learning is entirely data-driven, where the inherent relationships between inputs and outputs are automatically established, and the feature representations are learned directly from the data without manual intervention.[81] The step involving the extraction of features is no longer dependent on the construction of hand-crafted features by experts before the classification phase of the oil spill.

Various DL models have demonstrated excellent results in oil spill detection using SAR and optical images, due to their ability to automatically extract discriminative learned features for recognizing oil spills and their look-alikes. Moreover, the generalization capabilities of these models can account for the case-specific nature of traditional methods. These models have been used to perform various tasks such as oil spill detection and recognition,[82] Classification on the basis of fragments, definition and semantic segmentation.[83,84] Among the widely adopted architectures in deep learning are convolutional neural networks (CNNs), autoencoders (AEs), recurrent neural networks (RNNs), deep belief networks (DBNs), and generative adversarial networks (GANs).[85,86]

CONCLUSIONS

1. The paper addresses one of the major issues of modern technogenic society, that is the pollution of water areas by oil and petroleum products, which can be partially resolved through the use of modern technologies for early oil spill detection.
2. The technologies used for solving this issue include the following: the technology of scattered light, fluorescence, microscopy, as well as remote, optical, and wireless sensing methods, each with specific conditions of application and detection ranges.
3. A review of multiphase sensors for crude oil facilities and transport pipelines has led to the conclusion that these sensors are not suitable for operation in natural aquatic areas. A potential solution is the implementation of hybrid and remotely operated systems.
4. Of particular interest are modern developments in the field of remote determination of oil slick thickness: remotely operated systems, microwave sensors, and the use of multispectral and ultrasonic sensors (with frequencies of 2,25 MHz and 5 MHz) installed in unmanned aerial vehicles (UAVs).
5. The most advanced technologies for oil spill monitoring are based on Artificial Intelligence, particularly Artificial Neural Networks and Deep Learning Techniques. DL

algorithms represent a set of individual deep neural networks (DNNs) that automatically study complex discriminant features from large volumes of data in a hierarchical manner to extract information through multiple high-level layers of abstraction. Additionally, for classification of oil spills and their analogues, other algorithms can be applied: artificial neural networks (ANN), SVM, decision tree (DT), K-nearest neighbor, genetic algorithm, random forest (RF), maximum likelihood, and linear discriminant analysis.

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CONFLICT OF INTEREST

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