Oil Spill Detection & Monitoring with Artificial Intelligence: A Futuristic Approach

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Abstract
Scientists striving to save the environment have made oil spill detection and monitoring in marine water a priority in recent years, and this trend is projected to continue. To preserve the ecology especially marine life, an oil spill accident on the water's surface must be identified as soon as possible to perform timely monitoring and cleanup operations. If the oil spill is not dealt with promptly and efficiently, the harmful impact on marine life will only worsen over time. When an oil spill occurs in a marine system, quick identification and monitoring can lead to accurate cleanup and recovery of hydrocarbons across the water surface, resulting in the preservation of the marine ecosystem and human lives. The use of artificial intelligence (AI) in the detection and monitoring of oil spill accidents in the aquatic environment has the potential to result in a more effective response process to an oil spill. The purpose of this paper is to explore and review the viability of using artificial intelligence (AI) techniques like machine learning (ML), and deep learning (DL) in the detection and monitoring of oil spills over water surfaces to expedite oil spill cleanup and other response operations.

Keywords
Artificial Intelligence (AI), Machine Learning (ML) Detection, Deep Learning (DL), Artificial neural network (ANN), Remote Sensing (RS), Oil spill

1. Introduction

Globally we utilize around 4 billion tons of oil around the world. The risk of oil leaks in offshore areas has increased with the number of enterprises exploring hydrocarbons and transporting crude oil. Although oil spills from maritime accidents and offshore blowouts are infrequent, the consequences for the environment, human livelihoods, and the local economy can be devastating when they do occur. As a result, we have several questions, such as -What issues do we need to consider? -What skills and methodologies are available? -How do we give a well-planned and performed reaction to limit the impact? A leak at sea provides an opportunity to restrict the portion of oil that may reaches the coast over the time, but the key to being successful in limiting the amount of harm that occurs. You must be well-prepared and move quickly. We examine various tactics for responding to oil spills at seas, such as the use of chemical dispersants and thermal methods like in-situ burning, to ensure that the oil is cleared from the marine ecosystem. However, because oil's natural tendency is to spread out, it is a difficult task to monitor. In addition, because oil weathers at sea, its qualities alter, there is only a little window of opportunity in which to act before the oil is completely consumed.

Several techniques exist to clean up oil spill, but the key is to get the right tools to the right place quickly. In the event of an accident, time is critical, so in specialist centers, spill cleanup equipment is packaged and ready to go. A race against time is underway in the oceans from time to time. This is all to stem an oil spill that some environmentalists are already calling an ecological disaster. A large

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amount of thick toxic sludge has so far leaked from various freighters that ran aground off the onshore of various countries. Efficacious oil spill cleanup responses deal with the disastrous effects on the marine ecosystems [1]. These responses or jobs are exceptionally controlled by the parameters like, physiochemical properties of oil, marine environment and weathering conditions like temperature, Pressure etc. Rapid decision-making components include detecting and monitoring oil spills, characterization, hazard assessment, clean-up process selection, optimization of procedures, and garbage management. Over the years, many oil spills have been recorded and the response those oil spills have been conferred and reported to cope with the consequences on the marine ecosystem and the human health. With the practices to resolve the oil spill problems, a huge data set and information has been recorded in the literature. Thus, we may utilize that information and data set to reach decision rapidly and to achieve results [2]. Digital Platform has offered significate ease in working environment in the petroleum industry, from data collection through data interpretation for better decision-making and the prevention of issues that arise during operations, among other things. The current study provides an extensive overview of technology such as artificial intelligence applications spanning from detection of oil spill to effective potential of decision-making during clean-up operations [3].

2. Detecting and monitoring the oil spill

Detection and monitoring offer a crucial role in oil spill catastrophe readiness. Precise detection and monitoring of oil spills benefit the maritime ecosystem's sustainability [4]. Conventional oil spill detection processes, such as aerial and field investigation, are incapable in detecting and locating an oil spill promptly. Remote sensing (Satellite-based) has grown in popularity in recent decades owing to its vast range, diverse viewpoints, and consistency in acquiring multimodal data. Oil spills have been identified and tracked using a variety of remote sensing data [5]. There are numerous review articles in scientific literature on the detection of oil spills using remote sensing. These research articles offered the insights and merits of using the data information in selecting appropriate methodologies for recovering spilled oil over Marino water [6,7]. Figure 1 demonstrate the schematic procedure of detection and monitoring the oil spill in marine environment.

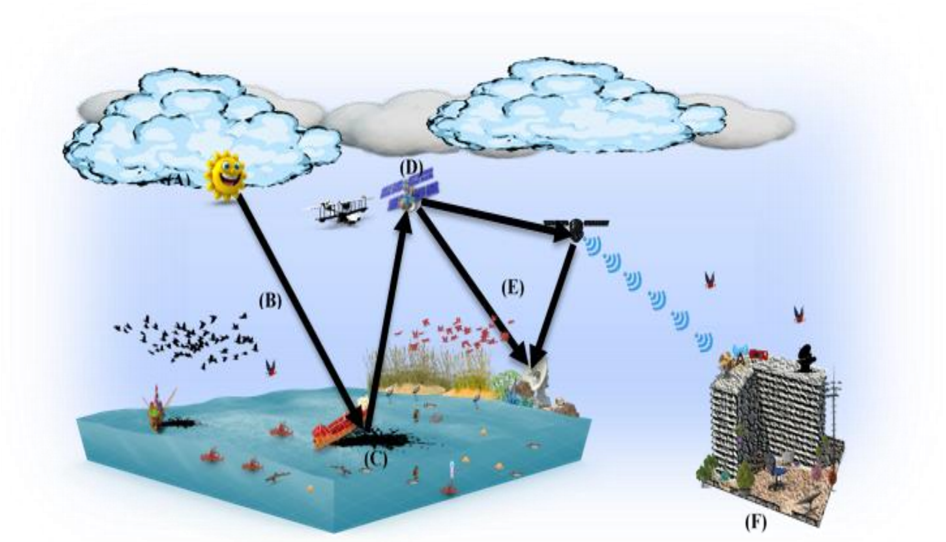

Figure 1: (A) Energy Source; (B) Radiation and the Atmosphere; (C) The Target's Interaction; (D) Energy is captured by the sensor.; (E) Transmission, Reception, and Processing; (F) Observation and interpretation

3. Oil Spill Detection and monitoring with remote sensing

Remote sensing is the Data/information acquisition method used to detect and gather the information about the oil spills such as: Co-ordinates, areal extent and the movement of oil slicks over the marine water. Figure 2 demonstrate how efficacious oil spill remote sensing can support oil spill countermeasures and, perhaps most importantly, how it can help predict slick path [8]. Remote sensing information (data) has been frequently utilized since last 4 decades, to spotting and evaluating the oil spill phenomenon in the marine environment. Remote sensing gathers the information by active and passive ways. Active sensors emit radiation that is directed toward the target and collects reflected radiation from that target whereas passive sensors collect/measure naturally available energy like solar radiation. Visible, infrared, thermal infrared, the microwave is the example of RS technologies (as indexed in Table 1) for detecting, characterizing, and monitoring oil spill over water surfaces [9].

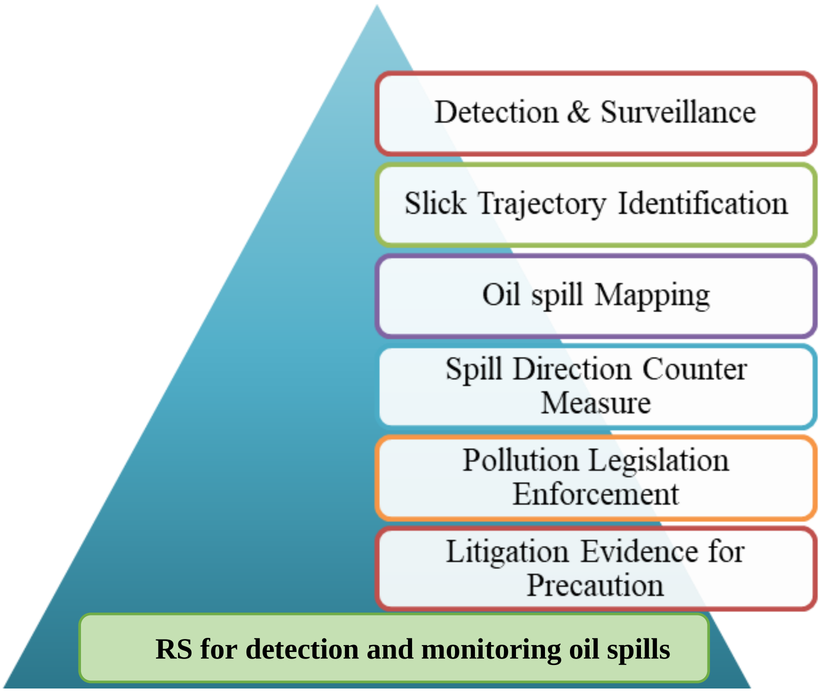

Figure 2: The data set/ information gathered by an effective RS Technique

Each methodology has its own merits and demerits in terms of obtaining relevant data for speedy and successful oil spill detection & monitoring. Data collecting from a single data source might be difficult, and a compromise situation in picking an appropriate technique from among those available may occur. Choosing the proper technique at the right moment is thus a huge responsibility. The various remote sensing techniques are listed in Table 1, along with information about how they work and how they collect data.

Table 1: RS methodologies for detecting oil spill over marine water

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 [10] [11] [12].
	Infrared	Absorption of light at specific wavelengths.	Identification of oil slicks [13][14].
	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 [15].

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. [4][16].

Microwave and optical remote sensing collect data. Microwave sensors receive reflected waves using longer wavelengths, whereas optical sensors utilize infrared and visible rays. It has been reported that both the sensors can successfully detect oil spills. However, microwave sensors are preferred over optical as they can collect information (data) at any period of time [4] [17] [18] [9]. Radar microwave technology is reported as most widely used technique for detecting oil spill. [19] [20] [21] [14]. Satellites emit the microwaves and use reflected waves in identifying the oil spill over the water surface. Because of its viscoelastic properties, oil slows the growth of waves and speeds up their dissipation [22]. The dark spots on captured image are not all oil spills, they could be lookalikes. Many object like ship wake, natural films of allege, wind fronts [23], and wind shadows [21] [23] may appear, same dark spots. An efficient detection technique needs to differentiate between spilled oil and lookalikes [24].

Several methods for detecting oil spills using satellite images have been developed, including image segmentation, dark spot detection, and feature extraction. These are accomplished through the use of stages. This technique divides images into zones of interest [25]. As a result, isolated image sections become easier to investigate. It is also faster than other methods [26]. To obtain the most precise features for classification, dark areas must be identified [27]. Various practices for spotting spilled oil, with minimum false detection rates and with high performance have been presented at Scientific platform [28] [29] [30]. After detection, features are extracted to quantify shape and size, backscattering and texture boundaries and thickness [31]. Researchers use the retrieved traits to categorize oil spills and their lookalikes [32] [21] [33]. Remote sensing captures optical and SAR images from target locations. Collected data set are pre-processed before the feature extraction. Several methodologies such as: Picture enhancement, atmospheric and geometric correction, are used to prepare the data for an efficient and relevant information extraction. Statistical, geometric, texture, contextual, and SAR polar metric features are studied. To classify oil spills, researchers and professionals often use their experience to extract and select features.

The analysis of a large remote sensed dataset of features may be result in the introduction of unnecessary attributes, processing delay, and classification inaccuracies, all of which can harm oil spill detection due to a lack of systematic investigations [34] [35]. As a result, skilled manpower is required for the oil spill detection process, which includes deep analysis of optical and SAR images, feature extraction, and feature selection to make critical decisions about remedial clean-ups. In addition, the increased workload on the operator may lead to inefficient and ineffective decisions. As a result of this, the need of digital platforms in the faster decision-making for oil spill clean-ups to save the ecology is encouraged.

4. Oil Spill Detection and Monitoring using artificial intelligence

Artificial intelligence (AI) is the science of creating intelligent machines that have been computationally trained to understand human intelligence [36]. Based on computational techniques such as AI, an effective marine oil spill management system can be developed. The role of AI in detection and monitoring oil spills can be divided into two parts: Models of (ML) and models of (DL) models [37] [38]. ML and DL make it easier to diagnose and monitor an oil spill on the water's surface, allowing for faster decision-making and effective hydrocarbon recovery. We can detect an oil spill disaster in time even in remote areas by applying these techniques to a dataset obtained from satellite images. These methods aid in the accurate detecting and monitoring of oil spills using remote sensing datasets. The developed intelligent models, which can be trained using previous oil spill historical data, require little human interaction and consume very little processing time. As a result, the harmful chemical components' contact time with the ecosystem is reduced, resulting in minimal damage.

4.1. Machine Learning

Human learn from their prior circumstances and machine follow commands the by human and train the machine to learn from the prior data and of what human can do as much faster referred as machine learning, but it's lot more than just learning it's also about understanding and reasoning.

There are several different types of learning algorithms to reproduce the individual learning and improve accuracy over time. ML have been offered wide ranges quicks decisions and responses to the oil spill phenomenon's using satellite images and others data. ML have been capable of distinguishing between the oil spill. Various ML models are constructed to tackle tough categorization by inspecting outcomes from provided features in recursive and iterative manner, rather than being explicitly programmed to perform the task [36].

4.1.1. Supervised Learning

Supervised learning uses algorithms that uses the well –labeled training data to train the machine to predict the outcome. Assume, we have three types of oil (each with different density): diesel, machine oil, mustard oil. Here machine learning uses the density as labeled training data and learns which feature corresponds to which labels, when a new data set of oil is introduced to the machine.

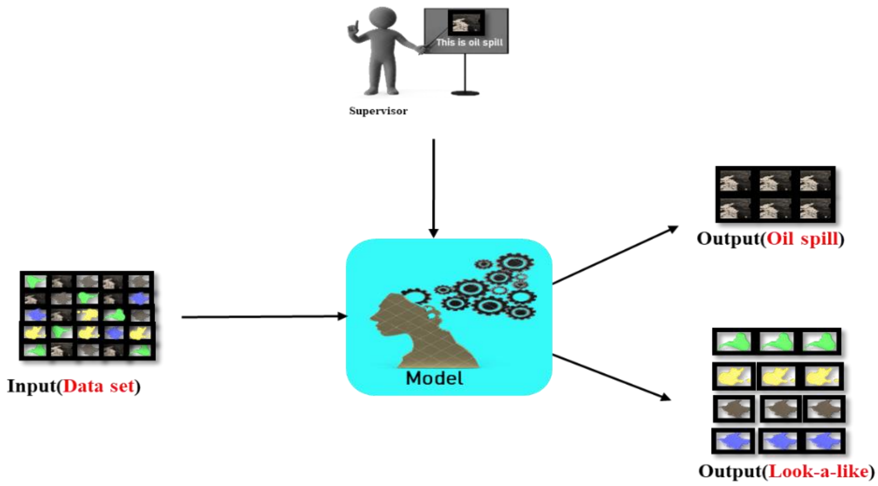

Figure 3: Supervised Learning algorithm for differentiating between oil spill and look-a-like

4.1.2. Unsupervised Learning

Unsupervised is that techniques of machine learning, in which machines are trained with unlabeled data, based on feature similarity machine forms different clusters and discovers the output on its own, without any guidance. Assume, a data set is given to machine which contain images of oil spill and look-a-like, the algorithm is never trained on this type of data set, so it has no knowledge of its features, so algorithm will categories or classify the images based on similarities between images.

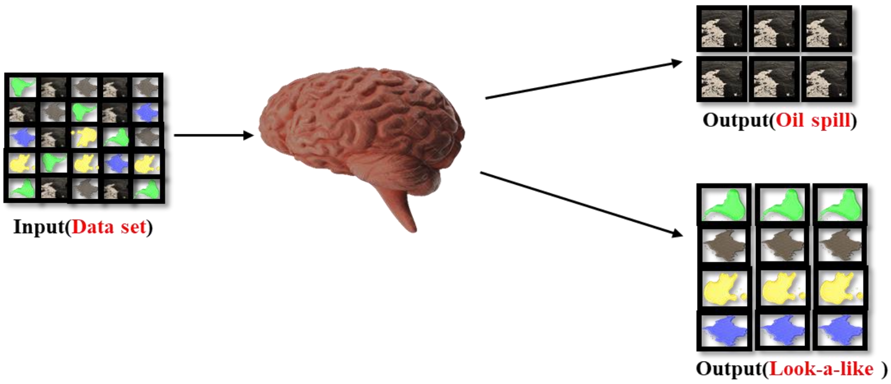

Figure 4: Unsupervised Learning algorithm for differentiating between oil spill and look-a-like

4.2. Classifying oil spills using Artificial Neural Network (ANN)

ANN is an information processing paradigm which is biologically inspired computer program and work exactly similar like human brain. The highly interconnected processing units (artificial neurons) are used to determine the relationship between input attributes and output response [39]. Figure 5 demonstrate, the basic artificial neural network structure comprises of 3 layers: Input, Hidden (potentially numerous), and output layer. Singha uses 2 ANN model, which exhibit an accuracy of 95.2% for oil spots detection and 91.6% accuracy for classifying oil slicks & look-a-likes [40] [31]. With the continuation Ma & Zeng deployed a 5steps ANN model, namely target extraction, feature extraction, feature selection, ANN training & ANN classification they also used PCA to reduce dimension of data [41]. The research studies carried out by Park and Chen demonstrated artificial neural network (ANN) architecture to categorize oil spills from dataset (optical images), and SAR photos with epochs, a learning rate, and hidden layer of neurons. The accuracy of reported of ANN model was in the range of 72 to 99% [42] [30].

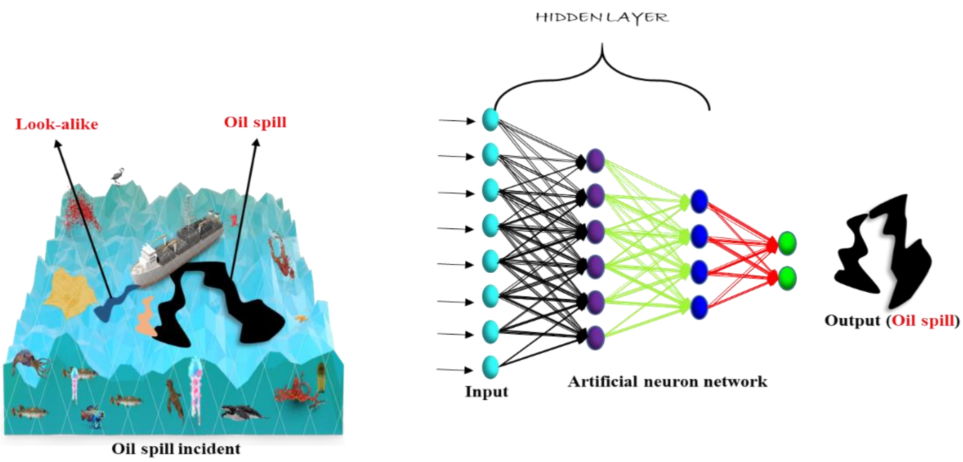

Figure 5: Topological Structure of a Basic ANN

Choosing the right ANN hyper parameters (number of hidden units, batch size, etc.) can make a big difference in accuracy and computing performance [23]. Iterative testing is commonly used to assess the suitability of numerous combinations of these factors. [42].

4.3. Support Vector Machine (SVM)

SVM are the set of supervised learning algorithms, which aims to find out a hyper plane that optimally separates two classes. Optimum hyper plane is determined by using test data set. SVM has ability of handling high- dimensional attributes space & good classification results with a small number of training sample. These SVMs seek to locate a separating hyperplane (decision boundary) that will minimize misclassifications and increase generalization. The High-dimensional data had been mapped into an optimized separating hyperplane for nonlinear decision surfaces [43] [8] whereas previous SVM used linearly separable situations to find out the ideal hyperplane [44]. Li and Zhang demonstrated that fewer number of sample can allow for better accuracy in the case of ANN based model for differentiating between oil spill spots and look-a-likes [45]. However, many researches has suggested that using a big data set can reduce the duration for training the model. Mira et al., (2017) introduced a recursive feature removal in SVM to detect an oil spill spot in the satellite images and results shows high accuracy in oil spill classification [30].

4.4. Decision Tree (DT)

A decision tree is a powerful & popular technique or algorithm used for classification & prediction. It is a tree like structure, in which each internal node denotes a test on an attributes, all branch can represent all the outcomes in test, each and every leaf node can hold a class labels. Same like ANN and SVM, DT is easily trained and implemented and the outcome can be easily interpreted, because it controls nonlinear relation between attributes and values from multiple scales and classes, DT is frequently used to help build rulesets for object-based classification of remotely sensed data. Topouzelis and Psyllos (2012) introduced a decision forest model which was able to detect oil slicks and look-a-likes with an accuracy of 84.4% from 9 of the 25 attributes studied [47]. Singha et al., (2012) introduced that employing a decision tree to choose attributes and identify oil spills spots in the data set containing images and enhance automated accuracy [31]. The decision tree improves accuracy by dividing training data set into subsets based on the concept of repeatedly evaluating one or more attribute values. Same like other (ML) models, DT does not assume a variable-specific distribution or variable independence.

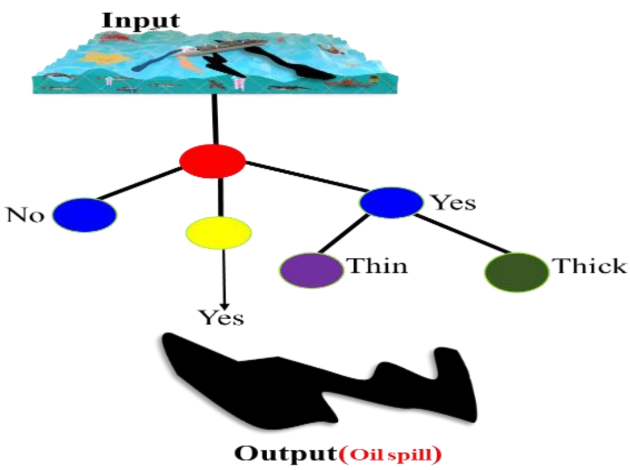

Figure 6: Decision Tree for spotting oil spill over marine water

4.5. Random Forest (RF)

Random Forest algorithm provide "The selection for classification problem based on decision tree approaches". In the random forest algorithm decided, its outcomes on the behalf of the decision tree and predict the problem statements. Random decision is kind of ensemble learning methods for the classification and regression problems. The decision in random forest is based on the majority voting process, it randomly subdivides a pre-set number of variables for detection of oil spill and performed well even if there is so much of noise and outliers without requiring excessive overfitting [44]. Tong and Chen demonstrated a 3-step approach for detecting oil spill and got an efficiency ranging from 82.22% to 92.99% (48).

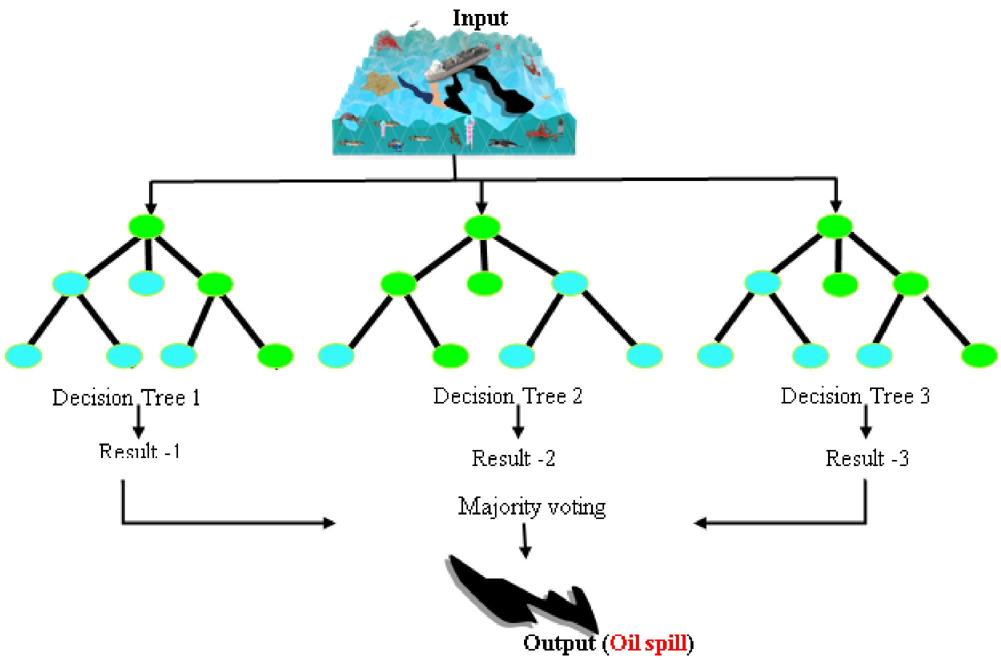

Figure 7: Random Forest algorithm for spotting oil spill over marine environment

5. Conclusion

The current study on the AI platform for spotting and monitoring oil spill over the marine water has the following findings:

- RS provides a large and complex dataset for cleaning up oil spills. This data allows quick response.
- Automatic detection models have been reported in literature to differentiate between spilled oils and its lookalikes on marine water.
- Machine learning algorithms extract and select features from image datasets. In automated oil spill detection, ANN and SVM are commonly used.
- Deep learning models are more accurate at detecting marine oil spills because of their high feature extraction and self-learning capabilities.
- Digitalization in oil spill detection and monitoring enhances the effectiveness and efficiency of the clean-up's jobs

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