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Advance synthetic aperture radar images for characterization of oil spills disaster in ocean using Daubechies analysis

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Abstract:

Background: Researchers have developed various algorithms to identify the occurrence of an oil spill in these oceans. However, knowing the type of oil that is spilled in the ocean is important to assess and plan the restoration process. To predict the type of oil that is spilled in the ocean by using machine learning techniques. Fifty satellite images of three types of an oil spill, namely petroleum, crude oil, and diesel were examined to identify the type of oil spill over the affected area. The oil spills were initially identified from the images using K-Nearest Neighbor algorithm. Color-based, Statistical, Textural and Geographical features are extracted after applying various types of wavelets to obtain the features relevant to the physical parameters and type of oil in the ocean. The features were then trained and classified using K-Nearest Neighbor algorithm to identifying the type of oil.

Methods: For wavelet analysis (Daubechies analysis db1, db2, db3, db4, db5, db6, db7, db8, db9, db10) and machine learning (k-nearest neighbor algorithm) applied to optimize the oil spill feature sets. Features included color-based, statistical, texture and geological features. This experiment was conducted on SAR images. The features were classified using a k-nearest neighbor algorithm. Seventy percent of features used for training and thirty percent for testing.

Results: The results show that oil spill classification achieved by wavelet transforms and machine learning algorithms outperformed very well with similar parameter settings, especially with 70% training data and 30% testing data using confusion matrix. It also represents 99% accuracy for petrol oil using Daubechies 5 analysis which indicates better characterization of oil spills. Results denote oil spill detection using Synthetic Aperture Radar (SAR) remote sensing which provides an excellent tool in oil spill characterization various features can be extracted from SAR data set.

Keywords- Satellite Image, Oil Spill, Machine Learning Method, Wavelet Analysis, KNN classifier.

1. Introduction

Every year there is a strong environmental impact due to large oil spills that includes as diesel, petroleum, crude oil, etc. which affects the marine environment and their life cycles. These oil spills are increasing day by day with an average of 53% all over the world. Researchers have estimated that almost 706 million gallons of oil enter the ocean every year including those from land drainage and improper disposal of used oils. Offshore drilling and production operations, leakage from ships or tankers, drilling rigs, maintenance of the ship, onshore hydrocarbon particles and natural seepage of oils contribute to the various causes of oil pollution as illustrated in Figure 1, the discharged oils are generally sticky, heavy and adhere strongly to surfaces. They do not easily disperse or dilute and are prone to forming emulsions or lumps. Depending on the climatic conditions, speed and flow of wind, the slick also drifts towards the coast area thereby impacting marine life and mammals such as reproducing or respire, movement, ability to feed reduction, thermal control loss, chemical toxicity

which lead to disruption of cell walls and damage cellular function for marine animals at molecular level [1], natural habitats chemical and physical alteration, flora and fauna smothering effects, sub-lethal or lethal toxic effects on fauna and flora [2],marine reptiles and mammals such as dolphins and whales are at risk from floating oil when surfacing to breach and breathe [3], cause acute and chronic toxicity and destroying food web [4]. Gulf of Mexico oil spill impact reduction in planktonic blooms, fish larvae killed and a generation lost [5], Korea oil spill caused aesthetical and physical problems to reduce growth production of plankton [6]. Indian coast oil spill caused the death of marine animals and effects in mangroves growth [7]. If the oil is left unaddressed in the ocean the chemical and physical processes of the environment change the properties of the oil in a few weeks time, creating more havoc to the environment. This makes it important and essential to tackle and clean the spills as soon as possible.
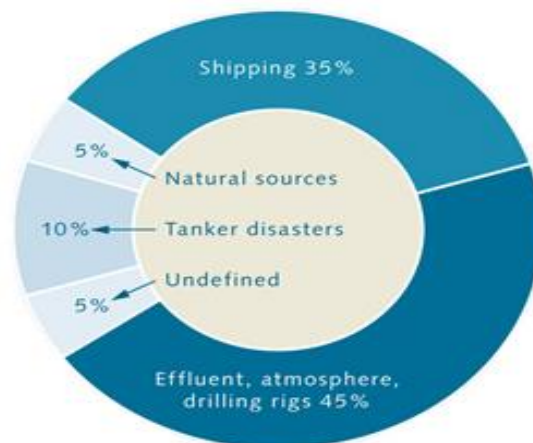
Figure 1. Oil Spills in the Ocean

The integrated coastal and marine management plays an important role in monitoring environmental impacts including the assessment, planning, and management of marine assets and coastal resources.

2. Effects of Oil Spill

Marine life: For marine animals, the oil spill has a negative impact which results in death. As we know mostly the oil floats on water because of this sunlight absorption and oxygen withholding capacity of water decreases. Due to a lack of oxygen in water, it results in the death of marine animals. The oil spill is water pollution in which immunity of the marine animals reduces. Marine mammals like dolphins and whales get affected because the oil clogs their blowholes making it impossible for the animals to breathe. Oil spill affects food chain globally as well as affect plants from the ocean bed. Figure 2 depicts the oil spill effects.

Eco-system: Oil spill create negative impact over the resident's areas due to direct exposure which occurs close where people live and work they can come to contact with components of oil spills such as breathing air contaminated and skin direct contact. Indirect exposure includes water bathing and eating food contaminated. It also creates diseases and harmful infections.

Birds: Oil covered birds are a symbol of damaged environment wreaked due to oil spills, it damage ground-nesting, cause long term effects on whole species, deadly to birds, it makes birds flying impossible and destroys birds insulation and waterproofing natural by leaving them overheating and vulnerable.

Mammals: Animal life near shore are most effected through oil spills as results in the death of mammals due to water scarcity and body temperature regulation in which mammals cant scents due to oil spills.

Tourism Industry: It suffers huge setback such places, due to sticky oil, birds death, and tarballs, due

to which various function such as swimming, fishing, sailing, and parachute gliding ant perform. Due to oil spills, day to day activity halt until it applied the cleanup process.

Economic Losses: Oil spills economic losses such as ceasing of activities such as polluted water which affects fisheries and fishermen, affected area reduction of tourism. Property value decreased, disturbance of sea traffic and land such as export and import activities. Local ship worker and fishermen lose jobs due to oil spills based on government restriction and bans for the affected areas. Financial means lacking and proper maintenance of boat period of times [8].

Figure 2. Oil spill effects on wild animals and the ecosystem

Various evolutionary methods are developed and implemented for continuous monitoring, tracking, and management of the various conditions in the sea including oil spills. Regular monitoring helps in the timely identification and management of oil spills. Knowing the nature and type of oil spills can help in planning the cleanup process within a short time thereby speeding up the restoration process which in turn helps in preventing other environmental problems and damages.

3. Literature Survey

Babichenko et.al.2006 used MODIS-TERRA for data collection using SVM technique for extracting features on the geometrical, gray level, statistical to observe density liner and density quadratic based on petroleum oil detection and observation the type of oil spill classification, it also defines the Satellite image which works best for oil spill characterization and transformation for collection of data sources [9]. Similarly Brekke.et.al 2005 used database on RADARSAT-1 using Technique DLA for extracting Features specificity and sensitivity, it tests the type of oil calculation using method DLA which define the type of oil spill over the affected area with different samples images taken from different sources and regions, DLA helps in detecting type of petroleum oil [10]. Brown.et.al. 2005, used the database on SAR using technique SVM to extract feature specificity and Sensitivity for oil spill detection using characterization method, which defines the type of oil such as crude oil, SVM act as a good tool for identifying the type of oil over the oil spill disaster [11]. Brown et al 2006b, work on CPG data using techniques PARAFAC algorithm on oil fraction for detection of petroleum oil type.

It helps in the classification of oil among different sample data representations under testing conditions [12].Wang. Z, Yang .C et al, 2016, used synthetic aperture radar data for chemical analysis to detect oil spill identification, correlation, and differentiation to detect petroleum and crude oil base on testing, which helps in identifying the oil types and stage of effects [13]. Fant et.al 2006, research took place using Acute ecotoxicity and sample of sediments using technique advance chemical analytical techniques for determining fraction petroleum for identifying the type of oil such as crude oil and fuel oil using correlation establishment [14]. Brown et al 1998, used SAR image for classification type off oil spills using thematic mapping technique to identify the type, size, and thickness for crude oil identifications using various oil spill disaster locations [15].

Fingas st at 2005, worked on GC-MS imaginary model using molecular modeling technique for chemical analysis to characterize the type of oil spills over the affected location, it works on petroleum model detection [16]. Goodman et al. 1994, used GC-MS images for Biomarkers methods to extract the source of spilled oil and correlation observation, a researcher works on Petroleum with multivariate analysis, this work help to identify the oil type and source [17]. Grüner et .al 1991, used SAR image for oil spill characterization based on thresholding method, resulted image represents crude oil with sediments concentration over the periodic time and observation [18]. Hengstermann, et .al, 1990, used SAR image for survey using Gaussian Mixture model for image classification such as crude oil and petroleum for testing with probability consistency, this research help identify the type of oil-based on oil spill, airborne data for monitoring with unmixing based methods to classify the oil type for assessment and slick parameter sample oil tested is light oil and petroleum. This research regularly monitors and test the mineral oil with sample test observation and testing [19]. B. Jones st al, 2001, worked on Geo reference imagery to identify oil degradation bacteria using methodology Biochemical test for crude oil identification, which helps in identification types of oil over the spread slicks in the ocean [20].

4. Methodology

The investigation used several materials and followed certain methods in carrying out the present research work. A brief account of materials used in the work is presented here, followed by that of methods adopted and procedures followed. Initially, satellite image data were acquired from a number of sources on the internet pertaining to different types of oil. Various algorithms were applied to detect and identify the types of oil. The type of oil spill was characterized by using machine learning algorithms. Methodology has been shown in Figure 3.
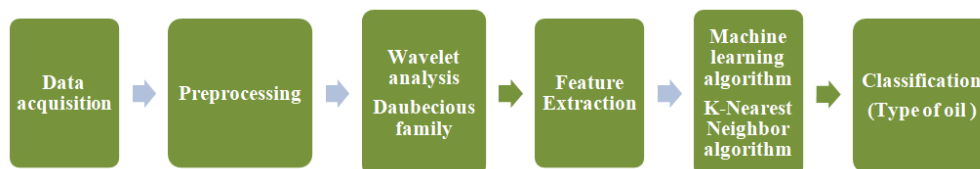
Figure 3. Oil spill characterization

Data Acquisition
One of the main ingredients of any research methodology is the acquisition of appropriate data. In this research around 50 microwave satellite images with a frequency of 300 MHz, to300 GHz has been used which belongs to different oil spill regions around the world. Such as Gulf of Mexico, Chennai Ennor- Truvottiyur region, South Korea, Chilov and Pirallahi, Russian, Thailand on different days. Data Accrued from different sites for research purpose they are INCOIS, ISRO, NASA, and NRSC. INCOIS provides information related to ocean and advisory to society, government, industry through complete ocean observation. Table 1 shows the satellite data. It regularly observes and monitors disaster over the affected area. It becomes one of the biggest sources, for collecting data through the website for research work. NASA, it also provides satellite images for research work. It performs tracking and monitoring of larger area for geological survey and data collection for research. ISRO and NRSC produce regular oil spills SAR images to perform research-based operations such as

tracking the condition, calculation of effects, managing plan, and design work.

Table 1. Satellite data

Region	Type of Satellite	Number of Images	Year of Oil Spill	Type of Oil
Indian coast	SCATSAT-1	10	28 January, 2017	Petroleum
California	ENVISAT- ASAR	4	7, July 2015	Petroleum
Gulf of Mexico	ENVISAT- ASAR	8	27 April, 2010	Crude Oil
Korea	ENVISAT- ASAR	5	7 December, 2007	Petroleum
Russia	ENVISAT- ASAR	5	19 April, 2017	Diesel
Other Regions	ENVISAT- ASAR	10	16 November 2018	Crude Oil
Other Regions	ENVISAT- ASAR	8	4 April 2017	Petroleum

Pre-Processing

In Pre-processing, actual SAR data is converted into geographical projection and commonly readable format. This process will improve data quality and further helps in oil spill detection. This process for oil spill detection involves data cleaning, data integration, data transformation, and data reduction. Data cleaning is employed for cleaning the data by filling missing values thereby smoothing bearing data, detecting or eliminating outliers and resolving irregularities. Data integration will integrate data from varied sources into a coherent data storage format. In Data transformation, the data are converted into required forms for detection of oil spillage. It includes normalization, smoothing, aggregation, a generalization of the data. Data reduction includes reducing the dimensions or number of attributes, dimensional contraction, data reduction or compression for oil spill monitoring and detection. Masking process will hide all small islets, inner-most water and land area where due to a dampening of wind shadow, easy detection of dark patches can be found in SAR data. Also, the small neighbor pixel is modified according to each pixel equation that is totally not related to other neighbor-hood value of the pixel and thereby helps in mapping from one pixel to a new pixel.

Discrete Wavelet Transform

It is a wavelet transform technique which helps to analysis a wavelet scales with translations rules. It transforms the signal into mutually orthogonal groups of wavelets which differ from continuous wavelet transform called a discrete wavelet transform. Wavelet can be implemented using scaling properties. In discrete wavelet transform for characterization here Daubechies family (db1, db2, db3, db4, db5, db6, db7, db8, db9, db10) Wavelet were used for analyzing the features such as color-based features, Statistical Features, Texture Features and geological based features has been examined, which helps to measure the performance of type of oil spills.

Feature Extraction

Color-based feature

Color space RGB is the most common feature on computer image, it is a primary color, each pixel composed of three points red, green and blue gun electrons separately, it transforms image data color space to other uniform perceptual before extracting feature. RGB based feature extraction helps to the characterization of oil type.

Geological features

It is a physical feature of the ocean surface, it influences ocean surface shapes and appearance such as lava flow, oil spillage, rock layer bending, etc. In this research spreading and Complexity geological features has been examined.

Spreading

It is a released of liquid hydrocarbon oil into environment especially term used for marine ecosystem

depends on man-made or natural disaster and form pollution. Spreading defined as $s = 100\lambda/(\lambda_1 + \lambda_2)$, whereas λ_1 and λ_2 eigenvalues with covariance matrix λ_1 greater than λ_2. Assume a low value for thin and long objects and objects closer to a circular shape with high values.

$$Spreading = 100\lambda/(\lambda_1 + \lambda_2)$$

Complexity

The quality and state of bring complicated or intricate based on the oil spill disaster. It is denoted as $c = P/2\sqrt{\pi A}$ for simple geometry region with small numerical values and larger values with complex geometry for regions.

$$Complexity = P/2\sqrt{\pi A}$$

Statistical features

The statistical feature is a mathematical working with a collection of data, organization interpretation and analysis. It is a process of subset selection for model construction, uses for statistical features models to make easier to solve, training time shorter, the curse of dimensionality and characterize work. It consists of mean, standard deviation.

Mean

Sum of all observation divided by a number of observation for a particular spillage area. Mean helps to detect statistical features.

$$\text{Mean} = \sum_{i=1}^{3} p_i \, cos^{-1}(e_i(1))$$

Standard deviation

Pixel intensity values belong to the object with a spillage area of oil spills. The formula is given as-

$$Standard\ deviation = \sqrt{<(\emptyset_{HH} - \emptyset_{VV})^2>} + <(\emptyset_{HH} - \emptyset_{VV})^2>$$

Texture features

The texture is a feature used to partition images into regions of interest and to classify those regions, the texture provides information in the spatial arrangement of colors or intensities in an image, the texture is characterized by the spatial distribution of intensity levels in a neighborhood, such as Entropy, Ellipticity, Intensity, correlation coefficient.

Entropy

Entropy- it determines the measure of unpredictability and randomness, where p_i is entropy and λ_i eigenvalues.

$$Entropy\ (p_i) = \frac{\lambda_i}{\sum_{j=1}^{3} \lambda_j}$$

Ellipticity

Ellipticity- It represents the deviation in terms of a degree from its circularity/ sphericity, s_3, define the ratio of backscattered coordinate.

$$sin(2x) = -\frac{s_3}{ms_0}$$

Intensity

Intensity defines as a measurable amount of a pixel property, such as brightness, dark spot, force, SLink scattering matrix with Quad-Polarization SAR data.

$$Intensity = S_{VV}^2$$

Correlation Coefficient

It is used to measure the strength relationship between two objects or variables. Coh denotes correlation coefficient with polarimetric SAR observation.

$$Coh = \frac{|<T_{12}>|}{\sqrt{<T_{11}><T_{22}>}}$$

5. Machine Learning

It is seen as a subset of artificial intelligence. Machine learning algorithms build a mathematical model based on sample data, known as "training data", in order to make predictions or decisions without being explicitly programmed to perform the task. Machine learning algorithms are used in a wide variety of applications, such as email filtering, and computer vision, where it is infeasible to develop an algorithm of specific instructions for performing the task.

K-Nearest Neighbor Algorithms
K-Nearest Neighbour has been shown in Figure 4. This is done using K-NN classifier, class membership is the output. On a training data set, machine learning algorithms have excellence performance than neural networks. Based on pre-training, machine learning algorithms such as k-nearest neighbor have a stronger capability to achieve the optimized solution of the problems. The results show that oil spill classification achieved by wavelet transforms and machine learning algorithms outperformed very well with similar parameter settings, especially with 70% training data and 30% testing data using confusion matrix.
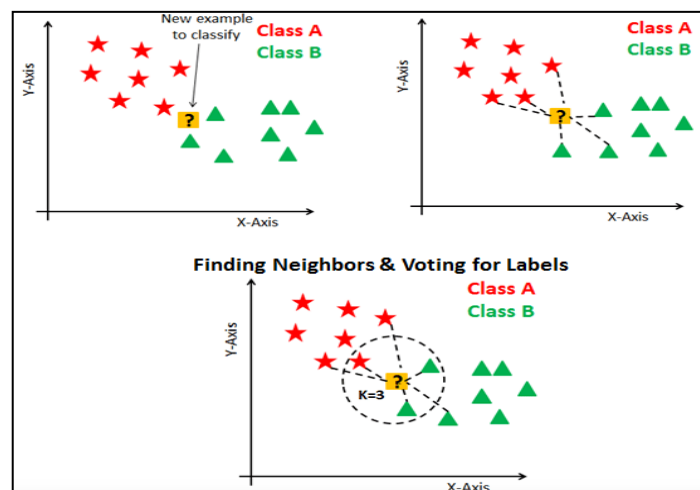

Figure 4. K-Nearest Neighbor

6. Performance Metrics

A confusion matrix is a table that is often used to describe the performance of a classification model (or "classifier") on a set of test data for which the true values are known. In this research work classification of oil is calculated through finding total accuracy of oil types between three sets of classes such as petrol, diesel and crude oil using confusion matrix using K – Nearest Neighbor classification machine learning method.

7. Result and Discussion

To examine the feature the KNN classifier, scatter plots of the main original features and the features derived by wavelet transform using DAUBECHIES with VV and HH transition/receiving combinations, as the most effective feature in oil spill classification. It is observed that k-nearest neighbor algorithms extract information from features and improve their separability to distinguish none mineral samples and mineral oil. As a feature optimizer, the pre-training worked can reveal a reduction of noise and the latent relationship in features. It improves the overall performance of the followed k-nearest neighbor classification procedure. On the training data set, machine learning algorithms have excellence performance than neural networks. Based on pre-training, machine

learning algorithms such as k-nearest neighbor have a stronger capability to achieve the optimized solution of the problems. The results show that oil spill classification achieved by wavelet transforms and machine learning algorithms outperformed very well with similar parameter settings, especially with 70% training data and 30% testing data using confusion matrix. The performance was analyzed by K- Nearest Neighbor (KNN) classifiers. KNN assigns a class based on the predominant class among the k nearest neighbors. The value of k was chosen as the number of classes used for classification. In this research work, the features derived from the collected data set with 70% and 30% for all oil spilled images. Then the 70% features were used for training the classifier and 30% features were used for testing. The analysis results have been listed in Table 2 and Table 3. The testing and training features belonged to random subjects and varied in each run of the program.

Table 2. Color-based, statistical, geological and other features using *DAUBECHIES* analysis with K-Nearest Neighbor classifier

Discrete Wavelet Transform Daubechies1 analysis			
Color-based feature			
	Accuracy Petrol (%)	Accuracy Diesel (%)	Accuracy Crude (%)	Total Accuracy (%)
Red	89	50	87	75
Green	87	60	92	80
Blue	83	40	78	67
All Color Features	67	70	94	77
Statistical Features			
	Accuracy Petrol (%)	Accuracy Diesel (%)	Accuracy Crude (%)	Total Accuracy (%)
Mean	85	77	76	79
Standard deviation	88	67	86	80
Total Features	89	78	83	84
Texture Features			
	Accuracy Petrol (%)	Accuracy Diesel (%)	Accuracy Crude (%)	Total Accuracy (%)
Entropy	77	56	76	70
Ellipticity	82	91	67	80
Intensity	77	79	89	82
Correlation Coefficient	88	77	87	84
Total Texture Features	79	80	96	85

Geographical Features			
	Accuracy Petrol (%)	Accuracy Diesel (%)	Accuracy Crude (%)	Total Accuracy (%)
Spreading	66	88	76	77
Complexity	79	79	88	82
Spreading and complexity	85	97	77	87

Table 3. Overall accuracy of color-based, statistical, geological and other features using *DAUBECHIES* analysis with K-Nearest Neighbor classifier

Daubechies Analysis			
	Accuracy Petrol (%)	Accuracy Diesel (%)	Accuracy Crude (%)	Total Accuracy (%)
Daubechies 1	85	97	77	87
Daubechies 2	78	92	77	82
Daubechies 3	98	92	88	93
Daubechies 4	95	90	87	91
Daubechies 5	**99**	89	96	95
Daubechies 6	77	87	97	87
Daubechies 7	89	97	87	**91**
Daubechies 8	84	79	**97**	87
Daubechies 9	96	84	93	91
Daubechies 10	75	**98**	87	87

It represents oil spill characterization Daubechies 5 analysis with 99% for petrol is higher than compared to other measures.

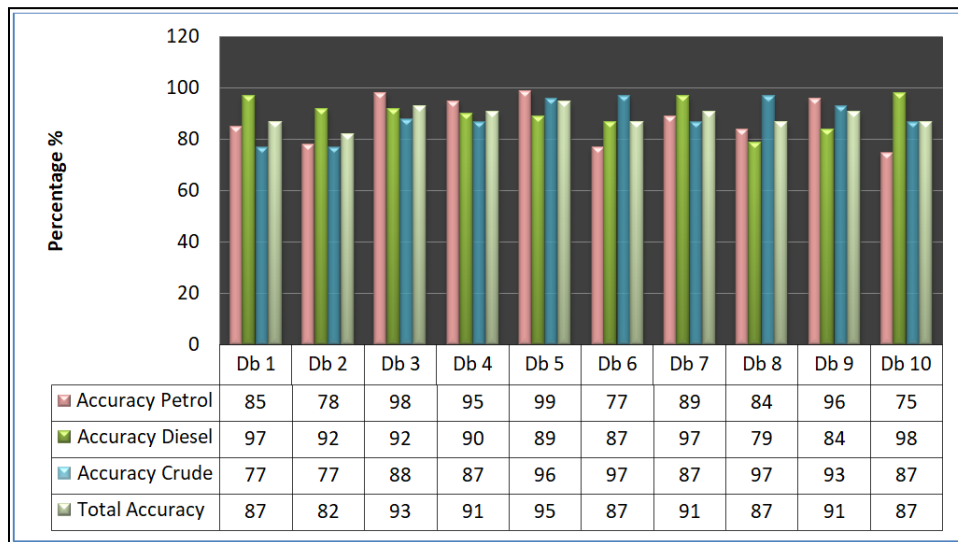|	Db 1	Db 2	Db 3	Db 4	Db 5	Db 6	Db 7	Db 8	Db 9	Db 10
Accuracy Petrol	85	78	98	95	99	77	89	84	96	75
Accuracy Diesel	97	92	92	90	89	87	97	79	84	98
Accuracy Crude	77	77	88	87	96	97	87	97	93	87
Total Accuracy	87	82	93	91	95	87	91	87	91	87

Figure 5. Result using Daubechies Analysis

Figure 5 represents oil spill characterization; using Daubechies analysis, it also illustrates that Daubechies 5 with 99% provide higher accuracy in petrol than compared to other measures.

8. Conclusion

Researchers have developed various algorithms to identify the occurrence of an oil spill in these oceans. However, knowing the type of oil that is spilled in the ocean is important to assess and plan the restoration process. To predict the type of oil that is spilled in the ocean by using machine learning techniques. Fifty satellite images of three types of an oil spill, namely petroleum, crude oil, and diesel were examined to identify the type of oil spill over the affected area. The oil spills were initially identified from the images using K-Nearest Neighbor algorithm. Color-based, Statistical, Textural and Geographical features are extracted after applying various types of wavelets to obtain the features relevant to the physical parameters and type of oil in the ocean. The features were then trained and classified using K-Nearest Neighbor algorithm to identifying the type of oil. For wavelet analysis (Daubechies family analysis) and machine learning (k-nearest neighbor algorithm) applied to optimize the oil spill feature sets. Features included RGB, spreading, complexity, standard deviation, entropy, ellipticity, intensity, correlation coefficient. This experiment was conducted on SAR images. The features were classified using the k-nearest neighbor algorithm. Seventy percent of features used for training and thirty percent for testing. The results show that oil spill classification achieved by wavelet transforms and machine learning algorithms outperformed very well with similar parameter settings, especially with 70% training data and 30% testing data using confusion matrix. It also represents 99% accuracy for petrol using Daubechies 5 analysis which indicates better characterization of oil spills. Results denote oil spill detection using Synthetic Aperture Radar (SAR) remote sensing which provides an excellent tool in oil spill characterization various features can be extracted from SAR data set.

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