CHAPTER 5

DUAL THRESHOLD MSVM BASED OIL SPILL DETECTION FROM RADARSAT-2 SAR SATELLITE DATASET

5.1 Proposed System

In this research work it provides a new oil spill detection method called as Dual-Threshold method where it utilizes intensity estimation within a determined boundary. It can be used for any size of images and it can maintain the boundary of oil spills to the highest extent. Hence it reduces the false alarm rate in detection. MSVM approach can classify various kind of classes and used in any types of SAR images. MSVM applied to learn the training data and used for testing on SAR images. The oil spill detection from SAR image is taken from the benchmark dataset [86] using the morphological operation. The morphological operations provide more efficiency in terms of detection since it investigate the image in binary level difference. The Binary images may contain countless limitations, in some circumstances binary regions are taken and set an operation to establish by simple thresholding that are secured by noise, textures and structure, and modifies the images based on the shape. It is considered to be one of the data processing methods.

A morphological operator is defined by its structuring element and the applied to dataset. The input image is taken, based on characteristics of its shape, which are encoded in the structuring element. The mathematical details are explained in Mathematical Morphology.

The Synthetic Aperture Radar (SAR) which is an active microwave sensor is utilized for capturing the two dimensional images. The image brightness is a contemplation of the microwave backscattering properties of the surface. As of now, the critical tool in oil spill monitoring is the SAR that is deployed on satellites and it is considered as an important tool because of its wide area coverage and day and night all-weather capabilities. As of late, there has been a dangerous increment in the extent of incidents of marine pollution.

The catastrophe caused three months of oil flows in the coastal waters of the Gulf of Mexico. The Deep-water Horizon oil spill has consequential impacts on feeble maritime species, wildlife habitats, fishing in the Gulf', the coastal ecology, and also the tourism industry. For instance, the instantaneous impacts were extreme, with oil-soaked birds, fish, and turtles, appearing on shore along the seaboard. Normally, a gigantic devastation in marine ecosystems could be brought about by oil spill pollution. Therefore, the oil spill floating on top of water besides to diminishing the fauna populaces, influences the food chain in the ecosystem (Garcia-Pineda *et al.* 2013, Alpers 2002, Xu*et al.* 2014, Brekke and Solberg 2005).

Oil slick decreases the amount of sunlight that enters the water, and as a result of that the photosynthesis of marine plants and phytoplankton are constrained. The marine mammals are instantly exposed to an oil spill, then their insulating capabilities are decreased and hence making they endangered to temperature variations and much less light in seawater. The oil coats the fleece of sea otters and seals, diminishing its insulation capacity and resulting in variations of body temperature and hypothermia. The ingestion of the oil spill is the main cause of dehydration and also it damages the digestive system (Fiscella *et al.* 2000).

Besides, the oil spill and its cleanup have brought in an assortment of medical issues. The Deepwater Horizon spilled almost five million barrels of oil, constituting the world's most enormous inadvertent marine oil spill. Oil spills are hard to bring under control on account of the impact of coastal hydrodynamics like waves, tides and currents. Along these lines, there is a need for advanced technologies to attain the accurate surveying, and control of marine oil contamination (Marghany 2013).

The effect of not checking the oil spills is obscure, but rather the principle ecological effect is thought to be seabirds erroneously landing on them and the harm to the coastal ecology as spills hit the shoreline (Shepherd, 2004). Simecek-Beatty and Clemente-Colo'n (2004) depicts how oiled birds prompt the utilization of SAR for finding a sunken vessel which is leaking oil. Access to an expanded amount of SAR images implies a growing workload on the operators at analysis centers.

Furthermore, latest research demonstrates that regardless of the possibility that the operators go through extensive training to learn manual oil spill detection they can recognize the distinctive spills and provide them a diverse confidence level (Indregard et al., 2004).

Many researches in this field has been made continuously for more than 10 years, and this stage audits different strategies for satellite-based oil spill detection in the marine environment. The automatic detection algorithms can help in monitoring the images and prioritizing the alarms will be of awesome advantage. In any case, small-size oil spills were not recognized in light of the fact that the greater part of SAR satellites or airborne SAR overpasses the contaminated zone after the spills have grown beneath the influence of the sea surface dynamic changes. Furthermore, new oil spills of a few-meter (e.g., 3 m) length cannot be identified with SAR pixel resolution of 6 to 12.5 m. The principle question can be raised up whether such a GA can recognize a small oil spill spreading between the vast ones. The main focus of this research work is to explore the utilization of the DT (Yu Li et al. 2014) for the automatic detection of expansive or small oil spills in RADARSAT-2 SAR satellite data.

Oil spill detection is one of the emerging researches applied to save the public survive closer to coastal regions. This research work is mainly focused on public concern to make healthier in terms of coastal regions and ecological systems. Water quality, acoustic animals, marine lives are getting damaged due to the spilled oil on the water surface. Hence SAR and RADARSAT-2 SAR based sensors are used for monitoring the oil spill in all large area in all day under all weather. The imaging mechanism comprised of speckle noises, patches and other problems like blur, rub on the image caused due to various nature and physical phenomena which spoil the accuracy of oil spill detection. This stage detects and segment the oil spills on the SAR images using Dual-Threshold (DT) method classified using Multi-Class Support Vector Machine (MSVM) method.

5.2 Morphological Characteristics

In this stage morphological characteristics are used to detect oil spills because they looks-alike in shape, color and texture. Since, oil spills are created on the surface of the ocean due to several reasons then they have different morphological characteristics. In most of the coastal area the oil spills are tiny ones due to small leakage in oil tanks and deliberated discharges or engine oil leaks or because of washing operations on the ship engines.

In the literature survey it is proved that two characteristics of the morphological operations (Li et al. 2012; Shu et al. 2010; Migliaccio et al. 2005) such as Complexity (CT) and Ratio (Rt) among the pixels in terms of width and length dark spots detected. It may be in circle or in ellipse shape. The CT and Rt shows the similarities of the dark spot regions whereas this characteristics will not be changed while rotating or scaling the detected regions. The CT and Rt are calculated using the following formula as shown in the below equation 5.1

$$CT = P^2/A \tag{5.1}$$

In equation (5.1), P is the perimeter and A is the area of the dark spot regions. The boundaries of the oil is always has smooth and regular than the sea water because hydrocarbon and minerals have more tension-force than sea water. Usually speaking that, high value of CT of the dark spot provides lower possibilities of real oil spill. Similarly the ratio Rt is calculated using the length and width of the ellipse which has same standardized second central moments as the dark region where it defines the contour of the dark spot region. It is well known that most of the ships spill the waste oil during the travel. So the oil slicks lie beside the route. Oil spills are stretched and bent on the surface of the water due to wind and current. So that it is said that the higher the R of the dark spot, the lower the possibility of real oil spill.

5.3 Multi Class SVM

In the beginning, SVM is used for binary classification as {-1, 1} and it is extended to multi-class scenarios. SVM provide 2 classes on L samples. Whereas in the MSVM provides K number of binary classes over L samples in single optimization process. K classes are obtained based on a single objective function to train the entire K-binary SVMs. These classes are naturally differentiated within a single optimization process. The training set is labeled as equation 5.2 and 5.6.

$$\{(x_1, y_1), (x_2, y_2), \dots (x_l, y_l)\} \tag{5.2}$$

where l is the cardinality, $x_i \in R^d$ is the training vectors and $y_i \in \{1, 2, \dots, k\}$ is the label vectors and the formula used are:

$$\min_{w_m \in \mathcal{H}, b \in R^k, \xi \in R^{l \times k}} \quad \frac{1}{2}\sum_{m=1}^{k} w_m^T w_m + C \sum_{i=1}^{l} \sum_{t \neq y_i} \xi_{i,t} \tag{5.3}$$

subject to

$$w_{y_i}^T \varphi(x_i) + b_{y_i} \geq W_t^T \varphi(x_i) + b_t + 2 - \xi_{i,t}, \tag{5.4}$$

and if $\xi_{i,t} \geq 0$,

$$i = 1, 2, \dots, l, t \in \{1, \dots, k\} \backslash y_i \tag{5.5}$$

The output of the decision process is:

$$\underset{m}{\operatorname{argmax}} f_m(x) = \underset{m}{\operatorname{argmax}} \left(w_m^T \varphi(x_i) \right) + b_m \tag{5.6}$$

where $w \in R^d$ is weight vector, $C \in R_+$ is the regularization constant, and φ the mapping function projects the training data into suitable feature space $\mathcal{H}$, $\xi_{i,t}$ is the pair wise margin violation between the true class y_i, and other class t, The limitation of MSVM is increased computational time when enormous size of the training and testing dataset.

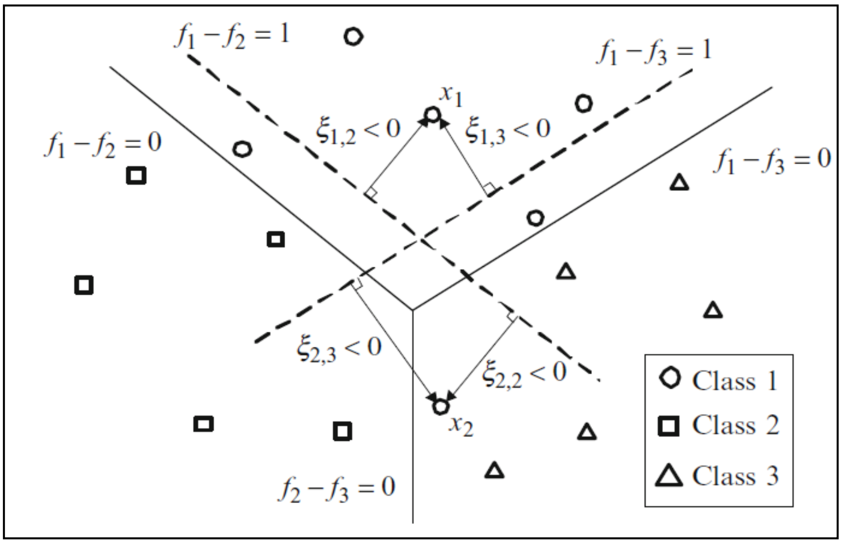

Figure 5.1 Multi Class SVM

In Figure 5.1, Class-1, Class-2 and Class-3 are shown in circle, rectangle and triangle symbols respectively. Boundaries are shown in bold lines whereas the dash lines show the positive margin lines of the first class. The margin violation of the first class is $\xi_{1,2}$ and $\xi_{1,3}$ for X_1 and $\xi_{2,2}$ and $\xi_{2,3}$ for X_2 and so on is shown in the above figure. The characteristic of the dark spots are mapped with the similar features for predicting the same and look-alike oil spills in classification. In order to obtain the morphological characteristics C, R the preprocessing image is converted into binary image for applying dilation operation. Dilation is a low-level segmentation process can be applied over binary images only. After dilating the oil spills the related information, looks alike and the features are extracted from the training images. Then the MSVM classifies is applied to create a model which represents the training samples under various classes.

The characteristics and the extracted features of the test results are mapped with the trained results to predict the oil spill or look alike. In the above Figure 5.3 illustrates the entire functionalities of DT-MSVM algorithm utilized in this stage. Also in order to implement and verify the performance of the proposed approach the entire process of the DT-MSVM is illustrated in the form of Pseudocode.

```
PseudoCode_DT_MSVM ( )
{
Read the entire dataset from the database
        Assume TRS as the size of the training folder, and separate 25% of the
        data for training process
        Assume TES as the size of the testing folder, and keep 75% of the data
        for testing process
    for I=1 to TRS
        PRImg(i) = specFilter(TRS.images(i))
        CT(i) = complexity(PRImg(i))
        RT(i) = ratio(PRImg(i))
        class(i) = Classify(CT(i), RT(i)) using MSVM
    end i
        TImg = read(TES Image)
        PRImg(TImg) = specFilter(TImg)
        CT(i) = complexity(PRImg(TImg))
        RT(i) = ratio(PRImg(TImg))
        class(TImg) = Classify(CT(TImg), RT(TImg)) using MSVM
for I=1 to TRS
    if (class(TImg) == class(i)) then
        oil-spil-detection-class = class(i)
    end if
```

```
end i
        Read TRSImg
        PRImg = SpecFilter(TRSImg)
        Lth = getLowThreshold(PRImg)
        CTl = complexity(PRImg)
        RTl= ratio(PRImg(PRImg))
        classL = Classify(CTl, RTl) using MSVM
        Hth = getHighThreshold(PRImg)
        CTh = complexity(PRImg)
        RTh= ratio(PRImg(PRImg))
        classh = Classify(CTh, RTh) using MSVM
    clss_oil_dpill_detection = fuse(classL, classh)
return clss_oil_dpill_detection
}
```

The above Pseudocode is implemented and experimented in MATLAB software and the results are verified. For experiment, SAR dataset is taken from RADARSAT-2 SAR dataset [86] publically available in ENVI-simulation software version 4.7, in the internet for comparing the obtained result from MATLAB. The images from RADARSAT-2 SAR issued to get environment visualization images in order to obtain backscatter images and the ROI is extracted.

After the images are applied on speckle noise filter to make the image as smoothen and the interferences are reduced. Finally DT method is applied to segment the dark spots. Low and high thresholds are used to segment the images over spatial density. Segmentation using DT method has reduced false alarm and it is proved in the experiment. Because the DT method repair images by enhancement and it make separation between the dark spots and sea background.

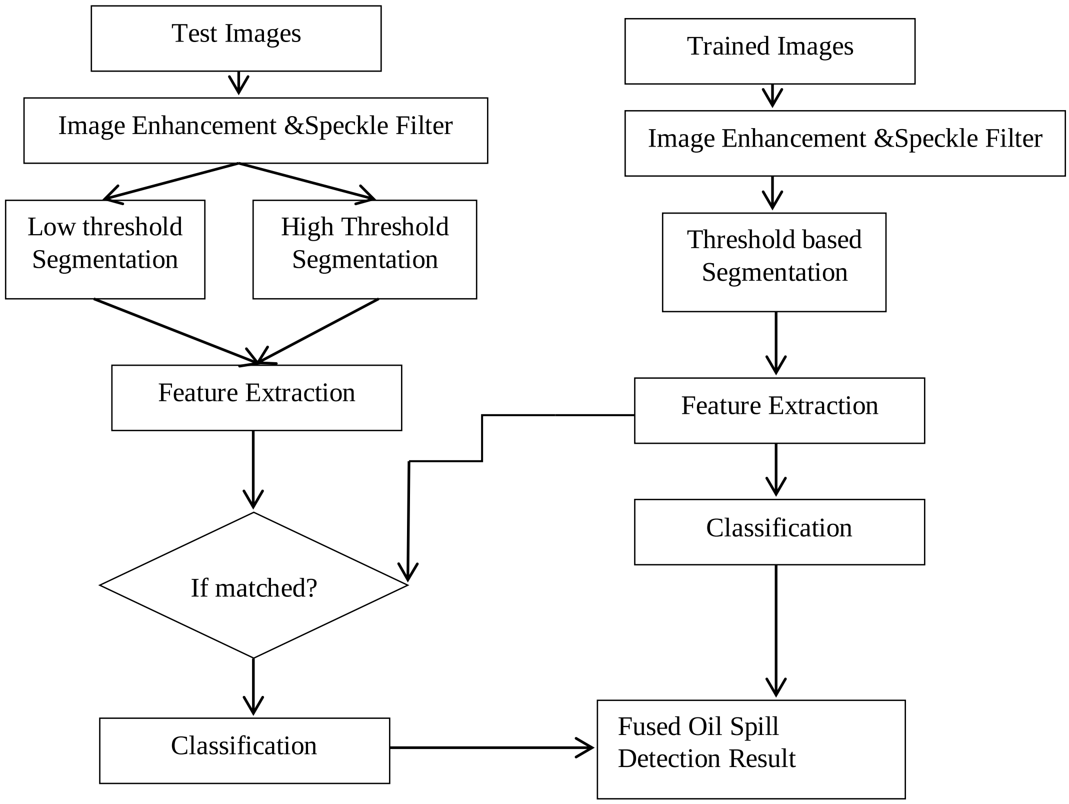

Figure 5.2 Overall Functionality of DT-MSVM approach

The intensity of the images is calculated using intensity estimator $g(\,)$of a pixel (x, y) in the SAR images and it can be calculated using the following equation 5.7.

$$g(x, y, t) = \frac{1}{n^2 2\pi t} \sum_{i=1}^{n^2} e^{\frac{(x-x_i)^2+(y-y_i)^2}{2t^2}} \qquad (5.7)$$

Where, t is the variation in the speckle filter and n says the size of the sample window.

The dark spots are classified according to the extracted values of the parameters such as CT and Rt. The MSVM is designed based on the training data stored initially. For high-threshold result, dark spots too minor or too nearby to the seashore were omitted. At last the results are obtained by fusing the results from both levels of the segmentations and it is represented mathematically as equation 5.8 as shown below

$$\begin{cases} CT_{(ij)} = 1, & (CT_{low(ij)} = 1 \; and \; CT_{high(ij)} = 1 \\ CT_{(ij)} = 0, & else \end{cases} \tag{5.8}$$

Where, CT_{low} denotes the low threshold CT value and CT_{high} denotes the high threshold CT value where CT illustrates the final results of the oil spill detection.

5.4 Experimental Results and Discussion

This approach is implemented and results are verified in MATLAB software. The performance of the proposed approach is evaluated by comparing the results with the existing approach in term of Sensitivity, Specificity and Accuracy based on oil spill detection and classification. From the performance evaluation, it is proved that the proposed Dual-threshold method with MSVM provide the best results.

In this stage there are 500 images taken for experiment whereas 200 images are applied for training process and the obtained class-labels, feature vectors and the other information's are stored in an appropriate mat files in MATLAB. Both training and testing procedures are carried according to the procedures illustrated in Figure 5.2. The input image is read from the training or testing folder.

Figure 5.3 Sample Input Images

Then the input image in Figure5.3 is preprocessed by removing the speckle noise removal method. This method uses speckle filter which removes the noise and make the image as smooth and good. The necessary result of preprocessing helps to improve the efficiency of image segmentation and classification. The enhanced image in terms of bright and contrast of the image helps to obtain the lower and higher threshold values of the image effectively. The brightness based and contrast based enhanced images are shown in Figure 5.4(a) and in Figure 5.4(b) respectively.

The morphological operations are handled on binary images only shown in Figure 5.5 Initially the image opened, dilated and reconstructed. After enhancing the images the two different threshold values are calculated in the images for oil spill detection. In accordance to the threshold values the dilation operation is applied for segmenting the oil spills. Then the CT and Rt values are calculated for the detected oil spills and the region is extracted from Figure 5.6 and fused oil spill detection in Figure 5.7.

Finally the GLCM method is applied for extracting the texture features for classification. The following features are extracted using GLCM in order to increase the performance of classification. The feature extraction is carried out only on the oil spill region. The features extracted using GLCM is shown in Table 5.2.

(a) Enhanced Image (Bright)

(b) Enhanced Image (Contrast)

Figure 5.4 Image Enhancement

Table 5.1 CT and Rt values of the Sample Input Image

Image	CT (complexity)	Rt (Ratio)
Low-Threshold	2.4634	0.015115
High Threshold	3.023	0.056350

Figure 5.5 (a) Binary Image

Figure 5.5 (b) Binarized Image for Morphological Operations

(a) Dilation Using Low Threshold

(b) Dilation Using High Threshold

Figure 5.6 Morphological Operations (Dilation)

In order to confirm and decide the oil spill detection the extracted feature values from the region is compared with the data extracted from look-alike patches and it is shown in Table 5.2. From the table the detected oil spill region is correct and it is confirmed by comparing with the looksalike values.

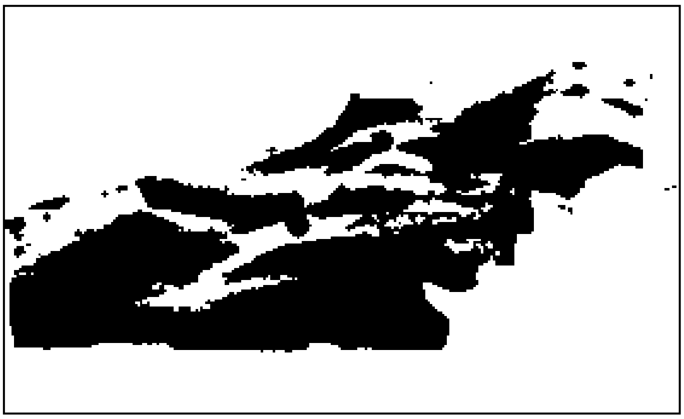

Figure 5.7 Fused oil Spill Detection

Similarly, Table 5.3 and Table 5.4 shows the obtained results in terms of various geometrical features extracted from oil spill and Look-alike respectively. Table 5.5 and Table 5.6 shows the texture features extracted from the oil spill and look-alike respectively. Similarly Table5.7 and Table5.8 shows the extracted features from backscatter for oil spills and look-alike.

Table 5.2 GLCM Features and obtained values for Oil Spill region and look-Alike

Feature	Oil Spill	Look alike
A	980	1423
P	981763.23	1862412.56
CT	2.4705	2.5045
Rt	2.84	2.89
W	256	168
L	512	689
EW	1.1543	1.156

EL	0.9823	0.9952
Homogeneity	0.9953	1
Contrast	0.00342	0
Entropy	0.0231	0
Correlation	0.231	0

Table 5.3 Feature Geometric Values for Oil Spill Region

Features	**DT-MSVM**	**Region Properties**	**Test**
Area	41819	41718	41718
Perimeter	2666	2859	2859
Complexity	3.677	-	195.965
Ellipse Length	1462.6	1354.6	-
Ellipse Width	28.59	-	33.39

Table 5.4 Feature Geometric Values for Look-Alike Region

Features	**DT-MSVM**	**Region Properties**	**Test**
Area	34148	34270	34148
Perimeter	2408	2578	2578
Complexity	3.669	-	194.67
Ellipse Length	800.51	717.87	-
Ellipse Width	42.81	-	49.97

Table 5.5 Texture Feature Values for Oil Spills

Features	**DT-MSVM**	**Test**
Contrast	0.42	0.56
Homogeneity	0.82	0.84
Correlation	0.70	0.45
Entropy	2.06	-

Table 5.6 Texture Feature Values for Look-Alike Region

Features	DT-MSVM	Test
Contrast	0.45	0.34
Homogeneity	0.80	0.88
Correlation	0.62	0.67
Entropy	2.03	-

Table 5.7 Backscatter Feature Values for oil Spill

Features	DT-MSVM	Test
Local Contrast	3.33	3.34
Window Homogeneity	21.29	21.29
Slick Homogeneity	25.20	25.20

Table 5.8 Backscatter Feature Values for Look-Alike

Features	DT-MSVM	Test
Local Contrast	2.80	2.80
Window Homogeneity	20.26	20.27
Slick Homogeneity	23.53	23.53

These obtained features are classified using Multi-Class SVM method and the performance is verified. The performance metrics are sensitivity, specificity and accuracy. The accuracy of DT-MSVM classifier is determined using the performance matrices with the presence of prevalence. To evaluate the performance, the obtained resultant performance matrices are compared with the existing systems such as SVM, CPF and ANN classifiers. From the analysis it is observed that the level of accuracy is increased to 99.03%, sensitivity is increased to 90% and specificity is increased to 99.02% by using DT-MSVM method. The accuracy level is calculated by using equation 5.9.

$$Accuracy = \frac{(TN+TP)}{(TN+TP+FN+FP)} = \frac{Number\ of\ true\ correct\ assessment}{Number\ of\ all\ assessment} \qquad (5.9)$$

The comparative results in terms of performance metrics is given in Table 5.9. From the obtained results and performance evaluation it is deiced that the proposed DT-MSVM method is suitable for SAR image processing and oil spill detection.

Table 5.9 Performance Evaluation that DT-MSVM performance is the same with ANN with slight variation.

Techniques	Accuracy	Sensitivity	Specificity
SVM [1]	90.54	84	91
CPF [2]	96.23	89	98
ANN [2]	98.45	89	99
DT-MSVM	99.03	90	99.02

5.5 Summary

This stage offers an innovative method, namely, DT-MSVM is anticipated for detecting oil spills from SAR images. At first, the SAR images are given as the input of preprocessing, where the speckle noise present in the image is eliminated based on the speckle filters. Then, the preprocessed image is segmented by using the morphological operations. After segmentation, the complexity and ratio values are computed as main features. Furthermore, the features of the segmented image are extracted by GLCM feature extraction technique. Based on these features, the oil slicks and look-alikes are identified by using the MSVM classification method. The performance of the proposed MSVM based oil spill detection system is evaluated and analyzed in terms of accuracy, sensitivity and specificity metrics. When compared to the existing ANN, CPF and SVM methods, the proposed DT-MSVM method provides the best results.