Image Processing for Oil Spill Detection and its Classification using Neural Networks

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Abstract -Oil Spills in ocean is an increasing threat to our ecosystem. Oil Spills happen due to either leakage of oil from ships due to accidents or due to illegal release of oil in the sea by some big companies. In both cases detecting oil spill is an important because oil spills causes environmental problems and endanger the marine life. Many fishes and marine birds die due to oil spill every year. With advent of computing technology and advanced image processing techniques, automatic detection of oil spills using SAR images has become an important area of research. The many challenges in accurately classifying an oil spill from that of look-alikes are a major area of research interest. In this thesis, we have proposed a method for detecting oil spills from that of look-alikes with very high accuracy is proposed. The proposed work has implemented various image processing techniques like thresholding and image segmentation to extract oil spill from the background, and then implemented a pattern recognition system using Artificial neural network which uses a set of features extracted from SAR image of oil spill or look alike and is trained to classify oil spill more accurately than that of look-alikes.

Index Terms -Synthetic aperture radar (SAR), Oil spill detection, marine pollution, feature extraction, image segmentation, Artificial neural network (ANN).

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I. INTRODUCTION

Oil spill is one of the worrisome causes of marine pollution. There are many adverse effects of oil spill that can be environmental, economical etc**.** The aquatic animals are the one most affected by the oil spills. In most cases, the layers of oil on the water surface simply choke the animals to death. Others that live face a number of other problems. The oil finds its way into the fur and plumage of the animals. As a result, both birds and mammals find it harder to float in the water or regulate their body temperatures. Economic loss results in case of oil spills due to accidents and also in the process of cleaning the oil spill, which is indeed a very difficult task.

Synthetic-aperture radar (SAR) is radar used to create images of objects, such as landscapes which can be either 2-D or 3-D representations of the object. SAR uses the motion of the radar antenna over a targeted region to provide finer spatial resolution than is possible with conventional beam-scanning radars. Processing of successive radar echoes is used to create SAR images by using Synthetic antenna aperture and thus allowing higher resolution images than possible with a physical antenna. Image processing techniques on these SAR images can be very much helpful in detecting these oil spills and thus enabling cleaning or treatment of affected parts of the water bodies.

The most prominent cause of problem in research of oil spill detection is to differentiate oil spills from look-alikes. Various weather or oceanographic phenomena can produce in the images same patterns like oil spills. These are called look-alikes and they make the detection of oil spills difficult. In this paper a method for oil spill detection using various image processing techniques and artificial neural network is proposed. The method is capable of differentiating oil spills and lookalike with a good accuracy rate using a learning ANN.

II. RELATED WORK

In the paper entitled "Oil Spills detection in SAR images using mathematical morphology", a new method for marine oil spills detection is presented. It is shown that morphological images analysis techniques are powerful tools to extract accurately dark spots in SAR images, which are candidates to be oil spills. The main goal is that this segmentation can be carried out with no prior knowledge about ocean conditions during the image acquisition process. Moreover, these techniques can also be useful to extract some features used in the decision process of the candidates. Due to the homogeneity of the proposed algorithm it is suitable to be implemented in a quite efficient way. This work is focused to detect oil spills produced for cleaning the tanks of the oil tankers. An accurate extraction of possible oil slicks is performed. Although the algorithm requires more steps than classical approaches, the computational load is low [1].

P.Alli proposed a novel system based on a fuzzy control filtering approach. It uses adaptively varying membership functions and incorporating fuzzy associative memory (FAM) with conventional multilevel median filter (MLMF) to detect the oil spills in SAR images. It also preserves object boundaries and structures, while removing noise effectively in the region of heterogeneous physical properties. This is an attempt to enhance spatial resolution and sensitivity of SAR images for better visualization and analysis. The system minimizes the output mean squared error by tuning the shape of the membership function. A parabolic membership function is used, for the first time, to adaptively fine tune the reduction of noise level in the tomograms. The

performance of the system is tested using oil spill SAR images. The system restores images corrupted with speckle noises of different levels. High impulse noise is effectively eliminated without significant loss in the sharpness of the image features [2].

In the paper entitled "Detection of Oil Spills and Underwater Natural Oil Outflow Using Multispectral Satellite Imagery", the capabilities of multispectral remote sensing images on detecting oil spills and underwater natural oil outflows in oil potential areas are demonstrated. An object based method for oil spill detection using high or very high multispectral images has been developed. The method exploits the knowledge provided by the systematic photo-interpretation of the temporal, spectral and spatial features of the high or very high resolution multispectral datasets. The developed method has been proved to work well in very high resolution satellite images such as IKONOS, QuickBird, RapidEye, and WorldView2, as well as high resolution satellite images (Landsat TM). When repeatedly applied on sequential multispectral imagery, the developed method can reveal potential natural underwater oil outflows. Research showed that the systematic application of the developed oil spill detection method on a sequence of high and very high resolution multispectral images can reveal natural oil outflows on the seawater surface [3].

K. Topouzelis presented another approach of NN use in oil spill detection. The Radial Basis Function (RBF) neural network is investigated in order to be compared with the Multilayer Perceptron. For both networks, several topologies are examined and their performance is evaluated. MLPs appear to be superior to RBFs in detecting oil spills on SAR images. The method was tested on SAR image windows, containing oil spills and lookalikes. RBF networks work faster than LMP. RBF almost guarantee convergence while MLP sometimes stick in local minima. The use of a hybrid algorithm of back propagation and conjugate gradient seems to solve this problem. Moreover, MLP has smaller memory requirements for the classification and has better generalization than the RBF [4].

The paper titled "Feature extraction and classification of oil spills In SAR imagery" discusses about the different feature extraction and classification method for oil spill detection and their preliminary results. SAR is the most promising sensor for oil spill detection, as they are not affected by weather conditions. A hybrid method is applied to enhance the image quality. A fusion technique of GMAC with FCM with thresholding is used to detect the dark spots. The features of dark area are extracted. Then they are classified either as oil spill or lookalike. To improve the accuracies more number of features can be considered. The comparison of different classification methods is desirable with same set of data and features [5].

Li Zhang presented a paper in which an automated method is proposed to segment and quantify the volume of cystoid macular edema (CME) for the abnormal retina with macular hole (MH) in 3D OCT images. The proposed framework consists of three parts: (1) preprocessing, which includes denoising, intraretinal layers segmentation and flattening, MH and vessel silhouettes exclusion; (2) coarse segmentation, in which an AdaBoost classifier is used to get the seeds and constrained regions for Graph Cut; (3) fine segmentation, in which a graph cut algorithm is used to get the refine segmentation result. The proposed method was evaluated in 3D OCT images from 18 typical patients with CMEs and MH. The true positive volume fraction (TPVF), false positive volume fraction (FPVF) and accuracy rate (ACC) for CME volume segmentation are 84.6%, 1.7% and 99.7%, respectively [6].

In a paper presented on image segmentation, De Oliveira has described that inn a first stage a cancer promotes an intense process of vascularization at the affected area increasing blood flow and modifying the local temperature of the body. Using a thermal camera, the infrared radiation emitted by the human body can be captured and then used in the measuring of body temperature, turning the results into an image. Moreover, thermography can detect suspicious regions in patients of any age, even in cases of dense breasts, where the detection of an abnormality cannot be accomplished by others exams. A fundamental step in the use of thermal images is the development of computer aided diagnosis (CAD) systems. These could allow the execution of exams by technicians, following well established routines and protocols, as already occurs in mammography exams, allowing doctors to have a greater possibility of dedication in the analysis and in the meaning of the exams. In this work, an automatic detection of the regions of interest (ROI) is proposed and compared with segmentations performed manually. This work presents a methodology for the automatic segmentation of lateral breast thermal images. For the evaluation of the results, different groups of ground truth are generated, which are available on the internet, in order to allow the verification of the results' correctness. Finally, the obtained results by the proposed methodology for the 328 images used in this work are demonstrated. The results showed average values of accuracy [7].

Tachioka, Y suggested that a recurrent neural network language model (RNN-LM) can use a long word context more than can an n-gram language model, and its effective has recently been shown in its accomplishment of automatic speech recognition (ASR) tasks. However, the training criteria of RNN-LM are based on cross entropy (CE) between predicted and reference words. In addition, unlike the discriminative training of acoustic models and discriminative language models (DLM), these criteria do not explicitly consider discriminative criteria calculated from ASR hypotheses and references. This paper proposes a discriminative training method for RNN-LM by additionally considering a discriminative criterion to CE. We use the log-likelihood ratio of the ASR hypotheses and references as a discriminative criterion. The proposed training criterion emphasizes the effect of improperly recognized words relatively compared to the effect of correct words, which are discounted in training. Experiments on a large vocabulary continuous speech recognition task show that our proposed method improves the RNN-LM baseline. In addition, combining the proposed discriminative RNN-LM and DLM further shows its effectiveness [8].

Another paper entitled "Oil Spill Detection by SAR Images: Dark Formation Detection, Feature Extraction and Classification Algorithms" provides a comprehensive review of the use of Synthetic Aperture Radar images (SAR) for detection of illegal discharges from ships. It summarizes the current state of the art, covering operational and research aspects of the application. Oil spills are seriously affecting the marine ecosystem and cause political and scientific concern since they seriously affect fragile marine and coastal ecosystem. It discusses the most common techniques to detect dark formations on the SAR images, the features which are extracted from the detected dark formations and the most used classifiers. The capability of space-borne SAR

sensors to detect oil spills over the sea surface is well known and proven. The possibility of using space radar imagery for long term monitoring of operational oil pollution at basin scale has also been demonstrated [9].

III. METHODOLOGY

In the current methodology of oil spill detection, few steps are done in a sequence to completely make the experiment and formulate the findings. Different SAR images are acquired and then each image is applied few image segmentation steps like image histogram equalization, image thresholding, cleaning the binary image to extract a blob. This blob is the region of interest that will be used in our work. Many features of this region of interest are collected to make the final feature set. Using a whole set of images, a feature dataset with pre-labeled class information was formed. This information or feature matrix is then divided into two sets, a training set and a testing set. The training set was then used to train the designed neural network. The test set was used to test the trained network to plot the overall result. The methodology block diagram is shown in Fig.1.
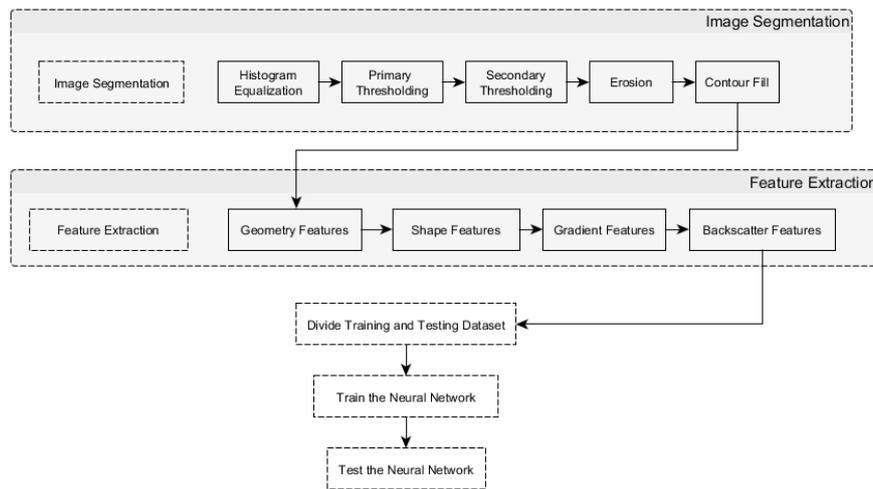
Figure 1: Methodology Block Diagram

Step-1: Image Processing and Image Segmentation

Image Segmentation is the primary step to extract the region of interest (ROI) from the image. There are different methods for image segmentation which can be used to extract the region of interest from an image. In our case, we have followed a method which is modified version of adaptive thresholding. We performed a few steps in sequence to extract the ROI from a SAR image.

Histogram Equalization

When an image is loaded, the first step performed on it is histogram equalization. Histogram equalization is an important step to balance the overall pixel gray scale distribution. With histogram equalization, the overall pixel distribution from pitch black (0) to white (255) is equalized. This helped a lot in the next step to decide the primary and secondary thresholding levels.
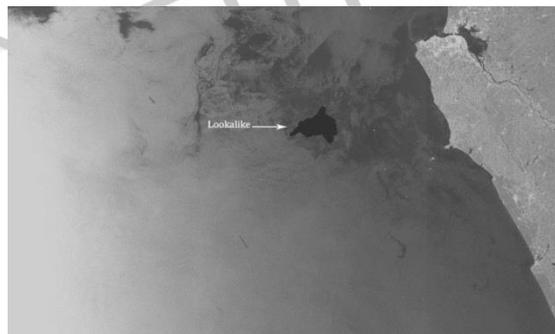
Figure 2: An image of a Lookalike sample

Primary Thresholding

Primary thresholding was performed to move those colours on the opposite end of the range which can be extracted by single level threshold. The selection was simply based on the fact that in SAR images, most of the portions like land surfaces etc have a white range because they reflect most of the waves back. Water has a gray range and spills have dark to black range. With primary thresholding, these gray areas were moved to white range of land region. Now the separation is only into bright area and dark spot which might be oil spill.
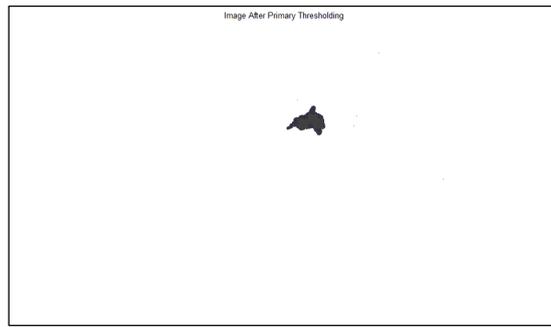
Figure 3: Image after Primary Thresholding
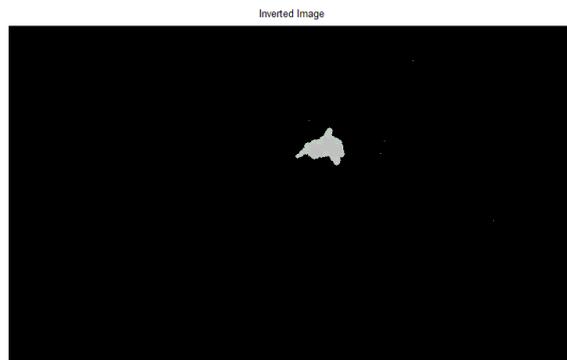
Figure 4: Inverted Image after Primary Thresholding (It's not binary)

Secondary Thresholding

Secondary thresholding is done on complemented image to extract exactly two regions, background and spot. The image is a binary image and has white spot and some noise and black background represented in binary form as 0 for black and 1 for white and is shown in Fig.5.
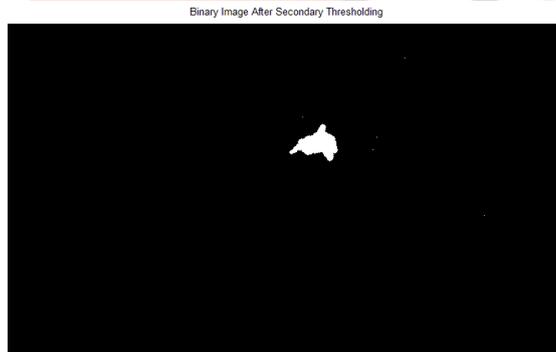
Figure 5: The Binary Image with lots of small white spots can be seen

Erosion

Erosion is a morphological operation. It is performed to remove all those small noises that the image has, which makes the spot stand out and leave only white region of interest in whole binary image.

Contour Fill

Contour fill is performed to fill any black spot or holes left in the closed contour i.e. the extract spot and the output image is shown in Fig.6

Figure 6: Isolated Spot from the image after performing morphological fill operation and erosion operation.

Step-2: Image Feature Extraction

There are different features that were extracted in order to form a dataset of the image which can be used to train our neural network. The features that were extracted from the binary image can be divided into four categories.

Shape Features:

1. Area: ROI
   Area is simply the total number of pixels in a given region, in our case, the extracted spot.

$$Area = \sum_{i=0}^{n} \sum_{j=0}^{m} roi\_x(i,j)$$

2. Perimeter: ROI
   Perimeter is the length of the closed contour of the spot. It is calculated by summation and has a unit of pixel.

$$Perimeter = \sum_{i=0}^{n} \sum_{j=0}^{m} boundary(roi\_x)(i,j)$$

3. Shape Complexity: ROI
   Shape complexity parameter of a shape or geometry is a measure of how complex a shape is. It is like how many simple geometry it has to form the shape. All real world objects have a complex shape, so a high value of complexity.

$$Shape\ Complexity = \frac{Perimeter}{2 \times \sqrt{\pi \times Area}}$$

Backscatter Features:

4. Mean: ROI
   Average Region of Interest is simply the mean pixel value of that region. It is a gray scale value parameter and it defines the average gray scale level of the region of interest.

$$Mean\ ROI = \frac{\sum_{i=0}^{n} \frac{\sum_{j=0}^{m} roi\_x(i,j)}{m}}{n}$$

5. Mean: Non-ROI
   Mean Non-ROI is again the mean gray scale level of the background.

$$Mean\ NonROI = \frac{\sum_{i=0}^{n} \frac{\sum_{j=0}^{m} non\_roi\_x(i,j)}{m}}{n}$$

6. Standard Deviation: ROI
   This parameter defines the standard deviation of the gray scale level from its mean value.

$$Standard\ Dev. ROI = \sqrt{\frac{\sum_{i=0}^{n} \frac{\sum_{j=0}^{m} (Mean\ ROI - roi_{x(i,j)})^2}{m}}{n}}$$

7. Standard Deviation: Non-ROI
   This parameter defines the standard deviation of the gray scale level from its mean value.

$$Standard\ Dev. NonROI = \sqrt{\frac{\sum_{i=0}^{n} \frac{\sum_{j=0}^{m} (Mean\ NonROI - non\_roi_{x(i,j)})^2}{m}}{n}}$$

8. Power to Mean Ratio: ROI

$$Power\ to\ Mean\ Ratio\ ROI = \frac{Standard\ Dev. ROI}{Mean\ ROI}$$

9. Power to Mean Ratio: Non-ROI

$$Power\ to\ Mean\ Ratio\ NonROI = \frac{Standard\ Dev. NonROI}{Mean\ NonROI}$$

Gradient Features:

10. Gradient Mean: ROI

$$Grad.Mean = \frac{\sum_{i=0}^{n} \frac{\sum_{j=0}^{m} (\nabla \text{ val\_roi}(i,j))}{m}}{n}$$

11. Gradient Standard Deviation: ROI

$$Grad.Standard\ Dev = \sqrt{\frac{\sum_{i=0}^{n} \frac{\sum_{j=0}^{m} (Grad.Mean - \nabla \text{ val\_roi}(i,j))^2}{m}}{n}}$$

12. Gradient Maxima: ROI

$$Grad.Maxima = \max((\nabla \ val\_roi))$$

13. Gradient Minima: ROI

$$Grad.Minima = \min((\nabla \ val\_roi))$$

14. Gradient Power to Mean Ratio: ROI

$$Grad.Power\ to\ Mean\ Ratio = \frac{Grad.Standard\ Dev}{Grad.Mean}$$

Geometry Features:

15. Convex Area: ROI

$$Convex\ Area = dx \times dy$$

16. Normalized Area: ROI

$$Norm.Area = \frac{Area}{Convex\ Area}$$

17. Aspect Ratio: ROI

$$Aspect\ Ratio = \frac{dmin}{dmax}$$

18. Circularity: ROI

$$Circularity = \frac{4 \times \pi \times Area}{Perimeter^2}$$

19. Convex Perimeter: ROI

$$Convex\ Perimeter = 2 \times (dx + dy)$$

20. Waviness: ROI

$$Waviness = \frac{Convex\ Perimeter}{Perimeter}$$

21. Contrast: ROI

$$Contrast = Mean\ NonROI - Mean\ ROI$$

These features extracted from the images composed a feature set.

Step-3: Training ANN

The images are then divided into training and testing set. The training set is then passed to an artificial neural network for training the network .We have simulated the whole system in MATLAB using its Neural Network Toolbox. The network we created for the experiment has two hidden layers with 11 nodes and 2 nodes for 1st and 2nd hidden layer, respectively as shown in Fig.7. The input layer has 21 nodes as we have extracted 21 features from our image dataset.
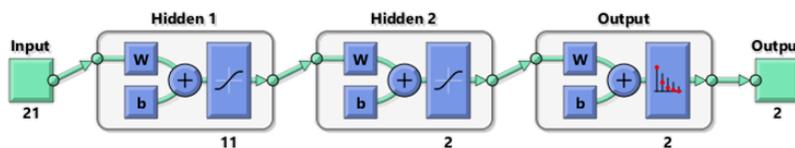
Figure 7: The neural network schema for our experiment

The Artificial Neutral is a feed forward network. We used a training function called Scaled Conjugate Gradient for training of the network.

Scaled Conjugate Gradient

Scaled Conjugate Gradient (SCG) is a supervised learning algorithm for artificial neural networks with super linear convergence rate. This algorithm is based upon a class of optimization techniques well known in numerical analysis as the Conjugate Gradient Methods. SCG uses second order information from the neural network but requires only O (n) memory usage, where n is the number of weights in the network. SCG yields a speed-up of at least an order of magnitude relative to Back Propagation (BP). The speed-up depends on the convergence criterion, i.e. the bigger demand for reduction in error the bigger the speed-up. SCG is

fully automated including no user dependent parameters and avoids a time consuming line-search, which CBG and BFGS use in each iteration in order to determine an appropriate step size [12].

After the training step is performed, the network is ready to be tested with the testing data set. The tests were performed and the results were analyzed and summarized.

IV. RESULTS AND DISCUSSIONS

Image Segmentation and Feature Extraction

As experiment we performed to automatically detect oil-spills required SAR images, so we collected 30 images from multiple sources to build our dataset. We then performed image processing and image segmentation techniques which includes Histogram Equalization, Primary Thresholding, Image Complement and Secondary Thresholding to extract the oil-spill or look-alike spot from the image. Further morphological techniques like Erosion and Contour Fill were used to remove small pixels and a thick spot was extracted as a result. After the extraction of spot, we calculated different features like area, moment, aspect ratio etc. of the given spot. This led to a feature set of 21 features. These features were used by an artificial neural network for training and classification of an image as oil-spill or lookalike.

Artificial Neural Network – Training Stage

We divided the available dataset of images into training and testing sets. Training dataset consisted of 12 images. During the training state the gradient and validation values are plotted in Fig.8 (a) and Fig.8 (b) respectively.
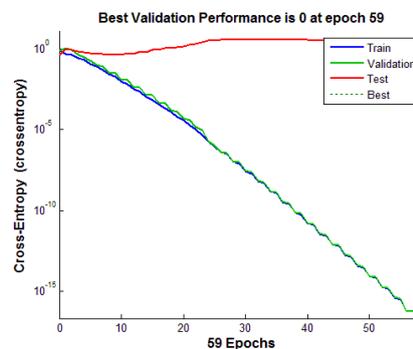
Figure 8 (a): Performance graph over training of the neural network.
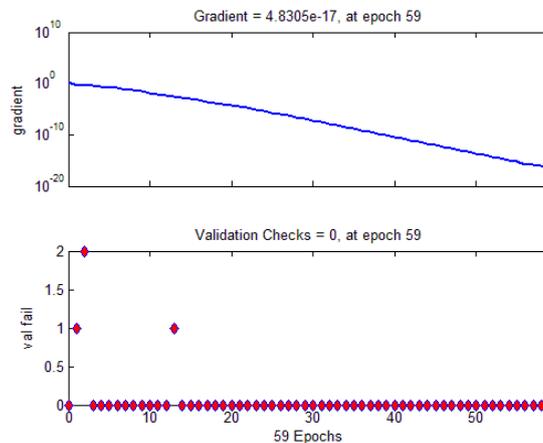
Figure 8 (b): Training State of the neural network

Artificial Neural Network Testing Stage

For testing stage, we used testing dataset consisting of 18 images. This way, we had exactly 9 images of lookalikes and 9 images of true oil-spill. The system's accuracy is summed up by the confusion matrix we generated. Fig.9 shows the confusion matrix generated by MATLAB program. This confusion matrix shows the overall and per class accuracy and error percentage and also shows the information like total number of test samples used and samples of each class and number of correctly predicted samples from both classes.
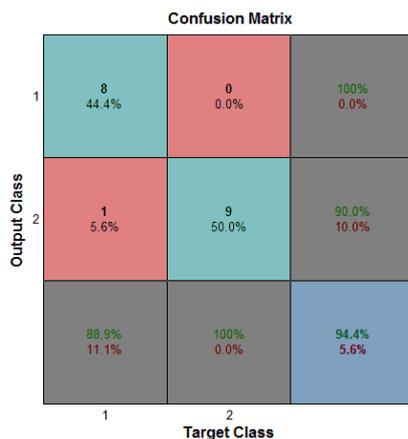
Figure 9: The confusion matrix of the testing (Generated by MATLAB)

Table 1 represents the performance level of our proposed methodology in form of an error matrix. It was possible to achieve an overall accuracy rate of 94.4% using a test set of 18 SAR images with 17 true classifications and 1 false classification.

Table 1 Performance Error Matrix

	Actual Oil Spill	Actual Look-alike
Predicted Oil Spill	8	0
Predicted Look-alike	1	9

V. CONCLUSION

We have studied oil-spill detection as an important field for environment protection. We have studied that oil-spill detection is very necessary for protecting marine life which is affected adversely due to these oil-spills which can be cause by natural incidents like accidents or sometimes oil is released in the sea by many companies illegally. We have studied the current development in automatic oil-spill detection using artificial neural networks. We then developed an improved oil-spill detection system with high accuracy of 94.4%. The system used artificial neural network as pattern recognizer and classifier.

The future scope of this work is to test with other configurations of ANN and features. We can also test the system with DNN (Deep Neural Networks) which are also known as multilayer convolution neural networks for detection and predication of high level of accuracy. The convolution neural networks learn in a very different manner and use another technique for shape, pattern and other important feature extraction and recognition. So, they can yield more ideal results.

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