Integration of Statistical Methods and Artificial Neural Networks for the Detection of Oil Stains in the Aquatic Environment

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Keywords: Linear Discriminant Analysis, Machine Learning, Oil Stain Detection, Classification, Predictive Model, Artificial Neural Networks.

Abstract: The growth in oil exploration and transport increases the risk of accidents in the aquatic environment. Early detection of oil slicks in the aquatic environment is essential to minimize the risk of accidents, as well as effective decision-making. Thus, a method for detecting oil stains is needed to reduce the damage caused by industrial activities to the environment. This article presents statistical methods of classification and machine learning to detect oil slicks on the ocean surface. For this, images from a Synthetic Aperture Radar (SAR) were used. The proposed model for detecting oil slicks uses Linear Discriminant Analysis (LDA) to generate an estimate of the class to which the database images belong (image without oil slick, and image with oil slick), and the Artificial Neural Network (ANN) to classify the data, in which these data come from the grouping of the image with the result of the LDA. With the results obtained, it is concluded that the proposed method of detecting oil slicks on the ocean surface can detect oil slicks with good accuracy.

1 INTRODUCTION

The world production of hydrocarbons, especially oil, began in the mid-twentieth century and has since grown exponentially. According to data from the National Agency of Petroleum, Natural Gas and Biofuels (ANP), total oil production in Brazil in 2019 was 1.017 billion barrels (ANP, 2020).

The growth in production, consumption, exports and imports of oil and its derivatives increases the probability of oil spill accidents. Consequently, it is important to develop efficient techniques to prevent, detect and monitor oil slicks.

Several studies are presented in the literature related to oil spills for the detection of oil stains. Some studies treat stain detection as a segmentation problem (Krestenitis, M. O., 2019), in which they use deep convolutional neural networks (DCNN) to perform semantic segmentation of the image in various areas of interest, including oil spill, which makes it easier to detect the oil stain.

Remote sensing based on Synthetic Aperture Radar (SAR) has been widely used for monitoring oil slicks in the ocean, due to its wide area coverage and its ability to operate in all climates. However, recently Andreotti and Peixoto (2020) developed an autonomous system (called ARIEL), combining an autonomous vessel (unmanned surface vehicle) and a drone. These two subsystems work together to monitor a region of interest where oil spills are likely to occur.

In this context of oil detection, the objective of this work is the elaboration of an algorithm for the detection of anomalies (oil stain on the surface of the ocean), with time and memory restrictions, so that it can be embedded in mobile sensors. To achieve this goal, the integration of statistical methods and artificial neural networks is proposed.

The focus of this work is the integration of statistical methods (linear discriminant analysis) and the simplest ANN (perceptron). Well, this detection is part of a work in progress, which wants to adjust the positioning of the sensor to monitor (track) the oil stain, based on the geographic positioning of the anomaly. Consequently, the effective contribution of this work lies in the development of an algorithm for detecting oil slicks on the ocean surface to be embedded in the sensor, so that the detection of the slick is done online, alerting if it detects an oil slick, avoiding greater damage to the aquatic environment and the coastal population.

Throughout this article, the steps of the proposed methodology for the detection of oil slicks in the

Sousa, M. and Neto, J.
Integration of Statistical Methods and Artificial Neural Networks for the Detection of Oil Stains in the Aquatic Environment.
DOI: 10.5220/0011799300003411
In *Proceedings of the 12th International Conference on Pattern Recognition Applications and Methods (ICPRAM 2023)*, pages 550-557
ISBN: 978-989-758-626-2; ISSN: 2184-4313

aquatic environment are presented, based on the integration of statistical methods and artificial neural networks (ANNs). In Section 2, the proposed oil stain detection system is presented, in which the block diagram of the proposed predictive model is exposed and from it it is reported on its blocks that are being explored: SAR measurements and critical modeling. Section 3 presents the results of computational experiments resulting from the implementation of the proposed integration method. In Section 4 the conclusion is presented.

2 OIL STAIN DETECTION SYSTEM

In this section, the proposed integration method is presented, in which its scheme is illustrated by the block diagram of Figure 1, then each block of the diagram is reported as: SAR measurement block, which exposes the base used in this work, block of the critic, which is where the proposed method is located, that is, where the Linear Discriminant Analysis (LDA) and the Artificial Neural Network (ANN) are located. In addition to also exposing the metrics to evaluate the performance of this proposed method.

2.1 Proposed Predictive Method

The proposed predictive method for detecting oil slicks on the oceanic surface is based on the integration of statistical methods, multivariate data analysis with the artificial neural network. The multivariate data analysis technique is used to estimate the class that the data belongs, that is, if SAR image has an anomaly or not, then this data is added to the concatenated vector of the image to add more information, helping in the classification. This method is contextualized as the critical module of the system dedicated to decision making, considering the process as the aquatic environment and oil slicks as disturbances, and this process is monitored by Synthetic Aperture Radar. Figure 1 illustrates this system in a block diagram.

According to Figure 1, the block diagram of the proposed predictive method, having as reference signal the clean aquatic environment (without stains), the critic is responsible for acquiring the classifier model from the interaction of the LDA and of ANN, which has as answer the classification of the image with oil stain or without oil stain. This answer is used for decision-making, because if an oil stain is detected, it is necessary to apply certain measures to contain the stains in order to minimize the environmental impacts that they can cause.

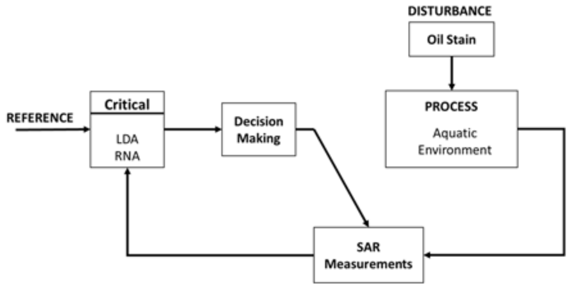

Figure 1: Block diagram of the proposed predictive method.

The process that is aquatic that you want to monitor, which can be close to the oil and gas exploration and production industries and where there is a large flow of ships, since most of the oil is transported by ships. Oil slicks are considered as process disturbances, and measurements of the aquatic environment are performed by SAR. These SAR measurements are inputs to the critic, which is based on multivariate analysis of data and ANN, and the key between the decision-making process and the measures applied by an external individual.

2.2 SAR Measurements

Remote sensing systems have been widely used to detect stains resulting from oil spills at sea. The radar is a simple system that basically consists of the transmission and reception of electromagnetic pulses, the Synthetic Aperture Radar (SAR) is a form of radar widely used to capture images, because as long as the monitored systems are active, that is, they provide with its own lighting, the SAR is capable of acquiring images during the day and also at night, as its radiation belongs to the microwave region.

In this study, the database provided by the Oil Spill Detection Dataset – MKLab, which contains 1112 images, 1002 for training and 110 for testing, used. In total there are 880 images with oil slicks on the ocean surface and 232 clean images without oil slicks. In Figure 1, this database is illustrated by the block of images of SAR measurements that describe instances of oil spills, similar (which look a lot like an oil slick, but are not), land, sea and sea areas.

For the monitoring of the aquatic environment, the SAR images contained in that base were used, which were acquired through the missions of the European satellite Sentinel-1, during the period from September 28, 2015 to October 31, 2017. Geographic coordinates, and date and time of the pollution event were provided by the European Maritime Safety

Agency (EMSA) through the CleanSeaNet service (Krestenitis, M. O., 2019).

The terrestrial range coverage of the SAR sensor used by the Sentinel-1 mission is approximately 250 km, with pixel spacing equal to 10 × 10 m, therefore, this radar can cover a large area of interest, in addition to capturing relatively small-sized instances. This employed system operates in the c-band, and the polarization of its radar is double, that is, transmitted vertical polarization – received vertical polarization (VV) and transmitted vertical polarization – received horizontal polarization (VH). To build the dataset, only the raw data from the VV band was processed, following a series of pre-processing steps to extract common views (Krestenitis M. O., 2019). The captured images have a dimension of $1250 \times 650 \times 3$ pixels, and in this work these images were resized to $63 \times 33 \times 3$ pixels. Figure 2 illustrates an image captured by this SAR system.

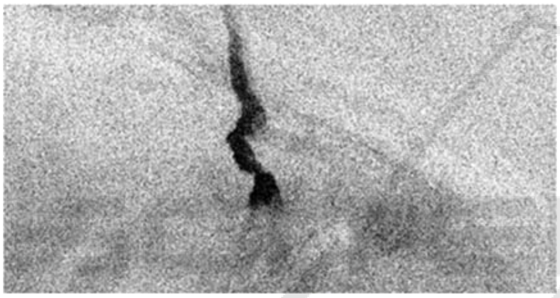

Figure 2: SAR measurements.

Based on Figure 2, an elongated black spot can be seen, which stands out in the image. This format of stains are usually oil spills and can be identified in the database.

2.3 Critic's Modelling

In this section, the modelling of the critical block is exposed, which is the integration of the linear discriminant analysis with the artificial neural network, to then perform the image classification. In which, the LDA adds more information at the time of classification.

2.3.1 Statistic Analysis

The statistical modelling proposed for detecting and classifying oil slicks on the surface determined in four steps: capture of non-segmented images, dimensionality reduction, class estimation and finally image classification.

Considering the oceanic surface, images of the surface are first acquired, that is, the surface to be monitored, then the dimensionality is reduced and the classes are estimated via multivariate analysis techniques. Finally, artificial neural networks are used to classify the images, with the images being classified into two groups: surface with oil stains and clean surface (without oil stain).

- **Linear Discriminant Analysis**

The linear discriminant analysis (LDA) technique was used to obtain class estimates from the 1.112 images (clean ocean surface or oil slick). The LDA is used to analyse the relationship between a non-metric dependent variable and a metric independent variable (explanatory variables or also called predictors) (Hair, J. F et al, 2019).

Algorithm 1: LDA.

- **Startup**

Read the images;

Resize the images;

- **LDA**
  - **Average of each class**

$$\mu_j \leftarrow \frac{1}{n_j} * \sum_{j=1}^{n_j} x_{ij};$$

  - **Covariance matrix**

$$\phi_j \leftarrow I_j - \mu_j;$$

$$S_{B_j} \leftarrow (\phi_j * \phi_j')/(n_j - 1);$$

$$S_B \leftarrow \frac{1}{(n_1 - 1) + \cdots + (n_c - 1)} * \sum_{j=1}^{c} (n_j - 1) * S_{B_j};$$

  - **Midpoint between classes**

$$m \leftarrow \frac{1}{2} * [\mu_1 - \mu_2]' * S_B^{-1} * [\mu_1 - \mu_2];$$

  - **Discriminating vector**

$$L \leftarrow [\mu_1 - \mu_2]' * S_B^{-1};$$

  - **Discriminant function**

$$D(x) \leftarrow L * x_i$$

  - **Classification**

$$\begin{cases} D(x) \geq m \rightarrow C_1 \\ D(x) < m \rightarrow C_2 \end{cases}.$$

  - **End of algorithm**

The development of the LDA is carried out from the following steps: the first step is to calculate the mean of the classes, to then calculate the covariance of the classes and then the common covariance matrix of the classes. The second step is to calculate the discriminant vector, which is used to construct the differential equation that satisfactorily classifies the classes, increasing the variance between classes and minimizing the variance within classes (Duda, R. O., Hart, P. E., Stork, D. G., 2001). The last step is the classification rule based on Fisher's discriminant function, but for that it is also necessary to calculate the midpoint between the classes. These steps of the LDA algorithm are presented below, in Algorithm 1.

According to the LDA algorithm, we have μ_j the average of class j, x_{ij} the samples of class j, n_j the number of images acquired from class j, c the number of classes, ϕ_j the subtraction of data from class j by the average of class μ_j, S_{B_j} the covariance matrix of class j , S_B the common covariance matrix of the classes, x the input data for the LDA classifier, m the threshold, the midpoint between the classes, and $D(x)$ the output of the classifier.

2.3.2 Artificial Neural Networks

For classification purposes, a feedforward artificial neural network (ANN) was also implemented, which is widely used for the classification of separable patterns. The ANN consists of several neurons with their synaptic weights and bias, which are processed by the linear combiner, given by

$$u_k = \sum_{j=1}^{m} w_j * x_j, \tag{1}$$

and

$$y_k = \varphi(u_k + b_k), \tag{2}$$

where $x_1, x_2, \dots, x_m$ are input signals, $w_1, w_2, \dots, w_m$ the synaptic weights of the neuron, u_k the output of the linear combiner due to the input signals, b_k or low, $\varphi(.)$ the activation function, and y_k the output signal of the neuron. The adjustment of synaptic weights can be done according to the error correction learning rule (Haykin, 2009), which is given by

$$w(n+1) = w(n) + \eta[d(n) - y(n)]x(n) \tag{3}$$

where $w(n)$ is the current weight and $w(n+1)$ the next iteration, η the learning rate, $[d(n) - y(n)]$ the error signal, which is the difference between the desired signal and the output of the perceptron.

The learning algorithm adopted for training the MLP network was error backpropagation, or also called backpropagation, which is widely used for supervised training. The algorithm adjusts the network weights by calculating the difference between the value estimated by the ANN and the observed value (HAYKIN, 2011). Algorithm 2 shows the steps to achieve the goal, which is to classify the images via ANN.

In the present study, the variable of interest, denoted by D, is the presence of an oil slick on the ocean surface. Therefore, the training targets in the ANN output layer were defined as follows: 1 – presence of stain and 0 – otherwise.

Algorithm 2: MLP.

- **Startup**

$Load\ data;$
$Read(data);$
$X\_Train(i,:) \leftarrow data(training);$
$X\_Test(i,:) \leftarrow data(test)$
$d\_Train \leftarrow classes;$
$d\_Test \leftarrow classes$
$b = [1 \ \cdots \ 1]_{1 \times l};$
$W = \begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix}_{N \times (p+1)}$
$epoca = 1000;$

- **Iterative Process**
  - **Weighted Sum**

$D \leftarrow \sum_{i=1}^{l} W * img(i,:);$

  - **Activation Function**

$R \leftarrow ReLU(D);$

  - **Weight Update**

$IF\ d \neq D\ THEN$
$\Delta W \leftarrow \eta * \big(d(i) - D(i)\big) * img(i,:);$

  - **End Loop**

Different ANN architectures are considered in this study. The choice of the number of neurons in the hidden layer of the network, as well as the number of hidden layers were done through experiments, always looking for networks with a smaller number of hidden neurons and with a good generalization power, reducing the problem of overfitting (overfitting).

The formation of the training and test sets for the implementation of the ANN used the division that already came in the database.

2.3.3 Metrics for Performance Evaluation

The classifier may present an error in its classification, consequently, it is necessary to use the evaluation metrics to evaluate the performance of the obtained predicted model. Consequently, the main objective of these metrics is to measure how far the model is from the ideal classifier (classifier that does not present errors). The following metrics used: accuracy, precision, recall, F1 measure, and ROC curve.

Accuracy (AC) measures how many images were correctly classified, regardless of class, so the greater the AC, the more the predicted model approaches an ideal classifier, and is given by the ratio between the number of correctly classified samples and the total number of samples, given by

$$AC = \frac{TP + TN}{TP + FN + TN + FP}, \quad (4)$$

where TP is the true positive are images showing oil slicks on the ocean surface (positive) that are classified correctly, TN being true negative are images without oil slicks (negatives) that are classified correctly, FP the false positive which are the images without stains that are classified as positive and FN the false negative which are the positive images that are classified as negative.

Precision (P) is defined by the ratio between the number of images with oil stains classified correctly and the total number of images classified as positive, given by

$$P = \frac{TP}{TP + FP}. \quad (5)$$

Therefore, Equation (5) can be understood as the number of images with oil stains that were classified correctly.

Recall, also known as sensitivity, is defined by the ratio between the number of images with oil stains classified correctly and the number of images with oil stains in the sample under study, given by

$$recall = \frac{TP}{TP + TN}. \quad (6)$$

The F1 metric takes into account both precision and recall, it is defined as the harmonic mean between precision and recall, given by

$$F1 = 2 \times (P \times recall)/(P + recall). \quad (7)$$

According to Equation (7), it is noticed that if the precision or the recall is equal to zero or very close to it, the F1 will be low, so the classifier model is not a model capable of getting its predictions right.

The ROC curve (Receiver Operating Characteristic) and the Area Under the Curve (AUC) also built to evaluate the performance of the ANN, as they are important tools to compare the performance of binary classification models. The ROC curve is a graphical representation of the performance of a quantitative data model according to its sensitivity rate (fraction of true positives) and the fraction of false positives.

It is used to evaluate the ability of a classifier to distinguish between existing classes, in addition to allowing visual analyses between precision and recall relative to different cut-off points, where the false positive rate is represented on the abscissa axis and the true positive rate is plotted on the ordinate axis. The AUC contributes to the interpretation of the ROC curve, because, as its name implies, it is the value of the area under the curve, and this value varies from 0 to 1 (or from 0% to 100%), in which the value of AUC for 1 indicates that the classifier model is great and that it did not make a prediction error, whereas if AUC is 0 it indicates that the model is bad and that it misclassified all inputs.

3 RESULTS

Considering that the objective of this work is to develop an algorithm for detection of oil slicks on the surface of the ocean. The proposed algorithm is based on the integration of a statistical method and an artificial neural network, as presented in the previous sections.

To obtain the results, the following steps are performed. First, the acquisition of the SAR measurements is performed. Next, the discriminant function is computed from the training data. Finally, the tests are carried out and the results of these two analyses (training and test) are stored, as they will be used as additional information in the ANN, along with the SAR image. These results of this procedure are presented in the rest of the section.

First, an analysis of the distribution of images was carried out, seeking to identify similarity between the distribution of images without oil stain and images with oil stain. This distribution analysis contributes to the choice of the predictive model. For this, four images from each group were randomly selected and the histograms of the pixels of the images were plotted, as shown in Figures 3 and 4.

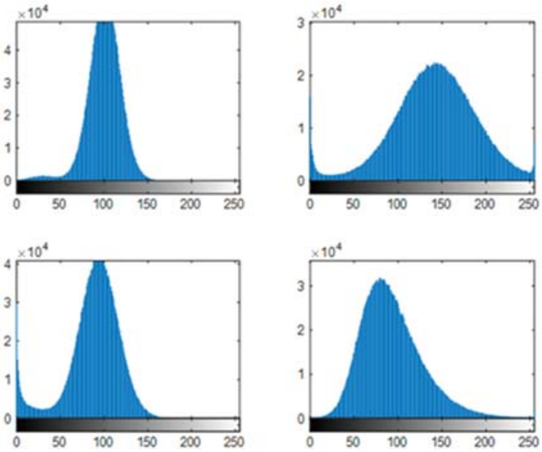

Figure 3: Pixel histogram of 4 images WITH oil stain.

According to Figure 3, the histograms of the oil stain images also show similarity to each other, where their peaks are close to 100, which shows that it has more pixels in the darkest colour, close to the black colour, and a normal distribution. When comparing the histograms of each group, it is observed that there is a difference between the distributions.

According to Figure 4, the histograms of the four images without oil slicks on the ocean surface show a similarity, where the peaks are closer to 150, that is, there is a greater number of pixels that approach the white colour. Another fact to be observed is that the histograms present characteristics of a normal distribution, which is the reference distribution for the statistical methods used in this study.

Then, the linear discriminant function was calculated using this training database, and the discriminant function obtained from this database was 100% correct, that is, it presented a true positive rate of 100% and a false positive rate also 100%.

To verify the effectiveness of the discriminant model, a test was performed with the test database, which contains 110 images. The values of the evaluation metrics are presented in Table 1.

Table 1: Test metrics with the LDA.

METRICS	PERCENTAGE
Accuracy	59.09
AUC	60.80
F1	69.39
Precision	86.44
Recall	57.95

According to Table 1, it is observed that the discriminant function calculated from the LDA presents a good classification, in which an accuracy of 59.09% and a precision of 86.44%. Looking at the

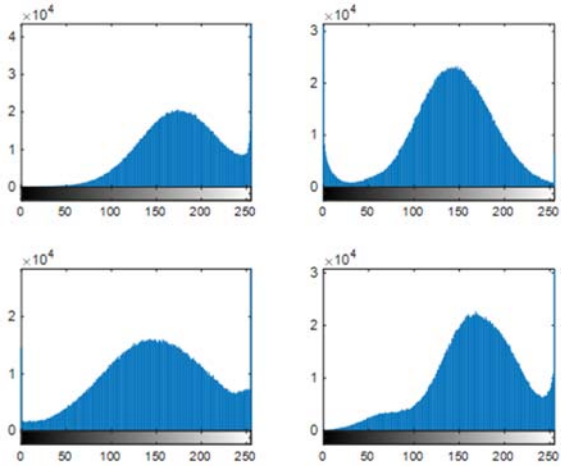

Figure 4: Pixel histogram of 4 images WITHOUT oil stain.

ROC curve, and knowing that it is a graphical technique used to assess the ability of the predictive model to perform proper classification, Figure 5 illustrates the ROC curve for the predictive model.

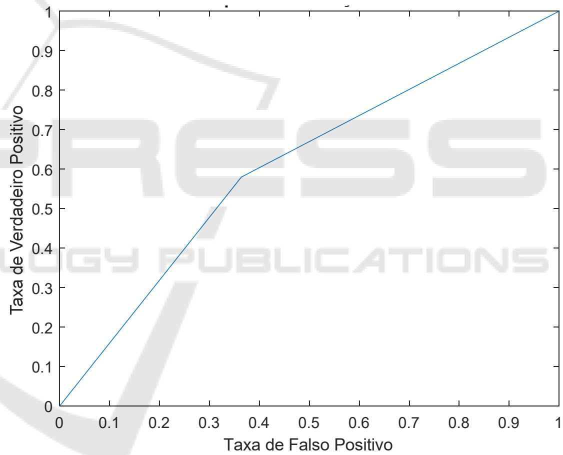

Figure 5: ROC curve for the LDA.

In order to improve the classification, the multilayer perceptron network was used to classify the database, plus the LDA estimate added to the SAR image database, adding more information and the results are presented below.

The first test carried out using a multilayer perceptron (MLP), consisting of an intermediate layer with 6237 neurons, which are the number of parameters of the input data, having as input only the images, in which the training bank consists of 1002 images and the test bank consists of 110. The results obtained for this test are shown in Table 2.

Table 2: Training and testing metrics, input - images.

METRICS	TRAINING	TEST
Accuracy	74.35	69.09
F1	62.00	70.00
Precision	75.00	71.00
Recall	74.00	69.00

According to Table 2, it is observed that the MLP network for images as input presented better metric values for training than for testing. In addition to being more efficient in classifying images that report oil spills on the ocean surface.

The second analysis performed on the MLP network, with an intermediate layer and 6238 neurons, which is the number of parameters of the input data with the classification obtained by the LDA. The results obtained for this test are shown in Table 3.

Table 3: Training and testing metrics, input - images plus LDA rating.

METRICS	TRAINING	TEST
Accuracy	99.90	65.45
F1	100.00	68.00
Precision	100.00	72.00
Recall	100.00	65.00

According to Table 3, the MLP was ideal in training, as metrics equal to 100% were obtained, but in the test, it presented values close to the test using only the images as input. However, it increased precision, and like the previous one, it was more effective in classifying images with oil stain.

The third analysis performed on the MLP network, with an intermediate layer and 6238 neurons, which is the number of parameters of the input data with the value obtained by the linear discriminant function. The results obtained for this test are shown in Table 4.

Table 4: Training and testing metrics, input - images plus response from the discriminant function.

METRICS	TRAINING	TEST
Accuracy	78.94	63.63
F1	71.00	67.00
Precision	82.00	73.00
Recall	79.00	64.00

According to Table 4, the MLP was good in classifying the images with oil stains, and observing the three tests, it was concluded that the added LDA information helped in the training and testing of the network, presenting better values for the metrics of evaluation.

The proposed method integrates approaches from the multivariate analysis technique, Linear Discriminant Analysis (LDA) and Artificial Neural Network (ANN) to allow the detection of oil slicks on the ocean surface, alerting if an oil spill is detected. According to the results presented, the developed algorithm presented a good average for the evaluation metrics and proved to be more efficient than the classification performed by the methods of the two separate approaches.

4 CONCLUSIONS

In view of the growth in oil production and transportation, techniques are needed to monitor the aquatic environment, and to detect oil spills or leaks. Consequently, the proposed method of integrating statistical techniques and artificial neural networks presents a means for detecting oil slicks on the water surface.

This study shown the possibility of detecting oil slicks on the surface of the aquatic environment without the need for image segmentation, being able to automate the detection of oil slicks on the surface of the ocean, alerting if an oil spill is detected.

In possession of the results, the statistical technique and artificial neural network integration method showed greater accuracy than the separate techniques, showing that the proposed method is more efficient for oil stain detection than the linear discriminant analysis methods. and multilayer perceptron network, isolated. This algorithm, therefore, proved to be able to be embedded in a sensor.

Due to the integration of multivariate analysis methods and artificial neural networks, the results showed that the proposed method is more efficient for oil stain detection than linear discriminant analysis methods and multilayer perceptron network without integration. It was observed that the integration of the two approaches presented greater precision than the same ones applied separately. Therefore, the proposed methodology is satisfactory to be embedded in a sensor node to perform local classification based on oil spills or other types of intrusions in coastal areas.

To continue the work and compare the proposed method with a network that uses deep learning, a Unet algorithm is being developed to detect the oil stain, and the next step is the algorithm to adjust the positioning of the sensor so that it can monitor the oil slick.

ACKNOWLEDGEMENTS

We thank the ANP Human Resources Program, which financed the research, the Federal University of Maranhão (UFMA) and its Graduate Program in Electrical Engineering (PPGEE), CNPQ, and Higher Education Personnel Improvement Coordination which encouraged the study in this area of great interest and importance technological.

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