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NOVEL DEEP INTELLIGENCE METHOD FOR THE DETECTION OF ENVIRONMENTAL POLLUTANTS USING SAR IMAGES ON OCEANS

J. Senthil Murugan[1], S. Surendran[2], M.A. Mukunthan[3] and S. Chandragandhi[4]
[1]*Department of Computer Science and Engineering, Veltech High Tech Dr. Rangarajan Dr. Sakunthala Engineering College, India*
[2]*Department of Computer Science and Engineering, Tagore Engineering College, Chennai, India*
[3]*Department of Computer Science and Engineering, Vel Tech Rangarajan Dr.Saguntha la R&D Institute of Science and Technology, India*
[4]*Department of Artificial Intelligence and Data Science, Karpagam Institute of Technology, India*

Abstract

The decline of marine ecosystems poses a substantial threat to the viability of local economies that are reliant on marine life for their continued survival. Artificial intelligence (AI) and machine learning (ML) are two of the several developing technologies that have the ability to address environmental challenges. In particular, ML may be used to better analyse the oceans, keep track of shipping, maintain track of debris in the ocean, unregulated and unreported (IUU) fishing, ocean mining, reduce coral bleaching, and stop the spread of marine diseases. In this paper, we examine the rising prospects and concerns related with the application of AI in the maritime environment, as well as their potential scalability for larger results, using some use-cases to illustrate our points. The results that were obtained when the model prediction was applied to random images are evidence that the model that was suggested provides better outcomes with fewer data points.

Keywords:

SAR, Ocean, Pollution, Deep Intelligence, Detection

1. INTRODUCTION

People including politicians and environmentalists, are expressing their concern with the rising amounts of pollution that can be found throughout the world. The amounts of pollution that have been found in both the air and the water are being fought against with a considerable amount of zeal. The majority of the observed rise in pollution levels may be directly attributed to human activity, which is the primary cause of this trend. waste may be found practically everywhere, including in bodies of water and other distant sites [1].

It is believed that there are currently 5.25 trillion bits of garbage distributed throughout the seas of the planet and it is only going to become worse. There is a growing body of research that suggests a significant portion of the items that end up in the ocean as trash are, in reality, harmful byproducts of industrial processes. Plastics, bottles, and other items that contain chemicals are only some of the many different kinds of harmful contaminants that can be found in the oceans and other bodies of water. Other sorts of toxic contaminants include radioactive materials and pharmaceuticals. Marine life is in jeopardy as a result of the pollution that is caused by these sources, which also has far-reaching repercussions on the environment. These sources are also to blame for the degradation of the environment [2].

The quality of the air, water, and food has all deteriorated of industrial pollution and the strain that population increase has placed on resources that were already in short supply. This is because population growth has placed a greater demand on resources that were already in limited supply. These, in turn, had an effect on both land and water, to the point that it manifested in changes to the temperature of the Earth, resulted in the extinction of numerous ecosystems, and resulted in the production of some completely new norms, all of which contributed to an increase in the likelihood that the planet would be destroyed. All of these factors combined contributed to an increase in the likelihood that the planet would be destroyed [3].

It is more important than it has ever been to keep an eye on pollution in the air, water, and soil in order to decrease the negative repercussions of these elements and to create long-term stability. This is in light of the fact that these changes are having an ever-increasing harmful influence on people health. The only way to halt the acceleration of the environment deterioration and guarantee that future generations will have access to the world resources is to conduct monitoring of this kind [4].

The decline of marine ecosystems poses a substantial threat to the viability of local economies that are reliant on marine life for their continued survival. Some estimates [5, 6] suggest that approximately 91% of the world fisheries have already been fished out. This information is based on reports and estimates. It is anticipated that the ratio of fish to plastic rubbish [7], which is an improvement over the previous ratio of 1:5, which existed in 2014. This suggests that we are heading in the direction of a road that could lead to serious repercussions; as a result, it is absolutely necessary for us to take steps to minimize the damage of our environment.

These technological breakthroughs are having a significant impact on how we learn, how we think, and how we live our lives as a result. Artificial intelligence (AI) and machine learning (ML) are two of the several developing technologies that have the ability to address environmental challenges. Both of these technologies are on the rise. AI would aid in the evolution of the machine, while ML would provide the framework for making predictions and taking action based on past data. ML would offer the framework for generating predictions and taking action based on previous data [8].

ML may be used to the marine environment to better comprehend oceans, keep track of shipping, maintain track of debris in the ocean, unregulated, and unreported (IUU) fishing, ocean mining, reduce coral bleaching, and stop the spread of marine diseases. All of these goals can be accomplished through the use of ML. All of these applications can be used to gather information that can be incorporated into the design of a device or application that can protect marine environments from the damage caused by human activity. AI and ML, when combined, have the potential to assist in the battle against marine pollution and the development of techniques that are friendlier to the environment while extracting resources from the ocean. This would be a situation in which everyone would benefit.

The challenge of identifying waste in water is not a new one; experts from a wide range of professions (civil engineers, biomedical researchers, and others, for example) have made substantial contributions to tackling various parts of the problem. The majority of the difficulties that people confront in the real world today are used by AI models to test and teach themselves on how to solve those challenges. For this reason, it is absolutely necessary to maintain the integrity of this vital ecosystem.

A unique deep learning object detection model was recommended for more research of this finding. This makes it easier to discover and categorize marine debris, such as that which may be found on beaches and in oceans, which is helpful for the purposes of waste mapping and the cleaning of water bodies. These goals can be accomplished through the removal of waste. In addition to this, this helps with cleanup operations and lowers the levels of water pollution, both of which are beneficial for the aquatic creatures that live in the water because they reduce the overall amount of pollution in the water.

2. RELATED WORKS

The increase in the human population meant that the earth resources could no longer keep up with the growing demand. The gathering of food and materials from the ocean transformed from being a luxury into a need. The oceans have been turned into overflowing garbage cans as a result of human activities on land that have contributed to pollution and the depletion of natural resources. These two contributors are responsible for nearly 80% of the total amount of pollution found in the oceans [8].

Scientists have predicted that by the year 2050, there will be more plastic than fish in the oceans throughout the world. The undesirable effects of climate change include, but are not limited to, higher average temperatures, increasing sea levels, and the inability of the ocean to act as a natural sink for carbon dioxide. However, these effects are not the only ones that will occur. The manufacturing of cement and industry on land, in addition to the unsustainable use of fossil fuels, are all contributing factors in the acceleration of climate change. Seven of the United Nation seventeen sustainable development objectives focus on reversing the damage to the environment that has been caused by human activity. These goals were established to ensure the world continued existence [9].

Machine learning refers to the process of training a computer to carry out actions that would generally be carried out by a human being. This method involves teaching a computer to carry out activities that would typically be carried out by a human being. Because of this, the information that was acquired is used to teach the computer how to detect, forecast, and evaluate a target based on the information that it has been given. The information that is gathered by sensors that are situated in the sky is typically relayed as fleeting flashes of light to the ground stations below. Objects floating on the surface of the water absorb near-infrared light in a way that is distinct from the way that water and pollution do, it is feasible to detect items floating on the surface of the ocean more easily using this sort of light. Because various types of floating rubbish on the surface of the ocean absorb light in unique ways, it is possible to educate robots to differentiate between the many different types of garbage [10].

Machine learning cannot, however, extract long-time series data or locally created signals that are only present in a very tiny portion of the remote sensing image. This is because these types of data and signals are only present in discrete regions. This calls for the creation of cutting-edge data mining techniques, which, when put into practice, will make the use of contemporary DL methodologies a great deal less complicated. The data that is required for surface pollution may be provided by satellites, whereas the data that is required for submerged contamination requires marine robots to collect it [11].

We examine the rising prospects and concerns related with the application of AI in the maritime environment, as well as their potential scalability for larger results, using some use-cases to illustrate our points. Our ultimate goal is to have a conversation about the potential for reducing pollution in maritime environments through the application of ML derived from the data collected, AI. In particular, we want to have a conversation on the prospect of utilizing AI to control the amount of pollution in maritime environments. It is vital to bear in mind that the use cases are nothing more than starting points for thinking about the huge array of AI-based solutions. This is something that must be kept in mind at all times [12].

3. PROPOSED NOVEL DETECTION MODEL

In this section, we develop a novel deeplabnets to detect the pollutants present in the dataset of SAR images. The discussion of which is given below:

3.1 DATASET

The research community that is relevant to this subject faces a significant difficulty in the form of the absence of a standardized dataset for oil spill detection. This lack of a dataset is a barrier to progress that must be overcome. This challenge requires a solution in order to be overcome. The processes that were pertinent to prior studies were restricted to specialized datasets, which were then updated based on the evaluation of the strategy. On the other hand, due to the fact that each of these methods employs a unique dataset, there is no standard that can be applied across the board to compare and contrast them with one another.

One of our primary goals is to present the community that works with the identification of oil spills using SAR image processing with a problem that has to be solved. This was one of the reasons why we conducted this research. The processes that were pertinent to prior studies were restricted to specialized datasets, which were then updated based on the evaluation of the strategy. On the other hand, due to the fact that each of these methods employs a unique dataset, there is no standard that can be applied across the board to compare and contrast them with one another.

In this section, you will discover a description of the dataset that was discussed in the previous section, as well as an analysis of the dataset. There was a search conducted on the ESA database known as the Copernicus Open Access Hub (https://scihub.copernicus.eu/), looking for SAR images of oil-polluted oceans. After that, downloads of these images were performed. The European Maritime Safety Agency (EMSA) informed authorities of the location of the pollution event as well as the time it took place through its CleanSeaNet project, which is a database maintained by ESA, was searched for SAR images of oil-polluted waters. After that, downloads of these images were performed.

The European Maritime Safety Agency (EMSA) provided the authorities with information regarding the location of the pollution occurrence as well as the time that it took place through the CleanSeaNet program. The data gathered from EMSA, which together make form a reliable ground truth subset, lend credence to the idea that the dark regions depicted on the SAR images represent oil spills. This assertion is corroborated by the findings of the study. SAR images have been provided courtesy of the European Sentinel-1 satellite projects, and data on oil pollution is accessible beginning on September 28, 2015 and ending on October 31, 2017.

The frequency of the C-band is utilized for transmission of the synthetic aperture radar (SAR) technology that is utilized by the Sentinel-1 satellites. The pixel spacing of the SAR sensor is 10×10 meters, which enables it to scan a ground distance of about 250 kilometers. These specifics demonstrate that the SAR sensor is able to investigate expansive regions, but it is unable to zero in on things that are quite modest in size, such as ships. The radar image shows indications of both the VV (vertical polarization sent and received) and VH (horizontal polarization sent and received) polarizations in their respective parts. The only data that was processed was the raw information from the VV band, which was used to create the SAR image dataset. In order to obtain typical representations, a number of pre-processing steps have to be carried out.

According to the information that was provided by EMSA, each and every oil leak was detected, and subsequent repairs were made. The raw SAR image was cropped to remove the clutter that was in the background. This made it possible to emphasize oil spills as well as maybe other pertinent contextual information. The cropped image was blown out, and the result was a resolution of 1250×650 pixels, which we were able to achieve. In order to bring the 1250×650 images onto the same plane, a radiometric calibration was performed on both sets of images.

We were able to lessen the amount of sensor noise that was discernible over the entire image by utilizing a speckle filter. In order to get rid of the speckle noise that was present as a result of the granular character of the noise, a median filter with a size of 7 by 7 was applied. The dB values were then translated into the actual brightness levels by using a linear transformation.

The raw SAR data was processed in order to produce a set of 1112 images, which are going to serve as the primary data for any additional study and applications that are carried out. These images are going to be utilized in the future as well. Oil spills, objects that are quite similar to them, ships, land, and the sea surface itself (the sea surface is always considered to be a background class) are the distinct classes of things that may be identified from one another within the images. In total, there are five unique classes of things that can be distinguished. In order to accomplish the greatest amount of work in the shortest amount of time, each and every image was assigned a label using a combination of information obtained from EMSA records and human identification. So that it can be used in conjunction with semantic segmentation algorithms, a one-of-a-kind RGB color has been assigned to each of the five classes that are contained within the dataset that has been provided. This was done in order to make the dataset more usable.

The ground truth masks that accompany the images of the dataset apply a color to each occurrence of interest that is present that correlates with the class that has been detected as being present in the dataset. Due to the fact that RGB values are insufficient, masks are helpful for displaying this semantic data. However, in order to meet the requirements of the standard, 1D target labels are required for both training and grading reasons. In addition to this, we are able to construct single-channel label masks by assigning a number value between 0 and 4 to each color category. Here is an illustration of a retrieved SAR image, together with the ground truth mask that correlates to it.

The initial collection of 1002 images that comprised the annotated dataset was divided into two subsets: one for training (containing of 90% of the pictures), and one for testing (consisting of 10% of the pictures). In the oil spill detection task that makes use of SAR pictures, the distribution of data points across classes is particularly uneven. In particular, samples that fall into the groups of oceanic or terrestrial are likely to make up the bulk of the total. On the other hand, oil spills and false positives have a tendency to spread throughout a more localized region when they are seen in SAR images.

Natural circumstances, such as low wind speeds and wave shadows close to shore, make it possible for doppelgangers to cover more land than normal. This is why they are able to travel further. It is reasonable to anticipate that the ship class of samples will have a lower occurrence rate at an oil spill scene given that ships are not frequently present in situations of this nature. On the other hand, when displayed, it seems that instances of particular classes make up a far smaller percentage of the total instances than instances of other classes do.

In order to discover a solution to this problem, we concentrated our efforts on generating a balanced dataset that has many samples from each category. This was done so that we could compare the results of the different categories. Our primary objective was to guarantee that each of the five classes received nearly the same quantity of contextual information from the SAR pictures. This had to be accomplished without lowering the complexity of the dataset or the degree of realism it possessed.

3.2 DEEPLABNET

The FCN served as the motivation behind the development of the DeepLab model, which is now widely utilized for semantic segmentation. To construct a scale-invariant encoder with huge field-of-view filters that does not require the inclusion of any additional parameters, the DeepLabv2 approach to the conventional method makes use of either atrous or dilated convolution in conjunction with atrous spatial pyramid pooling (ASPP). This combination of techniques is known as the atrous spatial pyramid pooling (ASPP). The following is a definition for the output y that can be achieved by conducting arous convolution on a one-dimensional input signal *x* while utilizing a filter with length *K*:

$$y[i] = \sum_{k=1}^{K} x\left[i + r \cdot k\right] w\left[k\right], \tag{1}$$

where

i - i^{th} vector y element,

r - rate parameter or stride

x - sampled signal ,

if $r = 1$ indicates the regular convolution.

By utilizing a method known as atrous convolution, we are able to expand the field of view of the filters and thereby take in a greater portion of the scene. Because of this, we are able to achieve this goal without having to increase the number of moving components or the requirement for more processing resources. In addition, by applying atrous convolution, we are able to regulate the level of granularity in the responses that are produced by the DCNN network. This is achieved by controlling the amount of data that is fed into the network. The ASPP primary objective is to deliver data to the model that is representative of a wide range of scales. The recovered feature map is utilized in this way as an input for a number of different atrous convolutional branches that each have their own unique rate of dilation. After that, the completed outputs of each of the branches are concatenated to produce a single output.

The ResNet-101 is used as the network backbone, and the feature map that is generated by the final convolutional layer is then input into an ASPP that has four branches and rates r = 6, 12, 18, 24, and the output of the ASPP is bilinearly upsampled so that the proportions of the original image can be brought back to their correct state. The naive decoder that is utilized during bilinear upsampling is adequate to meet the requirements, as a result of the high resolution that is reserved by atrous convolution. Combining the structure of DeepLab v2 with conditional random fields (CRFs) led to an improvement in the first findings produced by the segmentation process. The following is an expression for the used energy function under the assumption that x_i is the label assignment for pixel i:

$$E(x) = \sum_i \theta_i(x_i) + \sum_{ij} \theta_{ij}(x_i,x_j), \quad (2)$$

where

$\theta_i(x_i)$ - unary potential

$$\theta_i(x_i) = -\log P(x_i) \text{ and}$$

$P(x_i)$ - predicted label probability using CNN

$\theta_{ij}(x_i,x_j)$ - modeled pairwise potential.

CRF is not used as a component of a complete trainable architecture; rather, it is used as a post-processing step in order to improve the segmentation mask. This is in contrast to the widespread belief that CRF is used as a component of a comprehensive trainable architecture. The CRF phase of the processing pipeline was taken out because it did not lead to any improvements in the correctness of the data and hence had to be eliminated.

Previous approaches consisted of utilizing a multi-scale process of model input in order to deal with the large scale and form fluctuations that might occur when there is an oil leak. These variations can take place as a result of the oil leaking from a vehicle. The original image as well as two downscaled representations with dimensions that are respectively 50% and 75% of the initial dimensions are fed into three parallel branches of the network in order to build score maps. These dimensions are respectively 50% and 75% of the initial dimensions. A fourth branch is developed by stacking the score maps and applying a max operator at each position.

The predictions from the first three branches are merged and used to guide the creation of the fourth branch. Because the settings for each branch of the DCNN are identical, the amount of loss is determined with reference to the total output of the four parallel branches that comprise the network. In addition, the DeepLabv2(msc) nomenclature is applied in order to investigate this method of multi-scale analysis.

It is vital to bear in mind that the multi-scale scheme can be considered an extension of the initial model when comparing DeepLabv2 (msc) to the earlier models. A multi-scale method should be utilized for each model so that an accurate comparison may be performed; however, as doing so falls outside the scope of this study, it is not possible to do so. The study that was presented was modified to include the elements of backwards compatibility that are available in DeepLabv2 (MSC).

4. EXPERIMENTAL EVALUATION

Every one of the models was created with the help of the Keras framework, with the exception of the Deeplabv2 model, which was created with the help of the Tensorflow framework. During the training phase of each epoch, the size of one half of the images was changed by randomly scaling them up or down by a factor that was between 0.5 and 1.5 times their original size. This was done in order to train the neural network. In addition to that, 50% of the images underwent a random flipping operation in both directions.

In the end, the images were cropped in such a way as to contain a patch of a preset size and position that was picked at random. This was done in an effort to increase the generalization performance of the models, which was accomplished by cropping the images. It possible that the size of the patch being used will need to be adjusted in response to the overall design of the network.

In order to make it easier to compare and assess the results that were obtained, the patch size was defined to be almost comparable to 320×320 pixels for each deployed model. This was done in order to make the process of comparing and evaluating the findings as straightforward as possible. This was done in order to make the evaluation process simpler.

In addition, the training rate of each model was adjusted so that convergence could be attained in a period of time that was comparable across all models. This was done in order to ensure that the models could be compared favorably. In contrast, the DeepLabv2 model only required a lesser number of epochs of training time, despite the fact that the training technique required quite a bit of computational resources to carry out. This result was achieved through the utilization of a multi-scale technique.

The Adam optimization strategy was used in order to accomplish the task of optimizing each and every under-evaluation model in regard to the cross-entropy loss function. If we assume that p is the principal encoded label and q is the vector of predicted class probabilities, then we can define the idea of cross-entropy loss as follows:

$$H(p,q) = \sum_n p_i \log q_i \quad (3)$$

where, n - dataset class.

Table.1. Training and Validation results

Model	Phase	Accuracy (%)	Difference (%)	Loss
UNet	Training	97.00	4.780	0.050
	Validation	92.16		0.232
EMNet	Training	96.86	4.839	0.057
	Validation	92.00		0.317
FMNet	Training	97.09	4.516	0.050
	Validation	92.53		0.281
LeNet	Training	96.90	4.819	0.056
	Validation	92.05		0.252
DenseNet	Training	96.25	4.878	0.052
	Validation	91.94		0.242
DeepLabNet	Training	96.92	4.761	0.053
	Validation	92.10		0.228

Table.2. IoU

Classes	Evaluation Index	UNet	EMNet	FMNet	LeNet	DenseNet	DeepLabNet
Sea Surface	IoU	92.63	92.73	93.41	93.41	90.20	91.68
	Recall	95.72	96.12	96.87	97.12	93.18	97.10
Oil Spill	IoU	45.94	48.97	47.54	49.36	40.49	41.03
	Recall	53.13	55.42	55.64	55.66	41.30	42.99
Like-oil spill	IoU	39.00	37.28	37.50	40.91	33.35	35.49
	Recall	37.31	38.47	42.52	44.08	28.90	41.66
Ship	IoU	33.04	22.80	15.17	25.14	21.31	14.30
	Recall	29.28	22.95	16.80	21.13	14.14	2.66
Land	IoU	84.67	86.94	84.34	86.08	84.23	28.06
	Recall	90.19	94.57	91.69	92.81	91.00	34.32
	MIoU	59.37	59.76	58.59	61.17	55.97	29.73

5. EVALUATION

The proposed model is trained on data from a different domain, the model that was recommended is still able to detect and classify garbage objects that may be found in underwater images.

The successful outcomes that were achieved when the model prediction was applied to random images are evidence that the model is able to differentiate waste from water and garbage while it is being trained. These outcomes were acquired by applying the model prediction to a variety of different images. Recent years have witnessed substantial breakthroughs in the application of remote sensing in marine environments, despite the fact that it was not utilized for the first time in marine environments until considerably later than it was in terrestrial regions.

Despite the fact that maritime habitats were among the very last to adopt this technology, this has been the result. On the other hand, this website has made an effort to present some probable techniques that have been tried out and met with some level of success, despite the fact that this industry is still evolving and is constantly adjusting to new trends and developments. This article is meant to serve as little more than a jumping off point to better and more diverse solutions, which are only covered obliquely due to the fact that they are always being developed but can be investigated in greater detail in the sources that are cited.

The degree of success that AI will have in protecting the maritime environment is highly dependent on the amount of support that it receives from both authorities and users. One of the many obstacles that prevents the complete adoption of this technology is the fear of instantaneous penalties or fines for polluting, either as a nation or as a community. This fear is a result of the fact that data and analysis are performed in real time, which is one of the reasons why this technology is so effective.

6. CONCLUSION

Deep transfer learning is the technique that we employ in this experiment to locate bodies of water that have been contaminated by pollution. The findings that were collected show evidence that the model that was suggested provides better outcomes with fewer data points. This is demonstrated by the fact that the model requires less data points. The process of cleaning up diverse bodies of water will require fewer people and less time as a result of the potential application of this technology in the identification and classification of garbage present in the air. After some further annotated images of various waste products are contributed to the dataset in the future, it is projected that the accuracy of trash recognition from water will grow. This is something that may be looked forward to. These images are going to be added at a later time.

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