Oil Spill Identification using Deep Convolutional Neural Networks

David M. Feinauer
Department of Electrical and Computer Engineering, Virginia Military Institute, Lexington, VA, USA.
feinauerdm@vmi.edu

Ghazanfar Latif
Computer Science Department, Prince Mohammad Bin Fahd University, Khobar, Saudi Arabia.
glatif@pmu.edu.sa

Abeer M. Alenazy
Computer Science Department, Prince Mohammad Bin Fahd University, Khobar, Saudi Arabia.
201902295@pmu.edu.sa

Nizar Tayem
Department of Engineering and Technology, Texas A&M University, Commerce, USA.
Nizar.Tayem@tamuc.edu

Jaafar Alghazo
Department of Electrical and Computer Engineering, Virginia Military Institute, Lexington, VA, USA.
alghazojm@vmi.edu

Loay Alzubaidi
Faculty of Computer Information Systems, Higher Colleges of Technology, United Arab Emirates.
loay@kharboot.com

***Abstract*— Oil spill detection is an extremely important topic in which Machine Learning (ML) can be utilized because oil spills that go undetected can cause huge environmental negative impacts. The science of how an oil spill can cause devastation to wildlife has been widely viewed with sorrow and the early detection of oil spills can greatly reduce the negative impact oil spills have on the environment. If an optimal solution is found for oil spill detection, continuous monitoring can be achieved either through satellite images or images obtained from unmanned aerial vehicles such as drones. In this paper, we develop a dataset for oil spill detection collected from images from the Internet and other online resources. The dataset consists of 783 images of Oil Spills and 783 normal images. Since these are real-world images, research done on this dataset will produce a more realistic and practical solution. In this paper, we also propose an enhanced CNN model based on GoogleNet and VGG16 combined with transfer learning for the detection and classification of oil spills. The GoogleNet Transfer Learning model achieved better results of training accuracy of 97.5%, training loss of 0.0894, and validation accuracy of 95.6%. Since this is a new dataset, the results cannot be compared to anything in the extant literature.**

Keywords*— *Oil Spill, Oil Detection, Machine Learning, Convolutional Neural Networks, Deep Learning.

I. INTRODUCTION

Artificial Intelligence (AI) is a very useful tool in today's society and is applicable to many fields. Oil spill detection or estimation is one of the fields that AI has helped in expanding, increasing the number of studies that discuss and present new tools to make detecting oil spills much more effective and expedient. A lot of research has been conducted on techniques and features that are used in the process of oil spill detection. In the majority of recent studies involving AI techniques, AI is used as a means to more effectively detect oil spills, and as a means to estimate the amount of oil that is present in a spill. For the various methods proposed in the extant literature, there are advantages and shortcomings. Typically, the data can be collected using remote sensors for detecting oil spills and feature extraction is performed on the collected data. A key aspect of accurate detection and monitoring of oil spills is the use of remote sensing technologies combined with Machine Learning algorithms (ML), extracting oil spill information from the remotely sensed data in a semi-automatic fashion using machine learning techniques [1].

Spills of oil are generally defined as human-caused releases of liquid petroleum hydrocarbons into the environment; it is common for oil spills to be found on the water, ice, or land during oil examination, production, transportation, storage, and distribution [1]. It is known that there is a wide range of long-term environmental impacts associated with oil products entering the marine environment, depending on the chemical and physical composition, the concentration of the oil products, and a number of other environmental factors. Several factors are specific to port environments that influence the use of remote sensing technologies for detecting oil spills, among these are the type of oil (crude oil versus refined oil), the thickness of the oil (whether they are thin sheets of oil in ports opposed to thick patches in ocean environments), and the size of the oil patch [16].

Satellite synthetic aperture radar (SAR) is one operational tool for monitoring and assessing oil spills. There are many possible information gains that result from the use of SAR satellites, but its use is limited to only detecting the presence or absence of oil [2]. When responding to an oil spill, detecting different oil thicknesses and the amount of oil is crucial for first responders as the response can be improved if satellite remote sensing can establish all these aspects in a timely manner. There is no doubt that shipping accidents, particularly mishaps caused by oil tankers, release significant amounts of oil and pose a substantially greater threat to water ecosystems than other forms of pollution.

There are numerous benefits to using AI to estimate the oil spill amount as precise detection of oil spills and the prediction of their trajectories help to manage and conserve the marine ecosystem, monitor impacts on fisheries and animals, and resolve liability disputes. Most importantly, there has been an increasing trend of sudden oil spill accidents that relate to maritime traffic, an example of such an accident would be the rupture or leak of an oil pipeline, the leak of oil and gas, a collision between vessels, the illegal dumping of waste, or a blowout—all of which can significantly damage the marine environment and ecological resources. In these situations, the cleanup process may begin long after the oil spill incident occurs because of coincidence-based evaluation methods, and taking advantage of ML technology can reduce this delay.

The motivation for researching the possibility of automatic detection of oil spills along with other accompanying factors including estimating the amount of oil spilled or the area impacted includes aiding first responders in the allocation of resources for the cleanup in a timely manner, reducing the impact an oil spill has on the environment. The potential impact combined with increasing occurrences of incidents is why this is a pressing and important research topic.

The aim of this paper is to propose an ML-based system that can automatically detect oil spills and estimate other related factors such as the amount of oil spilled. The proposed approach can be further modified to receive data from remote sensors or SAR satellites. The importance of the solution lies in the fact that it can provide accurate information to first responders in order to allocate the required resources needed for the timely cleanup of the spill.

The rest of the paper is organized as follows: in section 2, research is presented from the extant literature related to oil spill detection. In section 3, the proposed approach for oil spill detection is detailed. The experimental results and analysis are presented in section 4. Section 6 concludes the study with a proposal for future work in the field. Section 7 contains the list of all references used in this paper.

II. Recent Studies

Owing to the increasing trends of incidents or accidents that result in the release of oil and other petro-chemicals to the environment and the potential for devastation or lasting harm to ecosystems, improving techniques for detecting, monitoring, and assessing oil spilled as a result of an incident remains an active research area. Designing techniques that more effectively turn data from satellite images and other remote sensors into information that is useful to those responsible for responding to the incidents is key to the success of any proposed technique. The field of machine learning poses many opportunities for improvements in line with this key objective.

In [1], the authors review different types of remote sensing and detection in the field of oil spills, and the first part of the review discusses the strengths and weaknesses of data gathered by remote sensing. Then the process of preparing data to develop classification models is introduced. Subsequent sections present and analyze certain feature extraction or selection methods to detect oil spills. Lastly, they give an overview of the different machine-learning technologies that are designed for oil spill detection. In [2], the authors present the idea to classify oil types as well as estimate their thickness. They introduce products that can classify emulsion thickness based on RADARSAT-2 images captured by polarimetry and provide timely strategic information to responders in the field based on satellite remote sensing, which was a challenge in the past. The authors tested the time needed to send these products to responding vessels by way of NOAA. In [3], the authors conducted a study to compare single and dual-polarized SAR image classification performance using the following ML models: support vector machine (SVM), deep neural network (DNN), and random forest (RF). The test image in this article is a TerraSAR-X dual polarized image and these three machine learning methods were used with this image to classify objects like the sea, oil, ship, and land.

In [4], the aim of the study is to establish a way to categorize oil spill detection into four classes which are: thin oil, thick oil, oil/water mixture, and finally clear water, which is mostly achieved by utilizing PolSAR data. Many textures and other features are extracted from these images. The features were manually engineered based on the backscattering behavior of oil and water surfaces, and automated selection was based on an optimization algorithm. In [5], the authors propose a method for oil spill detection by using the Simple Linear Iterative Clustering (SLI C) superpixel segmentation method based on a convolutional neural network (CNN), as it has been proven that the SLIC method improves the accuracy of oil spill classification greatly. The experiment carried out by the authors consisted of five groups and combined the superpixel segmentation with polarized parameters which led to better classification results. In [6], the authors propose and analyze the idea of oil spill detection based on polarimetric SAR. Different polarimetric SAR filters are compared with respect to their performance for the classification of oil spills, an automatic classifier (SAE) is used to extract polarimetric SAR features and use them to differentiate crude oil slicks from biogenic slicks on the sea surface. In [7], the authors propose the Oil Spill Convolutional Network (OSCNet) as a Deep Convolutional Neural Network (DCNN) for the detection of SAR oil spills, which can perform the second and third steps of the three-step processing framework. By comparing OSCNet's classification performance with that of traditional machine learning techniques, the experiments based on the same data set show a significant improvement.

In [8], the authors propose a way to overcome the limitations of classifying satellite images that are captured by sensors (in most cases different images get assigned to the same label). The solution they presented is to take a semantic segmentation with deep convolutional neural networks (DCNNs) approach. In addition, a publicly available dataset of SAR images is presented, to provide a benchmark for oil spill detection systems in the future. In [9], the authors propose a way of using synthetic aperture radar (SAR) images and discuss a deep-learning framework under development for the detection and categorization of oil spills. The data-driven neural network model for image segmentation achieves similar results to those produced by human operators in terms of oil spill detection, thanks to an extensive dataset. The authors also introduce a classification task, explaining that each oil spill is assigned different categories based on texture and shape characterization. In [10], the authors present the potential of using shipborne radar in the application of oil spill detection, and the shipborne radar is said to have large-scale and real-time monitoring that can capture high-resolution images. In this study, it is shown that the SVM is capable of extracting effective wave information from the original shipborne radar image, and it is demonstrated that the local adaptive threshold method is effective at segmenting oil films. In [11], the authors assess the machine learning and deep learning techniques that are used to classify maritime targets in SAR images. In this study, polarimetric images acquired by Sentinel-1's C-band synthetic aperture radar (SAR) system were used to evaluate target classification methods. When compared to the tested classifier, the Kruskal-Wallis test reveals a significant difference, suggesting that various classifiers provide differing accuracy outcomes.

In [12], the authors discuss the technical solutions available through spaceborne radar imaging to address illicit vessel oil discharges on the oceans, they briefly outline several turning moments and major historical events in order to monitor and reduce maritime oil spills, they propose various detection methods, assessing how well they work to find oil spills on the coastlines, and they address the current status of spaceborne radar imaging as well as future possibilities. In

[13], the authors discuss the purpose of Sentinel 2 imagery—to find oil spills from known natural outflows as well as mild oil spill events—and they detail the development of two object-based image processing techniques. The test methods used involve Sentinel 2 photos of a known location of natural oil outflow and a Sentinel 2 image of a recent oil spill occurrence near the south coast of Athens, Greece. In [14], the authors discuss the method needed to detect oil spills in satellite photos from Envisat and Sentinel-1, and the authors apply clustering, logistic regression, and convolutional neural network algorithms. For issues including an imbalance in the number of samples from the classes, metrics based on Precision-Recall curves were used. They estimate that the greatest result can be obtained by the combination of neural networks and convolutional techniques. In [15], the study shows that satellite-based oil spill detection is a practical and cost-effective method for mapping oil spills since the oil spill detection method based on synthetic aperture radar (SAR) produced accurate findings at wind speeds between 3 and 9 m/s. Although it requires a lot of computer power, near-real-time oil spill detection utilizing SAR images yields superior results.

In [16], the authors provide a new framework for detecting oil spills inside a port environment using unmanned aerial vehicles (UAV) and a thermal infrared (IR) camera, and in this paper, they split the framework into two parts: a training part and an operational part. In the training part, they offer a process for automatically annotating RGB images and matching them with infrared images to construct a dataset. In the operational part, they propose a pre-trained network and a low-power interference device to establish an onboard UAV oil spill detection system that operates in real time. In [17], the authors research oil spill identification and SAR image processing using deep convolutional neural networks (DCNN). This study establishes that neural networks have been cited as an effective alternative in the oil spill detection research field due to their robustness in classification aims. It is also noted that SAR sensors can contain additional contextual information such as ships, coastal buildings, or platforms, due to their capacity to monitor large areas. In [18], the authors propose a classification model that combines one-dimensional convolutional neural networks and spectral indices-based band selection (SIs) to achieve automatic oil film classification. In addition, the minimum Redundancy Maximum Relevance (mRMR) technique was tested for lowering the number of bands for comparison reasons. The findings demonstrate that the one-dimensional convolutional neural network (1D CNN) models' classification accuracy outperformed that of other machine learning methods like support vector machine (SVM) and random forest. In [19], a two-stage deep-learning architecture is introduced for the detection of oil spills using a highly imbalanced dataset. A unique 23-layer Convolutional Neural Network is used in the first step to classify patches based on the percentage of pixels with oil spills. The second step uses a five-stage U-Net structure to conduct semantic segmentation. To consider the decreased oil spill representation in the patches, the generalized dice loss is minimized. In [20], the authors present that by applying the artificial neural network (ANN) technique to the PlanetScope satellite, they were able to detect oil slick areas and capture their images. It was challenging to identify the oil slick location because the image had yellow dust areas and sunlight effects, and that is why a classification map for oil slicks was produced thereafter, using the maximum probability method and rejecting dust areas.

III. Methodology

Deep learning is a trend in the extant literature for applications related to image processing and computer vision. Thus, in this paper, we propose the use of CNN because of the successful use of CNN in a wide variety of existing applications such as those in [21-24]. The main objective of this work is to develop a CNN approach that can detect oil spills based on images that can potentially be taken using drones or satellites. The current dataset used in this paper is also considered a contribution as it is a new dataset that takes into account real-world images, making the proposed approaches more applicable and ready for deployment once a robust solution is found. The proposed CNN model is based on convolutional and pooling layers. The pooling layer is fitted after each convolutional layer. The nonlinearity property is achieved through the use of the Rectified Linear Unit (ReLU) which can potentially assist in achieving better accuracy and more fitted results [25]. The Softmax activation function is also used at the end to improve results.

A. *Experimental Data*

Since a standardized dataset does not exist for oil spill identification, the authors decided to add to the body of knowledge another dataset in addition to those existing. Thus, a dataset consisting of a total of 783 images of Oil Spills and 783 Normal Water / Flood images with varying locations and visual changes were collected from the internet and other sources. The images were labeled and subjected to preprocessing techniques for normalization, especially in terms of dimensions. A sample of the images from the developed dataset is shown in Figure 1. The dataset is developed for a binary classification problem meaning that there are two classes {0,1} that represent either oil spill or no spill.

The dataset serves as an excellent resource for those researching oil spill identification and classification because it is collected from real-world images with varying locations, backgrounds, and quality, making the identification process more complex yet more realistic for real-world real-time applications. The dataset is also divided into 80% training and 20% testing. The 20% dedicated to testing is further divided into 80% testing and 20% validation.

B. *Proposed CNN Model*

The use of deep learning techniques for the complete identification and classification of images is a trending concept in research. The modification of the deep learning models in terms of layers and hyperparameters makes a huge difference in the accuracy achieved. In this paper, we enhance the CNN model as shown in Figure 2. As shown in the figure, the CNN model consists of a convolutional layer with non-linearity provided by a Rectified Linear Unit (ReLU) operator. Features from the input images are extracted by the convolutional filters at each layer [26]. The features are then fed into the last layer that achieved classification and detection. The pooling layer assists in reducing the computations required in the training phase through the reduction of the image dimensions and thus overcoming the problem of overfitting. The proposed model shown in Figure 2 is based on GoogleNet where the images are input to the first convolutional layer, followed by the ReLU activation function, followed by a pooling layer. The process is repeated. The dropout layer which also assists in overcoming overfitting is used. The flatten layer is then applied to convert the multi-dimensional feature map into a single dimension. The dense/fully connected layer is then used for classification/detection. The final layer is the SoftMax layer utilizing the SoftMax function to obtain the probability distribution of a set of numbers from the input vector.

Fig. 1. Sample images from a newly collected Oil Spill and Normal Water/Flood experimental dataset

Transfer learning is also utilized here as well [27]. Transfer learning is the approach of utilizing the experience and knowledge gained in solving a certain problem and applying it to other related problems. Previously trained models with consideration and careful selection are utilized and hyperparameter fine-tuning according to the new dataset and according to the new classification problem is ensured [28]. In this paper, we utilize both the GoogleNet Transfer learning model and the VG16 transfer learning model for our experiments.

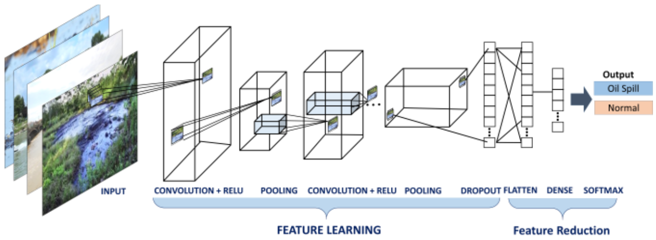

Fig. 2. Workflow of the CNN model for oil spill detection

IV. Results and Analysis

Table 1 shows the experimental results that are obtained. The experiment was set up for a Batch size of 200 and epochs of 30. It is evident that GoogleNet achieved the highest accuracy in all the metrics used. GoogleNet Transfer learning model achieved a training accuracy of 97.5%, training loss of 0.0894, and validation accuracy of 95.6%. The VG16 transfer learning model did not perform as well as GoogleNet, yet it still achieved high accuracy. The training accuracy using the VG16 transfer learning model is 96.2% while the training loss is 0.0005, and the validation accuracy is 94.4%.

TABLE I. Comparison of the Experimental Results for the Oil Spill Detection using GoogleNet and VGG16-based Transfer Learning

Method	GoogleNet Transfer Learning	VG16 Transfer Learning
Training Accuracy	97.50%	96.20%
Training Loss	0.0894	0.0005
Validation Accuracy	95.60%	94.40%
Validation Loss	0.1452	0.0066
Test Accuracy	95.41	93.77
Test Precision	95.71	94.73
Test Recall	95.08	94.33
Test F1 Score	95.4	95.82

Figure 3 shows the validation learning curves for accuracy and loss using the VGG16 transfer learning model. It is also observed that the curve shows exactly what is expected with perfect saturation (point of stability) towards (close to) 100 for accuracy and perfect saturation (point of stability) towards (close to) Zero for the loss. It is evident that our proposed method does not suffer from any overfitting or underfitting problems. The generalization gap also is clear within the image to ensure that the models are a good fit.

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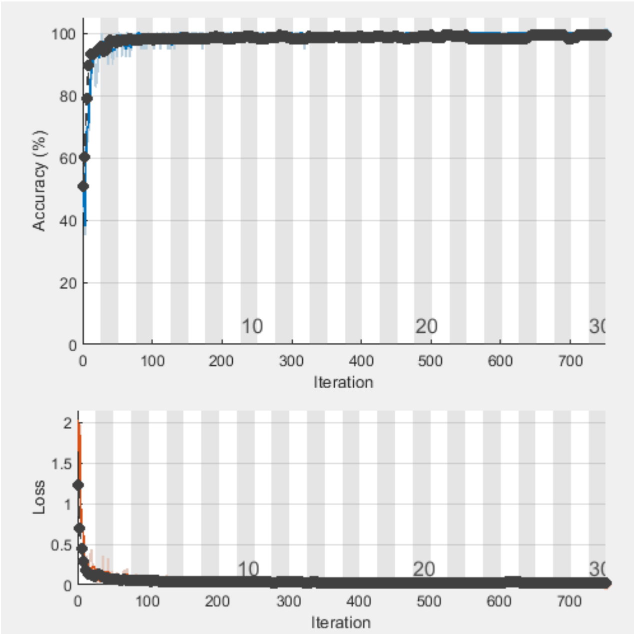

Fig. 3. GoogleNet Transfer Learning-based training/validation learning curves depicting accuracy and loss (black graph line represents validation).

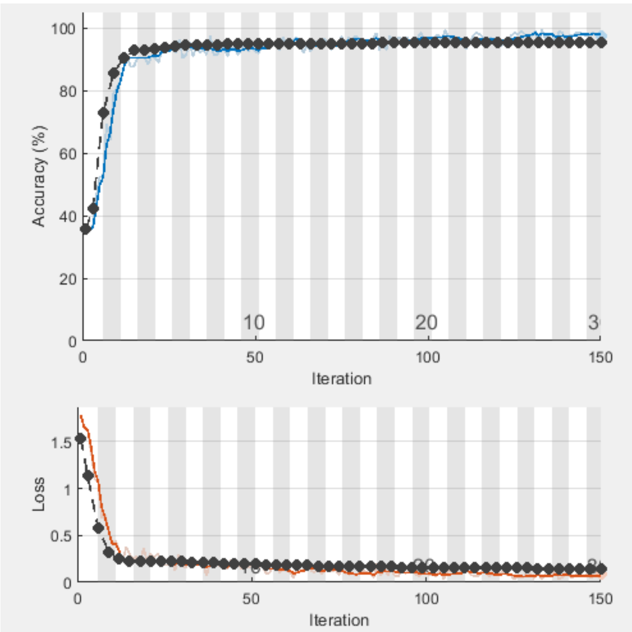

Fig. 4. VGG16 Transfer Learning-based training/validation learning curves depicting accuracy and loss (black graph line represents validation)

Figure 5 shows the confusion matrix for both the GoogleNet Transfer Learning model and the VGG16 transfer learning mode. The true positive (TP) for GoogleNet is showing 93.63% while the true negative (TN) shows 97.45%, both are very high accuracies. The false positive (FP) for GoogleNet shows 6.37% while the false negative (FN) shows 2.55% which is again an excellent result. For the VGG16 transfer learning model, the true positive (TP) shows 90.45% while the true negative (TN) shows 96.82%, both are still very high accuracies. The false positive (FP) for VGG16 shows 9.55% while the false negative (FN) shows 3.18% which is again excellent results.

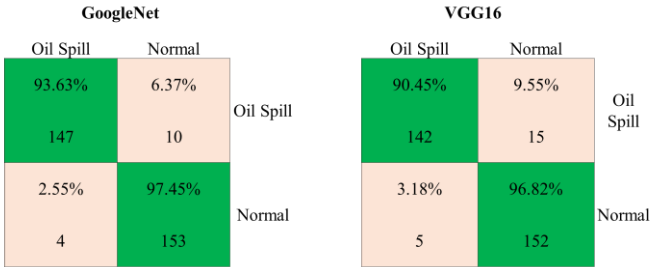

Fig. 5. Confusion Matrix of GoogleNet and VGG16 Transfer Learning Models.

V. Conclusion

Novel One might think that an oil spill is a rare incident, however, in reality, oil spills happen more frequently than one would think. In 2021, six spills were reported with one being very large, meaning greater than 700 tons, and five medium spills involving between seven and seven hundred tons of oil. These represent only the recorded spills from tankers, as there may be unrecorded spills as well as spills from sources other than tankers. When oil spills occur, in most cases, there are devastating effects on the environment and other effects. The earlier the oil spills are reported and detected, the earlier intervention procedures can be initiated to reduce the negative impact of the spills. In this paper, we propose a new dataset consisting of 783 images of Oil Spills and 783 Normal Water / Flood images. These images were collected from the internet and other online sources. Since these are real-world images, research done on this dataset will produce a more realistic and practical solution. In this research paper, we also propose an enhanced CNN model based on GoogleNet and VGG16 combined with transfer learning for the detection and classification of oil spills. The GoogleNet Transfer Learning model achieved better results of training accuracy of 97.5%, training loss of 0.0894, and validation accuracy of 95.6%. Since this is a new dataset, the results cannot be compared to anything in the extant literature.

For future work, we plan to do several more projects in the area of oil spill detection. First, we would like to enhance the size and number of classes for our dataset so that it can have classes of large spills, medium spills, and small spills with the fourth class being no spill. We also endeavor to have a dataset consisting of at least 4000 images; one thousand images of each class (it remains to be seen if such images exist). In addition, we want to continue to explore ML and Deep Learning algorithms for the detection and classification of oil spills to reach an optimal solution that can be deployed in real-life situations.

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