ICON Journal of Engineering Applications of Artificial Intelligence
Volume 02 | Issue 08 | 2026
e-ISSN: 3051-3820
p-ISSN: 3051-3812
Journal homepage: https://iconpublishers.com/icon-j-eng-app-ai/

Research Article

DOI: 10.5281/zenodo.21974652

Deep Learning Techniques for Oil Spillage Detection using Sar Images: Current Applications and State-of-the-Art

Aminu Abdullahi Umar, AS Imam and Muhammad Muneer Haruna*
Department of Mechatronics Engineering, Nigerian Defence Academy (NDA), Kaduna, Nigeria.

Corresponding author: Muhammad Muneer Haruna
Department of Mechatronics Engineering, Nigerian Defence Academy (NDA), Kaduna, Nigeria.

Received Date: 20 June 2026
Published Date: 17 Aug. 2026

Abstract
Edge detection is one area of image processing that gets a lot of interest because it is known to significantly reduce the amount of data and filter out extraneous information in a picture. Generally speaking, edges aid to preserve an image's essential structural features and establish its limits. Since color is an unavoidable feature that facilitates description, object recognition, and extraction from a scene, color picture edge detection is frequently used in color image segmentation. Edge detection typically provides sharp variations in color intensity inside an image. These alterations are common to object margins. Once an object's edges are detected, other processing tasks such as object recognition, text finding, and region segmentation become easier and more viable. Leaking pipelines, natural hydrocarbon seepage, and oil spill discharges from operating maritime activities including ships, oil rigs, and other structures pose a major hazard to marine ecosystems, fisheries, and populations along coastal regions. Satellite synthetic aperture radar (SAR) is a cutting-edge microwave instrument that monitors oil spills in the ocean regardless of the weather or sunlight.

Keywords: *Oil Spill Monitoring, Deep Learning Techniques, Sar Images, State-of-the-Art, Future Directions, Recommendations.*

I. INTRODUCTION

The coastal area is known to be home to oil explorations and exploitations. Oil spill incidents are common along the Niger Delta Coastal Area. The main sources of oil spills in the Niger Delta are vandalization of the oil pipelines by the local inhabitants, aging of the pipelines, oil blowouts from the flow stations, cleaning of oil tankers on the high seas, and disposal of used oil into the drains by the roadside mechanics. By far the most serious source of oil spills is through the vandalization of pipelines, either as a result of civil disaffection with the political process or as a criminal activity [1]. Major oil spills heavily contaminate coastal shorelines, causing severe localized ecological damage to the near-shore community. Oil spills and the resultant degradation of the surrounding environment have caused significant tension between the people living in the region (Niger Delta) and the multinational oil companies operating there. Spills have also necessitated the complete resettlement of some communities. Loss of agricultural land, for example, translates into loss of livelihood for farmers; social problems associated with displacements include loss of ancestral homes. A large area of the mangrove ecosystem has been destroyed, which was a major source of wood for the indigenous people. Health-wise Oil that is spilled and not recovered will have an impact on the local environment, spreading over a wide area and affecting both terrestrial and marine resources. Actions can make the situation worse; the development of the region has led to the degradation of some sites, reducing their value and use. Furthermore, while past statistical assessments identified tankers as the main marine polluters with crude oil (by releasing oily mixtures in ballast water or in cargo tank washings). To comply with marine legislation and the efficient surveillance and need for protection of coastal environments, the detection and tracking of oil spills and illegal oil discharges is of fundamental importance. In synthetic aperture radar (SAR) images, dark spots can be caused by a variety of phenomena, such as algae, low-wind areas, coastal areas, and oil spills. The three main challenges for oil spill detection in SAR images are:

i. **Speckle noise:** Speckle noise is a random, granular pattern that is present in all SAR images. It can make it difficult to distinguish between oil spills and lookalikes.
ii. **Similar appearance:** Oil spills and lookalikes can have similar appearances in SAR images. This can make it difficult to distinguish between them using traditional methods.
iii. **Lack of automatic methods:** There are currently few automatic methods for filtering speckle noise or for distinguishing between oil spills and lookalikes in SAR images.

To address these challenges in this research we propose:
i. Using a combination of features, this research proposes to use a combination of features, including wind speed, physical appearance, and geometrical and geographical parameters, to distinguish between oil spills and lookalikes.
ii. Developing automatic algorithms using deep learning: This research proposes to develop automatic algorithms using deep learning (CNN) for filtering speckle noise and for distinguishing between oil spills and lookalikes. The research aims to develop automatic algorithms and classification methods to distinguish between oil spills and lookalikes in SAR images, as well as to reduce speckle noise in the images. The proposed approaches are expected to make oil spill detection faster, more accurate, and more cost-effective.

II. LITERATURE REVIEW

The construction of a cost-effective remote sensing processing system has been the subject of research and development for approximately two decades (Bern et al. 1992, Skøelv and Wahl 1993, Wahl et al. 1994, Solberg et al. 2003). Microwaves are commonly used for ocean pollution monitoring by remote sensing. They are often preferred to optical sensors due to the all-weather and all-day capabilities. Among the available remote sensing satellite data, spaceborne Synthetic Aperture Radar (SAR) imagery is the most efficient and superior satellite sensor for oil spill detection. It captures two-dimensional images, and its image brightness is a reflection of the microwave backscattering properties of the surface [2]. SAR is considered an important tool in oil spill monitoring due to its wide area coverage and day and night all-weather capabilities. It is worth noting that airborne is another possibility for oil spill detection, but airborne surveillance is limited by the high costs and is less efficient for wide-area surveillance due to its limited coverage. As an example, the Side-Looking Airborne Radar (SLAR) is an older but less expensive technology than SAR but suffers from low range and resolution (Fingas & Brown, 1997). Friedman et al. (2002) compare a RADARSAT-1 SAR image with a corresponding Sea-viewing Wide Field-of-view Sensor (SeaWiFS, visible sensor) image. SeaWiFS measures high levels of chlorophyll for areas with algal bloom, while the SAR images have low backscatter levels in these regions. A drawback of the SeaWiFS sensor is its coarse spatial resolution of ~1 km. Hu et al. (2003) demonstrate the possibility of oil spill monitoring by the Moderate Resolution Imaging Spectroradiometer (MODIS) instrument, carried onboard the NASA satellites Terra and Aqua, by an example from Lake Maracaibo, Venezuela. The MODIS instrument has moderate resolution bands of 250 m and 500 m and a wide spectral range, which allows it to provide images of daylight-reflected solar radiation and day/night time thermal emissions. The MODIS instrument was originally designed for land imaging, and with medium resolution, it also shows potential for daily monitoring of the coastal zones looking for oil spills. However, as with all optical sensors, with the availability of cloud cover and the lack of sunlight, its use is limited. Hyperspectral sensors used for oil spill monitoring provide detailed identification of materials (slicks produced by algal blooms from oil spills) and better estimation (spectral signature of oil to distinguish between different oil types). This in turn eliminates the false alarm rate of ocean features that have the same color and appearance as oil. Salem and Kafatos (2001) found that a signature matching method based on airborne hyperspectral imaging (looking at chemical composition) is more accurate than the conventional techniques, where analysis is based on visual interpretation of the oil's color and its appearance in the satellite image. The NASA EO-1 Hyperion hyperspectral sensor is an example of a spaceborne technology demonstrator but suffers a major drawback from its small swath width of only 7.5100 km and is currently not a commercial spaceborne hyperspectral sensor in orbit. Oil absorbs solar radiation and re-emits a portion of this energy as thermal energy. Tseng and Chiu examined the use and capability of the visible and IR sensors for early detection and monitoring of oil spills. IR sensors observe thick oil slicks as hot and intermediate thicknesses of oil as cool, while thin oil is not possible to detect (Fingas & Brown, 1997). At night a thick spill can appear cooler than the water since it releases heat quicker than its surrounding water (Tseng & Chiu, 1994). Thick and thin oil layers and the boundary between water and oil were possible to detect by the IR channel, but the oil spills may not have a significantly different temperature signature from the surrounding water at night. Thus, making oil spills detectable in the visible images only under highly favorable lighting and sea conditions. UV technology can be used to detect oil spills, as the spill displays high reflectivity of UV radiation even at thin layers. The UV instrument is not usable at night, and wind slicks, sun glints, and biogenic material can cause false alarms in the UV data. These interferences are often different from those for IR, and a combination of IR and UV can provide a more reliable indication of oil and can be used for estimating oil thickness (Fingas & Brown, 1997). A microwave radiometer (MWR) is another passive sensor. The instrument looks at the microwave radiation in the wavelength cm to mm range that the ocean emits and therefore is almost weather independent (Trieschmann et al., 2003). Oil slicks emit stronger microwave radiation than the water and appear as bright objects on a darker sea. According to Robinson (1994), oil slicks can have strong surface-emissivity signatures, but as a spatial resolution of tens to hundreds of meters is desirable for the determination of oil slicks, this type of sensor for oil spill thickness monitoring is most appropriately pursued by aircraft sensors. Zhifu et al. (2002) did some experiments using airborne (AMR-OS) and shipborne (K-band) MWRs looking at various oil types and thicknesses. They found that MWRs are useful tools for measuring the thickness and estimating the volume of the spills, but the resolution is not fine enough to give accurate results. Fingas and Brown (1997) summarize studies done on this field and conclude that the potential of radiometers as a reliable device for measuring slick thickness is uncertain. In summary, SAR is still the most efficient and superior satellite sensor for oil spill detection, though it does not have capabilities for oil spill thickness estimation and oil type recognition. SAR is useful, particularly for searching large areas and observing oceans at night and in cloudy weather conditions. In view of this Convolutional Neural Network (CNN) being the most notable deep learning descriptor, it has attracted researchers' attention in recent years [12, 32–39] and yielded some of the best results in image classification problems. Therefore, this work proposes using a fully convolutional neural network for classification of SAR images.

III. METHODOLOGY

Recently, deep neural networks (DNNs) are becoming popular due to the principal advantage in their ability to learn arbitrarily complicated decision surfaces. A deep neural network is one that has a large number of layers and may contain hundreds or thousands of nodes, allowing for richer exploitation of the input data, while more layers allow for more intricate decision surfaces. A typical framework for an oil spill detection algorithm is as shown in figure 1. This work proposes a deep feature learning approach based on the Fully Convolutional Neural Networks (FCNNs) that perform speckle filtering, extract spatial contextual features, and classify SAR images for oil spill detection. CNN is a neural network where the individual neurons are tiled in such a way that they respond to overlapping regions in the visual field. It typically involves alternating convolutional layers and pooling layers, where convolutional layers extract features and pooling layers generalize features.

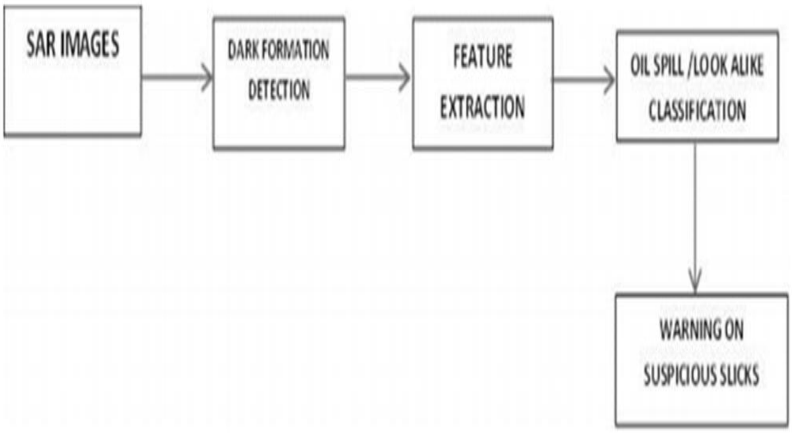

Figure 1: block diagram of Oil Spillage detection framework

This work will focus on:

i. The design, analysis, and evaluation of a CNN classifier for speckle reduction and classification.
ii. To compare the performance of the proposed FCNN speckle filter and classifier against previous speckle filter and classification methods.

To solve this problem, we implement a self-supervised learning method to learn the deep neural network from unlabeled hyperspectral data for oil spill detection, which consists of three parts:

i. data augmentation
ii. unsupervised deep feature learning,
iii. and oil spill detection network.

First, the original image is augmented with spectral and spatial transformation to improve robustness of the self-supervised model as shown in Figure 2.

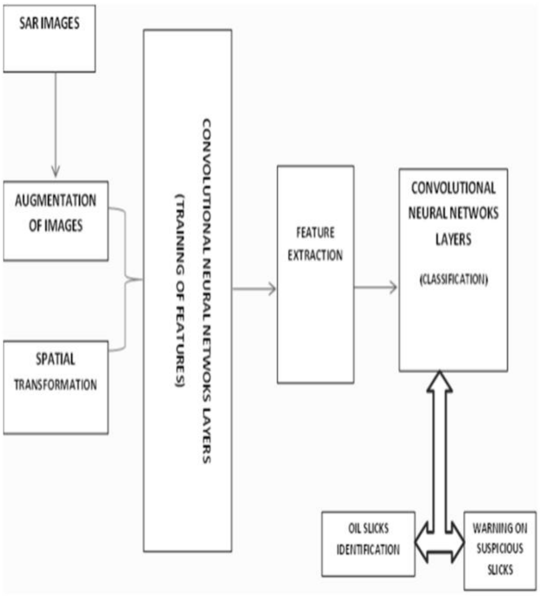

Figure 2: block diagram of Proposed Oil Spillage detection framework using Deep Learning

Then, the deep neural networks are trained on the augmented data without label information to produce the high-level semantic features. Finally, the pre-trained parameters are transferred to establish a neural network classifier to obtain the detection result, where a contrastive loss is developed to fine-tune the learned parameters so as to improve the generalization ability of the implemented method.

IV. CURRENT APPLICATIONS AND STATE-OF-THE-ART

Deep Learning Techniques (DLT), particularly CNNs, U-Net, and hybrid Transformer-based models, are transforming oil spill detection in Synthetic Aperture Radar (SAR) imagery by automating segmentation and distinguishing spills from "look-alikes" with up to 99% accuracy. Key trends include patch-based analysis for precision, multi-temporal analysis for tracking, and self-evolving algorithms that reduce human intervention.

i. **Automatic Detection & Segmentation:** Models like CNN-based U-Net or DeepLabV3+ efficiently segment oil slicks from the ocean background in SAR images, including on datasets like Sentinel-1.
ii. **Hybrid Models:** Combining CNNs with Vision Transformers (ViT) has improved detection, providing F1-scores up to 78.48% by better distinguishing spills from noise.
iii. **Look-alike Differentiation:** Advanced approaches focus on reducing false positives (e.g., from algal blooms, low-wind areas) by analyzing backscattering coefficients near the oil boundary.
iv. **Real-time Monitoring:** Automated pipelines, often using Python and geospatial libraries, allow for processing large amounts of SAR data to track oil spill progression.

V. FUTURE DIRECTIONS

i. **Self-Evolving Algorithms:** Developing models that automatically update parameters upon receiving new, unlabeled SAR data, allowing the system to learn continuously without human supervision.
ii. **Multi-Sensor Data Fusion:** Integrating SAR data with optical, hyperspectral, and meteorological data to improve accuracy and estimate oil thickness, which is not possible with SAR alone.
iii. **Improved Small-Spill Detection:** Enhancing algorithms to detect smaller or thinner oil slicks, which are often overlooked by conventional models.
iv. **Explainable AI (XAI):** Moving towards interpretable models that explain *why* a certain dark spot was classified as a spill, which is crucial for operational decision-making.

VI. RECOMMENDATIONS

i. **Robust Pre-processing:** Implement rigorous pre-processing steps, including noise reduction (e.g., Lee Sigma filter), land masking, and radiometric calibration to remove "look-alikes".
ii. **Patch-Based Methodology:** Use a patch-based approach rather than full-image processing to enhance detection of specific, finer details in complex ocean environments.
iii. **Dataset Expansion:** Create and utilize standardized, diverse datasets containing various oil types, ocean conditions, and look-alikes to improve model generalization.

iv. **Focus on Hybrid Architectures:** Implement hybrid CNN-Transformer models for superior segmentation accuracy and better handling of noisy SAR data.
v. **Leverage Open Data:** Utilize free and open-source data from satellites like Sentinel-1 for creating cost-effective monitoring systems.

VII. RESULTS

Deep learning (DL) techniques, particularly Convolutional Neural Networks (CNNs) and U-Net, applied to SAR images for oil spill detection yield highly accurate, automated, and rapid results [12]. These techniques achieve high classification accuracy (often >90%) and precision in identifying oil slicks, while effectively differentiating them from "lookalikes" like sea ice or calm water, even with complex background interference.

Key Results and Performance Metrics:

i. **High Accuracy:** Studies report accuracies ranging from 89% to over 99% for identifying oil spills.
ii. **Precision/Recall:** Models like U-Net and CNNs have achieved precision rates around 84-89% and improved Dice scores (approximately 0.8 to 0.85) for segmentation.
iii. **Superior to Traditional Methods:** Deep learning models, such as DBN and SAE, outperform conventional machine learning methods, especially with small datasets.
iv. **Real-time/Automated Detection:** These methods provide fast, end-to-end detection suitable for operational surveillance.
v. **Handling Complex Scenes:** Advanced models like OSDTAU-Net show superior ability in reducing speckle noise and identifying both large and fragmented oil patches, improving boundary delineation.

VIII. CONCLUSION

Conventional SAR techniques for detecting oil spills are frequently complicated, sluggish, and require big, balanced datasets. In order to overcome these constraints, a novel deep learning approach is used to resolve these issues by:

Other commonly used techniques are:

i. **CNNs and U-Net:** Commonly used for segmentation.
ii. **DeepLabv3+:** Known for high precision in segmenting complex SAR images.
iii. **DBN (Deep Belief Networks):** Used for distinguishing oil from lookalikes.

Key Takeaways:

i. **Automation:** Reduces the need for manual, subjective, and time-consuming manual analysis.
ii. **Data Source:** Primarily uses Sentinel-1 SAR imagery for cost-effective, routine monitoring.
iii. **Performance Drivers:** The success of these techniques lies in their ability to automatically learn, extract, and classify features, even in complex marine environments.

Future directions for deep learning (DL) in SAR-based oil spill detection focus on enhancing precision by integrating physical, polarimetric, and contextual features into models like CNNs, U-Net, and Transformers to distinguish spills from look-alikes. Key recommendations include using multi-sensor data fusion, developing lightweight, real-time algorithms, and creating robust, balanced datasets to overcome high-noise, small-sample, and false-positive issues.

Future Research Directions

i. **Physical-Informative Neural Networks:** Integrating SAR, physical, and polarization information directly into network training to enhance model interpretability, physical consistency, and distinguish spills from "look-alikes" (e.g., low-wind areas, algae).
ii. **Advanced Network Architectures:** Shifting toward sophisticated models like transformers and hybrid architectures (e.g., GSCAT-UNET) that improve segmentation accuracy, as seen with improvements in IoU to 93.7%.
iii. **Lightweight & Real-time Processing:** Developing lightweight models (e.g., replacing backbones with MobileNetV2) to enable rapid, on-board detection for real-time disaster management and operational monitoring.
iv. **Multimodal Sensor Fusion:** Combining SAR with optical or sonar data for comprehensive, 24/7 monitoring, reducing reliance on single-source data.

Recommendations for Improvements

i. **Addressing Dataset Imbalance:** Utilizing techniques such as data augmentation, synthetic data generation, and weighted loss functions (e.g., Focal Loss, Generalized Dice Loss) to handle the limited, highly imbalanced nature of oil spill data.
ii. **Improving Noise Reduction:** Implementing specialized, edge-aware modules like spatial and channel squeeze and excitation (scSE) or attention mechanisms to effectively reduce speckled noise.
iii. **Standardization of Benchmarks:** Creating large-scale, publicly available, annotated datasets to allow for better benchmarking of models across varied environmental conditions.
iv. **Operational Validation:** Moving beyond controlled testing to validate algorithms in diverse, real-world, and complex ocean conditions.

REFERENCES

1. P.C. Nwilo, O.T. Badejo," Oil Spill Problems and Management in The Niger Delta", International Oil Spill Conference (IOSC), Vol. 2005, No.1,2005
2. C. Brekke, A. H.S. Solberg, Oil spill detection by satellite remote sensing, Journal of Remote Sensing of Environment 95 (2005) 1–13
3. Assilzadeh, H., & Mansor, S. B. (2001). Early warning system for oil spill using SAR images. Proc. ACRS 2001—22nd Asian Conference on Remote Sensing, 5–9 November 2001, Singapore, vol. 1 (pp. 460–465).
4. Barni, M., Betti, M., & Mecocci, A. (1995). A fuzzy approach to oil spill detection on SAR images. Proc. IGARSS '95, vol. 1 (pp. 157–159).
5. Benelli, G., & Garzelli, A. (1999). Oil-spills detection in SAR images by fractal dimension estimation. Proc. IGARSS'99, vol. 1 (pp. 218–220).
6. Bentz, C., & de Miranda, F. P. (2001). Application of remote sensing data for oil spill monitoring in the Guanabara Bay, Rio de Janeiro, Brazil. Proc. IGARSS'01, vol. 1 (pp.333 -335).
7. Bern, T. -I., Wahl, T., Anderssen, T., & Olsen, R, Oil spill detection using satellite-based SAR. Completion report for Phase 0 and 1. Tech. rep., OCEANOR report no. OCNR92071, Trondheim. (1992b, 4–6 November).
8. Oil spill detection using satellite-based SAR: Experience from a field experiment. Proc. 1st ERS-1 Symposium, Cannes, France (pp. 829–834).
9. Bengio, S., Deng, L., Larochelle, H., Lee, H., and Salakhutdinov, R., Special Issue on Learning Deep Architectures, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 8, no. 35 (2013).
10. Hastie, T., Tibshirani, and R., Friedman, J., The Elements of Statistical Learning: Data Mining, Inference, and Prediction, Springer (2009).
11. LeCun, Y., Bottou, L, Bengio, Y., and Haffner, P., "Gradient-based learning applied to document recognition", The Proceedings of the IEEE 86, vol. 11, pp. 2278-2324 (1998).
12. Hussain, U. H., Dansharif, A. R., Mustapha, M. G., Abba, B. M., Isah, A., & Babangida, M. M. (2025). Application of Deep Learning Techniques for Oil Spillage Detection using Sar Images. In Global Journal of Research in Engineering & Computer Sciences (Vol. 5, Number 4, pp. 21–25). https://doi.org/10.5281/zenodo.16331685.