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Deep Learning Approaches for Marine Oil Spill Detection and Monitoring

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Abstract—Oil spill disasters severely impact marine ecosystems and coastal economies, causing lasting environmental and financial harm. Early detection is critical to mitigate damage, but traditional methods relying on Convolutional Neural Networks (CNNs) face limitations in accuracy and scalability when analyzing large datasets for real-time monitoring. These challenges highlight the need for advanced solutions to improve efficiency and reliability in detecting oil spills. To address these issues, the YOLO v12 model has been proposed for oil spill detection. YOLO (You Only Look Once) is a state-of-the-art real-time object detection algorithm that surpasses traditional CNN-based methods in speed and precision. YOLO v12 builds on previous versions, offering enhanced detection accuracy and the ability to process extensive datasets efficiently. Its streamlined architecture allows for single-pass image analysis, ensuring rapid identification of oil spills. This makes it particularly suited for time-sensitive applications where swift responses are essential to minimize environmental and economic consequences. Integrating YOLO v12 into detection systems enables continuous monitoring through satellite or drone imagery, significantly improving detection speed and scalability for vast water bodies. This innovation enhances environmental protection and strengthens disaster response operations, making it a transformative tool in combating the effects of oil spill disasters.

***Index Terms*—Oil spill detection, YOLO v12, real-time monitoring, environmental protection, marine ecosystems, disaster response, object detection, CNN limitations.**

1. Introduction

Oil spills are a significant environmental concern, arising from various sources such as ship accidents, pipeline breaks, explosions at oil rigs, and intentional discharges from ships. When oil leaks into water bodies, it spreads quickly, forming a thin layer on the surface known as an oil spill. The rapid dispersion of oil due to environmental factors can lead to widespread contamination, making it crucial to address the issue of marine oil spills, which pose severe economic and ecological threats to coastal zones and marine ecosystems [21]. The NEREIDs program, supported by the European Commission, aims to mitigate major oil spill accidents by utilizing metocean, shipping, and geological data to characterize oil spills in critical exploration areas [2].

This program has led to the development of oil spill models that simulate the trajectory and development of spills, assess the vulnerability of coastal areas, and identify effective measures to minimize environmental impacts [5]. Identifying and classifying oil spills is essential for preventing water contamination, but challenges remain due to natural phenomena and human activities that can interfere with the detection of spills [18]. Synthetic Aperture Radar (SAR) technology offers a powerful solution for detecting oil spills, as it can capture high-resolution images of the Earth's surface under various conditions, including at night and in poor weather [21].

Oil spills appear as dark patches in SAR images due to their low-backscatter response compared to surrounding clean water. However, the presence of speckle noise in SAR images complicates the application of traditional image segmentation methods, as this noise results from the complex interaction of coherent signals within resolution cells [10]. Therefore, developing accurate segmentation techniques is vital for effective oil spill detection and management [15].

2. Related Work

A New Technique for Segmentation of the Oil Spills From Synthetic-Aperture Radar Images Using Convolutional Neural Network [1] Fatemeh Mahmoudi Ghara, Shahriar Baradaran Shokouhi [1]. Oil spills have devastating effects on marine ecosystems and economies, necessitating efficient detection methods. Synthetic-aperture radar (SAR) imaging is a robust solution for identifying oil spills due to its ability to collect data across wide areas, in all weather conditions, and at any time of day. This study aimed to segment SAR oil spill images using two deep neural networks, U-NET and DeepLabV3, and to determine their comparative accuracy. Given limited SAR image datasets, the input size was augmented to 9,801 images to improve training outcomes. Using 300 epochs and a batch size of 5, models were trained on Google Colab. Results showed that U-NET achieved a detection accuracy of 78.8%, significantly outperforming DeepLabV3 at 54%. U-NET's architecture proved superior for oil spill segmentation in SAR images, highlighting its potential as a reliable tool for mitigating oil pollution.

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Learning And Tailored Data Augmentation [2] Ngoc An Bui, Youngon Oh, Impyeong Lee [2]. Oil spill detection is vital for safeguarding marine ecosystems and mitigating oil contamination. This research enhances detection by integrating unmanned aerial vehicles (UAVs) with a dual attention deep learning model. The model includes spatial and channel attention mechanisms to capture pixel relationships and channel characteristics for effective oil spill classification. A refined Generative Adversarial Network (GAN)-based data augmentation technique further boosts detection accuracy. Experiments using various dataset configurations, encoder-decoder models, and hyperparameter tuning achieved a mean IoU of 72.49%. The GAN-based augmentation improved IoU by 2.56%, highlighting its significance. These advancements provide reliable tools for marine environmental management, ensuring timely and effective responses to oil spill incidents.

A self-evolving deep learning algorithm for automatic oil spill detection in Sentinel-1 SAR images [3] Chenglei Li, Duk-jin Kim [3] Oil spill accidents significantly contribute to marine pollution, necessitating rapid detection for effective response. This study introduces a novel self-evolving algorithm for automatic oil spill detection in Synthetic Aperture Radar (SAR) images, comprising three interconnected modules: oil spill detection, new training data generation, and deep learning model enhancement. The algorithm autonomously detects oil slicks and generates additional high-quality training data through an adaptive thresholding method, addressing the challenges of false positives from look-alikes. By considering variations in backscattering coefficients near oil boundaries, the algorithm successfully distinguishes oil spills from similar surface phenomena. After 21 self-evolving training cycles, the F1-score improved from 0.8423 to 0.8896, demonstrating enhanced detection capabilities without human intervention. This approach not only mitigates the limitations of existing detection algorithms but also paves the way for further advancements in oil spill monitoring.

Deep learning-based approaches for oil spill detection: a bibliometric review of research trends and challenges [4] rodrigo n. vasconcelos, rodrigo n. vasconcelos [4]. Oil spill detection and mapping using deep learning (OSDMDL) is critical for understanding and mitigating oil spill impacts on coastal and marine ecosystems. This study introduces a novel approach by combining bibliometric analysis and literature review to evaluate scientific advancements in the field. Leveraging the Scopus database, the research highlights insights into neural network architectures, international collaborations, and impactful studies. Key findings include the prominence of multilayer perceptrons (MLPs) in 11 studies, followed by convolutional neural networks (CNNs) in five, and U-Net, DeepLabv3+, and fully convolutional networks (FCNs) in three studies each. These architectures underline the evolution of methods for improved oil spill detection. Additionally, the analysis uncovers trends in interdisciplinary research and international cooperation, emphasizing the role of collective effort in advancing remote sensing technologies.

Deep learning-based oil spill classification using unet convolutional neural network [5] Abdul Basit; Muhammad A. Siddique; M. Saquib Sarfraz [5]. Oil spills significantly harm marine ecosystems, and effective detection is crucial for mitigating pollution. This research utilizes the U-Net convolutional neural network, adapted from biomedical segmentation, to classify oil spills using

Sentinel-1 SAR images. The model segments regions such as sea surface, oil spills, look-alikes, ships, and land. The U-Net model achieves impressive results, with a mean Intersection over Union (mIoU) of 75.70%, marking a 10% improvement over previous methods. Notably, it performs well with IoU scores of 95.69% for sea surfaces, 60.85% for oil spills, and 96.79% for land. These results highlight its potential as a reliable tool for monitoring and managing marine pollution effectively.

3. Approach

The YOLO v12 model offers significant advancements in object detection, making it ideal for time-sensitive applications like oil spill detection. Unlike traditional models, YOLO v12 processes images in a single pass, optimizing both speed and accuracy, which is crucial for rapid identification of oil spills in marine environments. This efficiency minimizes the time between detection and response, helping to mitigate the harmful effects of oil pollution. YOLO v12's refined architecture enables it to handle large volumes of data, including satellite and drone imagery, ensuring that oil spills are detected in real-time. This capability is particularly valuable for monitoring vast bodies of water, where traditional methods may struggle. The scalability and operational efficiency of YOLO v12 enhance disaster response operations, enabling quicker action to reduce environmental damage. By improving detection accuracy and response time, YOLO v12 offers a robust solution for protecting marine ecosystems and supporting coastal economies affected by oil spills.

A. Data Collection

Data collection is a critical first step in any machine learning project, particularly in the context of oil spill detection using deep learning algorithms like YOLO v12. This phase involves gathering a comprehensive dataset that includes a variety of images depicting oil spills, look-alikes, and clean water surfaces under different environmental conditions. The data can be sourced from multiple platforms, such as satellite imagery, drones, and existing datasets like the Sentinel-1 synthetic aperture radar (SAR) images. It's essential to ensure that the collected data is diverse and representative of the scenarios that the model will encounter in real-world applications, as this diversity helps improve the model's robustness and accuracy in detecting oil spills.

B. Pre-Processing

Pre-processing involves preparing the collected data for analysis and model training. This step typically includes several techniques to enhance the quality of the images and make them suitable for input into a deep learning model. Common pre-processing tasks include resizing images to a consistent scale, normalizing pixel values to a range suitable for neural network training, and augmenting the dataset through techniques such as rotation, flipping, and noise addition. The goal of pre-processing is to reduce variability in the data, which helps improve the model's ability to learn and generalize from the training dataset. Additionally, it may involve segmenting the images to highlight areas of interest, such as oil spills, for more eective training.

C. *Feature Extraction*

Feature extraction is the process of identifying and isolating relevant patterns and characteristics within the pre-processed images that can help the model make accurate predictions. In deep learning, this is often accomplished using convolutional layers that automatically learn features from the data during training. These features can include edges, textures, and shapes that distinguish oil spills from other elements in the images. The effectiveness of feature extraction significantly impacts the model's performance, as well-extracted features can lead to better discrimination between oil spills and look-alikes. Advanced models like YOLO v12 utilize sophisticated architectures that enhance feature extraction, allowing for the detection of more subtle characteristics associated with oil spills.

D. *Model Creation*

Model creation involves designing and training a deep learning model using the processed data. This phase includes selecting an appropriate architecture, such as YOLO v12, which is optimized for object detection tasks. During training, the model learns to associate the extracted features with corresponding labels (e.g., oil spill or not) by adjusting its internal parameters through backpropagation and optimization algorithms. The training process typically involves splitting the dataset into training and validation sets to monitor the model's performance and prevent overfitting. Various hyperparameters, such as learning rate, batch size, and the number of epochs, are also fine-tuned during this stage to enhance the model's accuracy and reliability in detecting oil spills.

E. *Test Data*

Testing the model involves evaluating its performance on a separate dataset that it has not encountered during training. This test data is crucial for assessing how well the model generalizes to new, unseen images. The test set should be representative of the same conditions as the training data but must not overlap with it to ensure a fair evaluation. Metrics such as precision, recall, and Intersection over Union (IoU) are commonly used to quantify the model's performance on the test data. By analyzing the results, researchers can identify areas where the model excels and where it may need further improvement or refinement, ensuring that it is robust enough for real-world deployment.

F. *Prediction*

Prediction is the final step in the oil spill detection process, where the trained model is deployed to identify and classify oil spills in new images. During this phase, the model processes incoming data, applying the learned features and relationships to make real-time predictions about the presence of oil spills. The output can include bounding boxes around detected spills, confidence scores indicating the likelihood of a correct identification, and classifications of the type of spill (if applicable). Effective prediction enables timely response actions to mitigate the environmental impact of oil spills, making this phase critical for operational efficiency and disaster management in marine environments. The accuracy and speed of the prediction process are essential for ensuring rapid intervention and effective monitoring of oil spill incidents.

G. *Architecture Diagram*

The proposed system for oil spill detection utilizes the YOLO V12 algorithm, which is a state-of-the-art object detection model known for its speed and accuracy in real-time image processing. Unlike traditional deep learning models, YOLO (You Only Look Once) operates by dividing an image into a grid and simultaneously predicting bounding boxes and class probabilities for each grid cell.

This enables the system to detect and localize oil spills in satellite or UAV images more efficiently. In the architecture, the system first collects remote sensing data (usually SAR images from satellites like Sentinel-1) that provide critical information about the ocean's surface.

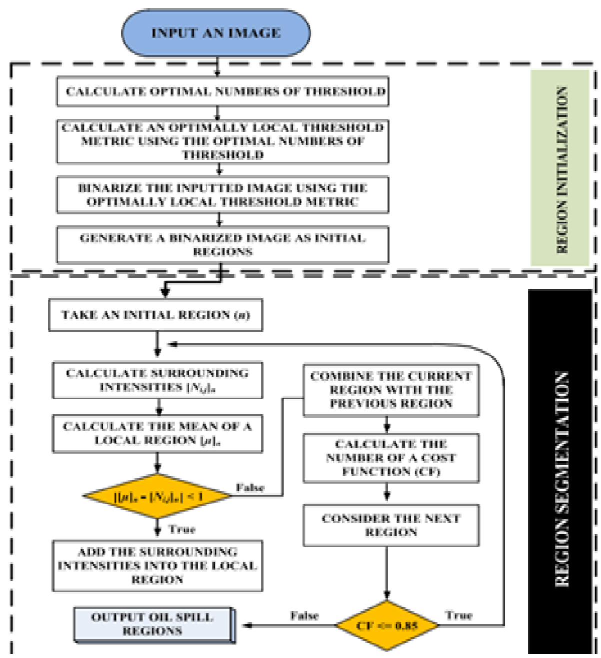

Fig. 1. Architecture diagram of the proposed system

The images undergo pre-processing where noise is removed, and the data is normalized for optimal model input. YOLO V12 is then used for the detection and classification of oil spills, sea surfaces in the images. The model's advanced architecture allows it to perform multi-class detection in real-time, making it ideal for the fast-paced nature of oil spill response.

It performs these tasks by predicting multiple objects in the same image and returning bounding boxes with associated class labels (e.g., oil spill, water, ships). After detection, post-processing techniques are applied to filter out false positives and refine predictions. This makes the YOLO V12-based system highly scalable and efficient, ensuring timely detection of oil spills and enabling quick response to minimize environmental damage. With high accuracy and real-time processing capabilities, YOLO V12 represents a powerful solution for large-scale environmental monitoring.

4. Experimental Results

This section of a research paper serves to interpret the findings and explore their implications. In the case of oil spill detection using YOLO v12, the results would detail the model's performance, highlighting key metrics such as accuracy, Intersection over Union (IoU), precision, recall, and processing speed. It would demonstrate how well YOLO v12 detects and classifies oil spills in real-time from datasets like satellite and drone images, showcasing improvements over previous models such as traditional CNN-based systems. For example, YOLO v12 might achieve a high IoU, indicating accurate identification of oil spill regions with minimal false positives. The model's ability to process large volumes of images quickly would be a key point, emphasizing its suitability for time-sensitive tasks like oil spill detection. The discussion would interpret these results, emphasizing how YOLO v12's enhanced accuracy and speed make it an ideal tool for real-time monitoring, improving environmental protection and disaster response efficiency. It would also address potential limitations, such as performance variability under different environmental conditions, and suggest avenues for future improvements, such as integrating YOLO v12 with other models for better robustness.

A. Precision

$$\text{Precision} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)}}$$

- True Positives (TP): Correctly predicted positive cases.
- False Positives (FP): Incorrectly predicted positive cases (actually negative).

Precision is a performance metric used to evaluate the accuracy of a model's positive predictions. It measures the proportion of true positive predictions (correctly identified positive cases) out of all the predictions that were classified as positive. A high precision score indicates that the model is making very few false positive errors, meaning that when it predicts something as positive, it is likely to be correct. Precision is particularly useful in scenarios where minimizing false positives is crucial, such as in medical diagnoses or fraud detection.

B. Loss

Loss is a measure of how well or poorly a model is performing. It calculates the difference between the predicted output and the actual output during training. Lower loss indicates better model performance. Common loss functions include Mean Squared Error (MSE) for regression tasks and Cross-Entropy Loss for classification tasks.

Loss is a measure used to evaluate how well a machine learning model's predictions match the actual outcomes. It quantifies the difference between the predicted values and the true values during training.

A lower loss indicates that the model's predictions are closer to the actual results, while a higher loss suggests a larger discrepancy. Different types of loss functions are used depending on the task, such as mean squared error for regression or cross-entropy loss for classification.

$$\text{Loss} = -\frac{1}{N}\sum_{i=1}^{N}\left(y_i \log(p_i) + (1 - y_i)\log(1 - p_i)\right)$$

- y_i is the actual label (0 or 1).
- p_i is the predicted probability for class 1.
- N is the total number of samples.

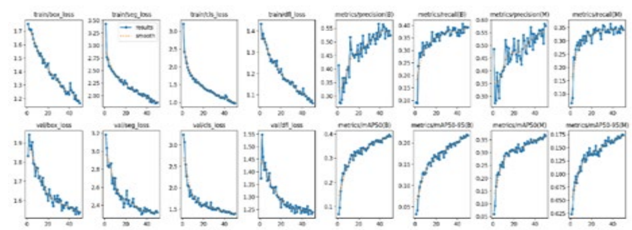

Fig. 2.

C. F1 Confidence Curve

The F1 score is a measure of a model's accuracy that balances both precision and recall. It is particularly useful when the data has an imbalance between classes. The F1 score is the harmonic mean of precision and recall, ensuring that both metrics are given equal importance.

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Where:

- **Precision** is the ratio of true positive predictions to the total positive predictions (both true and false positives).
- **Recall** is the ratio of true positives to the total actual positives (true positives and false negatives).

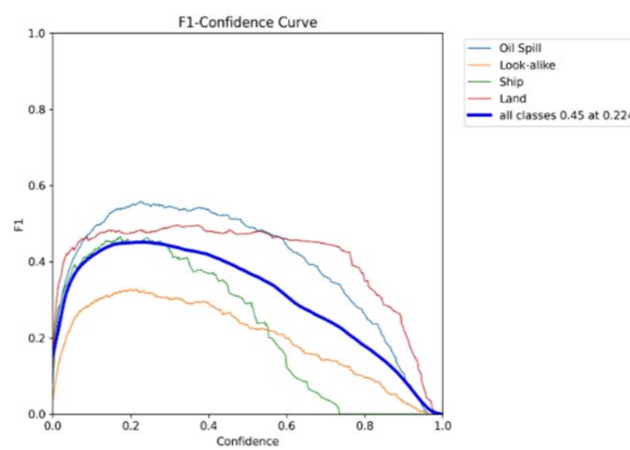

Fig. 3.

The F1 score ranges between 0 and 1, where 1 indicates perfect precision and recall, and 0 means the model performs poorly in both. It is especially useful when you want a balance between precision and recall.

The F1 confidence curve is a graphical representation that shows how the F1 score, a measure of a model's accuracy, varies across different confidence thresholds. The F1 score is the harmonic mean of precision and recall, and it provides a balanced measure of both metrics, especially useful when dealing with imbalanced datasets. The confidence curve helps to visualize the trade-offs between precision and recall at various threshold levels. As the confidence threshold changes, the model might become more conservative or lenient in making predictions, which impacts precision and recall, and consequently the F1 score. This curve aids in selecting an optimal threshold to maximize the F1 score, improving the model's overall performance.

5. Conclusion

The integration of the YOLO v12 model into oil spill detection systems represents a major leap forward in terms of both speed and accuracy. This model's architecture is designed to process images in a single pass, making it highly efficient for time-sensitive tasks like detecting oil spills. Its advanced capabilities allow it to quickly analyze satellite or drone images and pinpoint affected areas, ensuring rapid identification of oil spills. This swift detection is crucial in minimizing the environmental impact, as quicker responses can prevent the spread of oil and reduce the long-term damage to marine ecosystems. Another key benefit of YOLO v12 is its ability to handle large datasets efficiently. With satellite and drone surveillance providing continuous streams of data over vast bodies of water, the model's capacity to process high volumes of images makes it an ideal choice for real-time monitoring. This ensures that oil spills can be detected almost immediately, providing real-time alerts to responders who can act quickly to contain and manage the spill. The model's ability to scale with the size of the dataset also makes it adaptable to monitoring oceans, seas, and coastal areas, offering a flexible solution for various geographic scales. Ultimately, the use of YOLO v12 in oil spill detection not only enhances environmental protection efforts but also improves disaster response operations. By offering a reliable and scalable solution, this model ensures that monitoring efforts can keep pace with the growing demand for environmental safeguards in marine ecosystems.

References

[1] A. Raeisi, G. Akbarizadeh, and A. Mahmoudi, "Combined method of an efficient cuckoo search algorithm and nonnegative matrix factorization of different Zernike moment features for discrimination between oil spills and lookalikes in SAR images," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 11, no. 11, pp. 4193–4205, Nov. 2018.

[2] T. M. Alves, E. Kokinou, G. Zodiatis, R. Lardner, C. Panagiotakis, and H. Radhakrishnan, "Modelling of oil spills in confined maritime basins: The case for early response in the eastern Mediterranean Sea," *Environmental Pollution*, vol. 206, pp. 390–399, Nov. 2015.

[3] R. Lardner and G. Zodiatis, "Modelling oil plumes from subsurface spills," *Marine Pollution Bulletin*, vol. 124, no. 1, pp. 94–101, Nov. 2017.

[4] T. Soomere *et al*., "The potential of current- and wind-driven transport for environmental management of the Baltic Sea," *Ambio*, vol. 43, no. 1, pp. 94–104, Feb. 2014.

[5] A. Chrastansky and U. Callies, "Model-based long-term reconstruction of weather-driven variations in chronic oil pollution along the German North Sea coast," *Marine Pollution Bulletin*, vol. 58, no. 7, pp. 967–975, Jul. 2009.

[6] S. Singha, T. J. Bellerby, and O. Trieschmann, "Satellite oil spill detection using artificial neural networks," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 6, no. 6, pp. 2355–2363, Dec. 2013.

[7] K. Topouzelis, V. Karathanassi, P. Pavlakis, and D. Rokos, "Detection and discrimination between oil spills and look-alike phenomena through neural networks," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 62, no. 4, pp. 264–270, Sep. 2007.

[8] J. S. Murgan and V. Parthasarathy, "AETC: Segmentation and classification of the oil spills from SAR imagery," *Environmental Forensics*, vol. 18, no. 4, pp. 258–271, Nov. 2017.

[9] H. Guo, G. Wei, and J. An, "Dark spot detection in SAR images of oil spill using SegNet," *Applied Sciences*, vol. 8, no. 12, pp. 1–17, Dec. 2018.

[10] P. Wang, H. Zhang, and V. M. Patel, "SAR image despeckling using a convolutional neural network," *IEEE Signal Processing Letters*, vol. 24, no. 12, pp. 1763–1767, Dec. 2017.

[11] G. Chen, Y. Li, G. Sun, and Y. Zhang, "Application of deep networks to oil spill detection using polarimetric synthetic aperture radar images," *Applied Sciences*, vol. 7, no. 10, pp. 1–15, Sep. 2017.

[12] J. F. Penner and D. G. Long, "Ground-based 3D radar imaging of trees using a 2D synthetic aperture," *Electronics*, vol. 6, no. 1, pp. 1–13, Jan. 2017.

[13] F. M. Bianchi, O. Martine, M. Espeseth, and N. Borch, "Large-scale detection and categorization of oil spills from SAR images with deep learning," *Remote Sensing*, vol. 12, no. 14, Art. no. 2260, Jul. 2020.

[14] D. Malmgren-Hansen and M. Nobel-Jorgensen, "Convolutional neural networks for SAR image segmentation," in *Proc. IEEE International Symposium on Signal Processing and Information Technology (ISSPIT)*, 2015, pp. 231–236.

[15] J. Zhang, H. Feng, Q. Luo, Y. Li, J. Wei, and J. Li, "Oil spill detection in quad-polarimetric SAR images using an advanced convolutional neural network based on superpixel model," *Remote Sensing*, vol. 12, no. 6, pp. 1–26, Mar. 2020.

[16] R. Li *et al*., "DeepUNet: A deep fully convolutional network for pixel-level sea-land segmentation," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 11, no. 11, pp. 3954–3962, Nov. 2018.

[17] B. Liu, Y. Li, G. Li, and A. Liu, "A spectral feature based convolutional neural network for classification of sea surface oil spill," *ISPRS International Journal of Geo-Information*, vol. 8, no. 4, pp. 1–14, Mar. 2019.

[18] H. Guo, D. Wu, and J. An, "Discrimination of oil slicks and lookalikes in polarimetric SAR images using CNN," *Sensors*, vol. 17, no. 8, pp. 1–20, Aug. 2017.

[19] Y. Duan, F. Liu, L. Jiao, P. Zhao, and L. Zhang, "SAR image segmentation based on convolutional-wavelet neural network and Markov random field," *Pattern Recognition*, vol. 64, pp. 255–267, Apr. 2017.

[20] T. Y. Lin, P. Dollár, R. Girshick, K. He, B. Hariharan, and S. Belongie, "Feature pyramid networks for object detection," in *Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2017, pp. 936–944.

[21] C. Brekke and A. H. Solberg, "Oil spill detection by satellite remote sensing," *Remote Sensing of Environment*, vol. 95, no. 1, pp. 1–13, Mar. 2005.

[22] O. Garcia-Pineda, I. R. MacDonald, X. Li, C. R. Jackson, and W. G. Pichel, "Oil spill mapping and measurement in the Gulf of Mexico with textural classifier neural network algorithm (TCNNA)," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 6, no. 6, pp. 2517–2525, Dec. 2013.

[23] M. Krestenitis, G. Orfanidis, K. Ioannidis, K. Avgerinakis, S. Vrochidis, and I. Kompatsiaris, "Oil spill identification from satellite images using deep neural networks," *Remote Sensing*, vol. 11, no. 15, pp. 1–22, Jul. 2019.

[24] F. Ma, F. Zhang, D. Xiang, Q. Yin, and Y. Zhou, "Fast task-specific region merging for SAR image segmentation," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 60, Art. no. 5222316, 2022.

[25] F. Ma, F. Zhang, D. Xiang, Q. Yin, and Y. Zhou, "Fast SAR image segmentation with deep task-specific superpixel sampling and soft graph convolution," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 60, Art. no. 5214116, 2022.