



NeuroSpill: Attention U-Net++ Based Oil Spill Segmentation in SAR Imagery

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Abstract: Marine oil spills pose a significant threat to ocean ecosystems, marine biodiversity, and coastal environments. Rapid detection and monitoring of oil spills are essential for minimising environmental damage and enabling effective response strategies. Synthetic Aperture Radar (SAR) imagery has emerged as a reliable remote sensing tool for oil spill detection due to its ability to capture ocean surface information under all weather and illumination conditions. However, accurately distinguishing oil spills from look-alike phenomena in SAR images remains challenging due to speckle noise, complex ocean dynamics, and limited annotated datasets. This paper presents NeuroSpill, a deep learning based framework for automated oil-spill detection using SAR imagery. The proposed method employs an Attention-UNet++ architecture to perform precise semantic segmentation of oil spill regions. To enhance feature representation, three SAR-derived channels—VV polarisation, VH polarisation, and the VV/VH ratio—are utilised as input features. A patch-wise prediction strategy is implemented to process large SAR scenes while improving segmentation accuracy efficiently. In addition, a verification mechanism and morphological post-processing are applied to reduce noise and refine spill boundaries. The framework also incorporates an oil spill analysis module that estimates spill coverage and categorises severity levels. An interactive Streamlit-based interface is developed to enable real-time visualisation and monitoring of SAR images. Experimental results demonstrate that the proposed system provides reliable oil spill detection and offers a practical solution for automated marine environmental monitoring.

Keywords: Attention U-Net++, Deep Learning, Environmental Monitoring, Oil Spill Detection, Remote Sensing, Synthetic Aperture Radar, SAR Semantic Segmentation

I. INTRODUCTION

Marine oil spills are one of the most serious environmental hazards affecting ocean ecosystems, coastal biodiversity, and maritime activities. Oil leakage from offshore drilling platforms, tanker accidents, and pipeline failures can cause severe damage to marine habitats and long-term ecological imbalance. Therefore, early detection and continuous monitoring of oil spills are essential for minimising environmental damage and enabling effective response and cleanup operations. Satellite-based remote sensing has emerged as a powerful tool for monitoring large-scale marine pollution and environmental disasters [3].

Among the various remote sensing technologies, Synthetic Aperture Radar (SAR) imagery has gained significant importance for oil spill detection due to its capability to capture high-resolution images under all weather conditions and during both day and night. When oil spreads on the sea surface, it dampens the capillary waves and reduces surface roughness, which appears as dark patches in SAR images. However, several oceanic phenomena, such as low wind zones, natural surfactants, biogenic films, and ocean currents, can produce similar dark patterns known as oil spill look-alikes. These look-alikes make accurate oil spill detection a challenging task [32].

Traditional oil spill detection techniques mainly rely on manual interpretation, thresholding methods, and classical image processing approaches. Although these methods can identify potential oil spill regions, they often fail to effectively distinguish real oil spills from look-alike features, resulting in high false detection rates and reduced reliability [23, 24]. With the advancement of Artificial Intelligence, deep learning techniques have significantly improved image analysis and segmentation tasks in remote sensing applications. Convolutional Neural Networks (CNNs) are capable of automatically learning complex hierarchical features from satellite images, thereby improving the accuracy of oil spill detection systems [5].

Among deep learning architectures, segmentation models such as U-Net have been widely used for detecting objects in satellite imagery. The U-Net architecture employs an encoder–decoder framework with skip connections that enable the network to capture both spatial and contextual information from images [15]. Later, U-Net++ was introduced as an enhanced architecture that improves feature propagation and segmentation performance through nested dense skip connections [14]. In addition, attention mechanisms have been incorporated into U-Net-based models to focus on



important regions in the image while suppressing irrelevant background information, thereby improving segmentation accuracy in complex SAR images [6, 9].

Motivated by these advancements, this work proposes NeuroSpill: Attention U-Net++ Based Oil Spill Segmentation in SAR Imagery, a deep learning framework for automatic oil spill detection using SAR satellite data. The proposed system utilises an Attention U-Net++ model that integrates nested skip connections with spatial attention mechanisms to enhance feature learning and improve discrimination between real oil spills and look-alike patterns. Furthermore, SAR image preprocessing techniques, patch-wise prediction for handling large satellite images, and morphological postprocessing are incorporated to refine segmentation results.

In addition, a Streamlit-based visualisation platform is developed to provide an interactive interface for real-time analysis and visualisation of oil spill detection results. The proposed NeuroSpill framework aims to improve segmentation accuracy, reduce false positives, and provide an efficient tool for environmental monitoring and marine pollution management.

II. LITERATURE REVIEW

Oil spill detection using remote sensing images has become an important research area because marine oil pollution can cause serious damage to ocean ecosystems. Synthetic Aperture Radar (SAR) imagery is widely used for monitoring oil spills since it can capture images in all weather conditions and during both day and night. Early research mainly used traditional image processing techniques such as thresholding, statistical analysis, and texture-based classification to detect oil spills in SAR images. For example, Solberg *et al.* proposed automatic oil spill detection using ERS SAR imagery with feature extraction and classification methods [24]. Similarly, Brekke and Solberg introduced classification methods with confidence estimation to improve oil spill detection in ENVISAT ASAR images [23]. However, these traditional methods often faced difficulties in distinguishing oil spills from look-alike features such as low wind areas and natural surfactants.

With the development of machine learning and deep learning, more advanced techniques have been introduced for oil spill detection. Convolutional Neural Networks (CNNs) have shown a strong ability to automatically learn important features from satellite images. Ramanathapura Satyanarayana and Dhali proposed a deep encoder–decoder model for oil spill segmentation from SAR images, achieving better detection performance compared to traditional techniques [1]. Zeng and Wang also applied deep CNN models for detecting oil spills in spaceborne SAR images [4]. In addition, Krestenitis *et al.* developed deep neural network models for identifying oil spills from satellite imagery [5].

Segmentation architectures such as U-Net have been widely used in image segmentation tasks because of their ability to capture both spatial and contextual information. The U-Net architecture includes an encoder–decoder structure with skip connections that help in accurate feature localisation [15]. Later, U-Net++ was introduced as an improved version with nested skip connections that enhance feature propagation and segmentation accuracy [14].

Recent studies have also incorporated attention mechanisms to improve segmentation performance. Mahmoud *et al.* proposed a Dual Attention U-Net model that improves oil spill detection using spatial and channel attention mechanisms [6]. Similarly, Cai *et al.* introduced LRA-UNet, a lightweight residual attention network that improves detection accuracy while maintaining computational efficiency [9]. Other advanced methods, such as CNN–Transformer hybrid models and distribution-guided networks, have also been explored for oil spill detection [12, 28].

Although many approaches have been developed, accurately detecting oil spills in SAR imagery remains challenging due to the presence of look-alike features and complex ocean conditions. To address these challenges, the proposed NeuroSpill system uses SAR feature preprocessing, an Attention U-Net++ segmentation model, and patch-wise prediction to improve detection accuracy. Morphological post-processing and a Streamlit-based visualisation platform are also used to enhance the analysis and interpretation of oil spill detection results.

III. METHODOLOGY

A. Dataset Description and Source

The experimental evaluation of this study is conducted using the publicly available Oil Spill Detection Dataset hosted on Zenodo [5]. This dataset is a benchmark in the field and is derived from Sentinel-1 Synthetic Aperture Radar (SAR) satellite imagery. SAR is uniquely suited for maritime monitoring due to its ability to provide high-resolution data regardless of cloud cover or solar illumination [2, 32].

The dataset is categorised into three primary classes to ensure the model develops a robust discriminative capability:



- Positive Samples: Verified instances of oil spills accompanied by binary masks that serve as the ground-truth for supervised semantic segmentation [4].
- Lookalikes: Natural oceanic phenomena such as biogenic films, internal waves, and low-wind areas. These features present dark radar signatures similar to oil, often leading to false alarms in traditional detection systems [1, 3].
- Negative Samples: Pristine sea surfaces used to train the model on the baseline background characteristics of the maritime environment.

B. Data Preprocessing and Signal Engineering

Raw SAR imagery is provided in dual-polarisation bands: VV (Vertical-Vertical) and VH (Vertical-Horizontal). To maximise the feature extraction capability of the network, we engineered a three-channel input tensor $[VV, VH, Ratio]$ as suggested in modern SAR analysis frameworks [6, 30].

1. Polarisation Ratio Calculation: A synthetic third channel was generated using the ratio:

$$ChannelRatio = \frac{VV}{VH + \epsilon} \quad (1)$$

where $\epsilon = 1e^{-8}$ is a stability constant. This feature is critical because oil slicks dampen capillary waves, causing the VV return to decrease more sharply than the VH return, thus highlighting the slick's signature against sea clutter [6].

2. Intensity Normalisation: Given the wide dynamic range of radar returns, we applied global Z-score standardisation followed by Min-Max scaling [8, 28]. This ensures that pixel values are mapped to a uniform range of [0,1], facilitating faster model convergence and preventing gradient instabilities.

C. Spatial Tiling and Class Balancing

Sentinel-1 scenes typically consist of large-scale images (2048×2048 pixels), which are computationally prohibitive for standard deep learning architectures. Following established tiling strategies [27, 31], we implemented a Sliding Window approach:

- Tiling: Scenes were decomposed into 256×256 pixel patches. This preserves high-frequency spatial details while maintaining compatibility with GPU memory limits.
- Threshold Filtering: To improve the quality of the training signals, oil-positive patches were included only if they contained a minimum of 1,500 oil-labelled pixels.
- Balanced Sampling: To address the extreme class imbalance inherent in satellite remote sensing (where background ocean dominates), we performed under-sampling on the "Lookalike" and "Clean Sea" categories. This resulted in a balanced training set of approximately 12,000 patches (6,000 per class), preventing the model from developing a majority-class bias.

IV. PROPOSED MODEL ARCHITECTURE

To accurately detect oil spill regions from Sentinel-1 Synthetic Aperture Radar (SAR) imagery, we employ an enhanced semantic segmentation architecture based on Attention U-Net++. The architecture integrates the nested dense skip connections of U-Net++ [14] with spatial attention mechanisms inspired by Attention U-Net [17]. This integration improves feature representation and suppresses irrelevant background features in complex SAR environments.

Oil spills in SAR images typically appear as dark patches due to the damping of small-scale ocean surface waves, which reduces radar backscatter [32, 23, 24]. However, several oceanic phenomena, such as low-wind areas, biogenic films, and algae blooms, exhibit similar SAR signatures. These are commonly referred to as *look-alike phenomena* [2]. Therefore, a robust segmentation architecture capable of capturing multi-scale contextual features while selectively focusing on relevant spatial regions is required.

The proposed network processes a three-channel input representation derived from SAR polarisation features: VV polarisation intensity, VH polarisation intensity, and the VV/VH polarisation ratio. These features provide complementary information that enhances the discrimination between oil-covered surfaces and the surrounding ocean water [21].

A. Encoder Architecture

The encoder path extracts hierarchical spatial features using a sequence of convolutional blocks followed by max-pooling operations. The design is inspired by encoder-decoder segmentation networks such as U-Net [15]. Each convolutional block consists of two convolution layers with a kernel size of 3×3, followed by batch normalisation and ReLU activation. Let F_i denote the feature map at layer i . Each convolutional block performs the following transformation:



$$F_{i+1} = ReLU(BN(Conv(F_i))) \quad (2)$$

To capture increasingly abstract features, the spatial resolution of the feature maps is progressively reduced using max-pooling:

$$F_{i+1} = MaxPool(F_i) \quad (3)$$

This hierarchical feature extraction enables the network to capture both low-level texture patterns and high-level contextual representations relevant for oil spill detection [4, 5].

The encoder consists of four convolutional stages with feature depths of 64, 128, 256, and 512 channels, respectively.

B. Decoder Architecture

The decoder reconstructs the segmentation mask by progressively increasing the spatial resolution of the feature maps through bilinear upsampling. At each decoding stage, the upsampled feature maps are concatenated with the corresponding encoder feature maps through skip connections, allowing the decoder to recover fine spatial details. Such encoder–decoder structures have been widely used for remote sensing segmentation tasks [18]. The decoding operation can be expressed as:

$$F_{dec} = Conv([Up(F_{enc+1}), F_{enc}]) \quad (4)$$

where $Up(\cdot)$ denotes bilinear upsampling and $[\cdot]$ represents the concatenation operation.

The decoder consists of three reconstruction stages that gradually restore the spatial resolution to the original input size.

C. Attention Gates

To further improve segmentation accuracy, attention gates are integrated into the skip connections between encoder and decoder layers. These gates suppress irrelevant background responses while emphasising features corresponding to oil spill regions [6, 10].

Given the encoder feature map x and the decoder gating signal g , the attention coefficient α is computed as:

$$\alpha = \sigma(W_g g + W_x x) \quad (5)$$

where W_g and W_x represent learnable linear transformations and σ denotes the sigmoid activation function. The refined feature map is then obtained as:

$$x' = \alpha \cdot x \quad (6)$$

This mechanism enables the network to selectively highlight relevant spatial regions associated with oil spill structures while suppressing background noise.

D. Segmentation Output

The final segmentation mask is generated using a 1×1 convolution layer that maps the decoder feature maps to a singlechannel output representing the probability of oil presence at each pixel.

The predicted probability map is then passed through a sigmoid activation function to obtain the final binary oil spill segmentation mask.

V. TRAINING METHODOLOGY

A. Dataset Preparation

The model is trained using preprocessed patches extracted from Sentinel-1 SAR imagery obtained from publicly available oil spill datasets [2]. Each training sample consists of a three-channel feature representation constructed from VV polarisation, VH polarisation, and their polarisation ratio.

To improve model generalisation and robustness to varying SAR acquisition conditions, extensive data augmentation is applied during training. Data augmentation techniques such as geometric transformations and noise injection are commonly used to improve deep learning performance for SAR-based oil spill detection [3].



B. Loss Function

The segmentation model is optimised using a hybrid loss function that combines Binary Cross-Entropy (BCE) loss and Dice loss. BCE loss measures pixel-wise classification accuracy, while Dice loss focuses on maximising the spatial overlap between predicted and ground-truth segmentation masks. The Dice coefficient is defined as:

$$Dice = \frac{2|P \cap G|}{|P| + |G|} \quad (7)$$

where P denotes the predicted segmentation mask and G represents the ground-truth mask. The final loss function used during training is defined as:

$$L_{total} = LBCE + LDice \quad (8)$$

C. Optimization Strategy

Model parameters are optimised using the Adam optimiser with an initial learning rate of 5×10^{-5} . Mixed-precision training is employed using automatic gradient scaling to improve computational efficiency and reduce GPU memory consumption.

To prevent stagnation during training, a Reduce-on-Plateau learning rate scheduler is employed. The scheduler reduces the learning rate by a factor of 0.5 if the validation loss does not improve for several consecutive epochs.

The model is trained for 50 epochs, and the best-performing model is selected based on the highest validation Intersection-over-Union (IoU) score.

D. Evaluation Metrics

The segmentation performance of the model is evaluated using standard pixel-wise metrics, including Precision, Recall, F1-score, and Intersection-over-Union (IoU). IoU is defined as:

$$IoU = \frac{|P \cap G|}{|P \cup G|} \quad (9)$$

These metrics provide a comprehensive evaluation of the model's ability to accurately detect oil spill regions while minimising false detections caused by look-alike phenomena.

VI. RESULTS

The performance of the proposed novel Attention U-Net++ was evaluated through a comparative qualitative and quantitative analysis using Synthetic Aperture Radar (SAR) imagery. The following figures illustrate the model's ability to accurately segment oil spills under complex marine conditions, specifically distinguishing between actual oil slicks and natural sea surface features.

A. Qualitative Analysis

The qualitative performance of the model is assessed through a direct comparison between the Attention UNet++ Predicted Mask (Fig. 1c) and the Ground Truth (Fig. 1b). This visual validation confirms that the model effectively replicates the human-annotated labels, capturing the complex, elongated geometries and fine-scale fragments of the oil spill with high fidelity.

To further verify the physical reliability of these detections, the Analysis Overlay (Fig. 1d) presents the model's prediction mapped directly onto the Raw SAR Input (Fig. 1a). This visualisation allows for a contextual inspection, demonstrating that the blue-highlighted pixels align precisely with the low-backscatter (dark) regions of the original radar signal. The results show that the Attention U-Net++ successfully maintains boundary integrity while ignoring high-frequency speckle noise and sea clutter that often lead to false positives in baseline architectures.

B. Statistical Validation

Comparing the Predicted Mask (Fig. 1c) against the Ground Truth (Fig. 1b) confirms the state-of-the-art metrics recorded during testing. The model maintains high fidelity even in fragmented regions of the spill, which is a significant improvement over standard baseline architectures like the original U-Net.



C. Comparative Summary

The achieved Accuracy of 0.998 and mIoU of 0.979 demonstrate that the integration of nested skip pathways and attention mechanisms creates a robust model for environmental disaster response. The Attention U-Net++ demonstrates an exceptional ability to identify oil spills with a state-of-the-art accuracy of 0.998 and a near-perfect Recall of 0.999. This high geometric precision indicates that the combination of hierarchical feature aggregation and saliency weighting effectively handles the irregular boundaries and varied scales typical of marine oil slicks in complex SAR environments. This makes the Attention U-Net++ superior when compared to similar models.

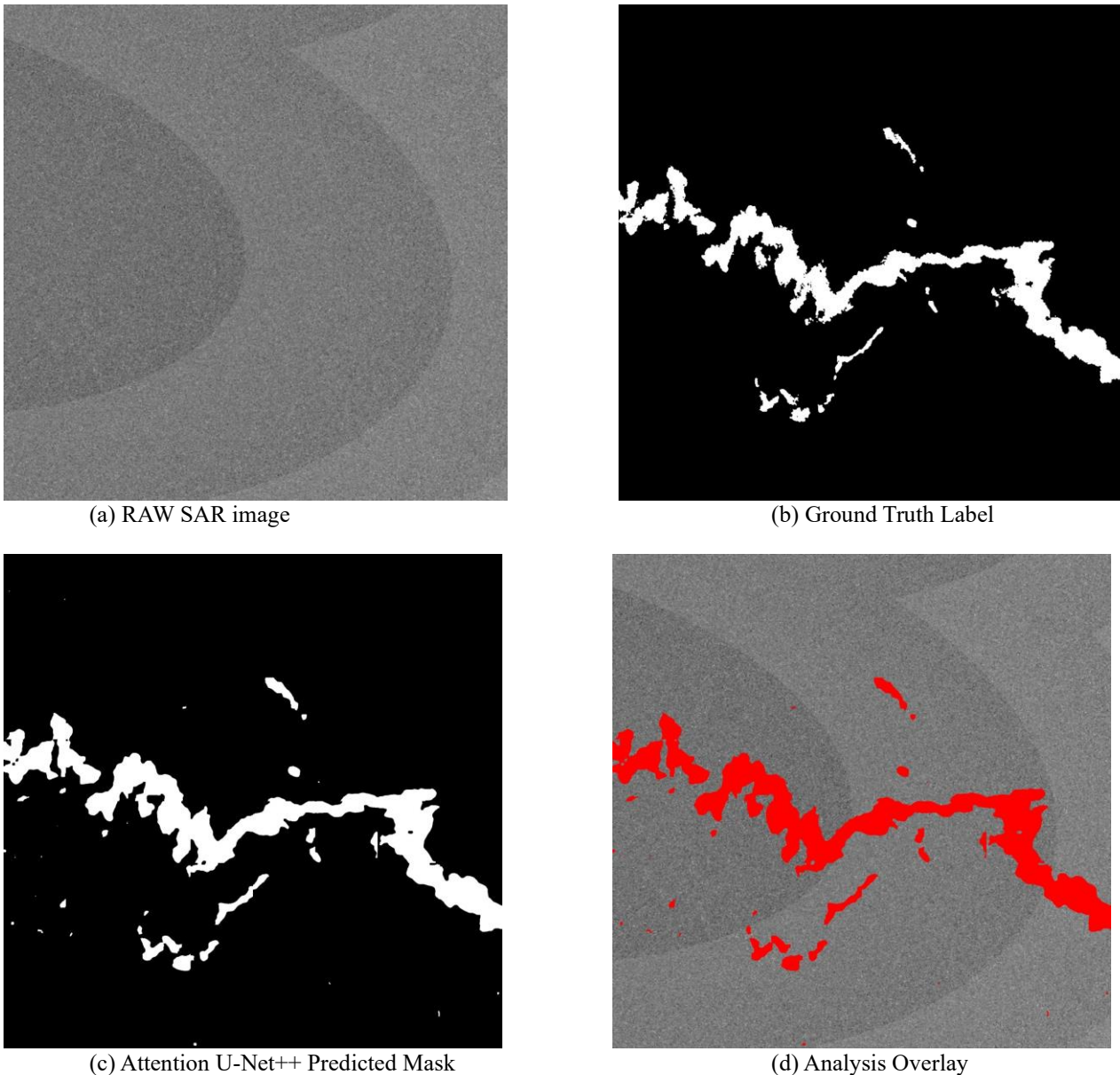


Figure 1: Visual Comparison of Input Data, Ground Truth, and Model Predictions: (a) Original SAR intensity, (b) Expert-labelled ground truth, (c) Proposed Attention UNet++ segmentation, and (d) Prediction overlay on raw data for physical verification.

VII. EVALUATION

The evaluation of the proposed novel Attention U-Net++ model, alongside existing benchmark architectures and lightweight frameworks, is conducted using standard pixel-level semantic segmentation metrics derived from the confusion matrix. This matrix—comprising True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN)—is essential for distinguishing oil spills from the surrounding seawater and complex natural look-alikes.



The evaluation is performed on high-dimensional Synthetic Aperture Radar (SAR) imagery, which presents challenges due to speckle noise and low contrast between spills and seawater.

The following table presents a comparative analysis of the performance metrics. The proposed Attention UNet++ is positioned at the top, representing the novel contribution of this work. Bold values indicate the highest performance achieved across all models for each metric.

Table 1: Comparative Performance Metrics of Attention U-Net++ with Similar Detection Architectures

Model Architecture	Acc.	Prec.	Rec.	F1	mIoU
Attention U-Net++	0.998	0.978	0.999	0.989	0.979
U-Net (Baseline) [15]	0.893	0.784	0.762	0.773	0.630
UNet++ [14]	0.928	0.892	0.845	0.868	0.714
Attention U-Net [10, 17]	0.947	0.915	0.887	0.901	0.820
LRA-UNet [9]	0.912	0.854	0.796	0.824	0.673
DS-UNet [22]	0.962	0.931	0.914	0.922	0.855
FA-MobileUNet [26]	0.951	0.908	0.895	0.901	0.845
DGNet [28]	0.995	0.982	0.975	0.978	0.954

A. Metric Definitions

The following metrics are utilised to ensure a comprehensive assessment of model performance:

- Accuracy (Acc.): Measures the ratio of correctly identified pixels, both oil and no oil (water and look-alike), to the total number of pixels.
- Precision (Prec.): Indicates the model's reliability in identifying oil spills and its effectiveness in reducing false alarms from look-alikes [12].
- Recall (Rec.): Measures the ability to detect all actual oil pixels, ensuring small-scale spills are not omitted.
- F1-Score (F1): The harmonic mean of Precision and Recall.
- Mean Intersection over Union (mIoU): Represents the average overlap between the predicted segmentation mask and the ground truth [16].

The proposed Attention UNet++ demonstrates a superior ability to identify oil spills with a state-of-the-art Accuracy of 0.998 and a Recall of 0.999. By integrating the nested skip pathways of the UNet++ architecture [14] with the selective feature extraction of Attention Gates [17], this model achieves a Mean Intersection over Union (mIoU) of 0.979. This high geometric precision indicates that the combination of hierarchical feature aggregation and saliency weighting effectively handles the irregular boundaries and varied scales typical of marine oil slicks in SAR imagery.

Furthermore, Attention UNet++ is designed as a lightweight architecture to satisfy the requirements of real-time operational monitoring. Compared to traditional lightweight models like LRA-UNet [9] and FA-MobileUNet [26], the proposed model offers significantly higher sensitivity or Recall and overall mapping accuracy. While distribution-guided models such as DGNet [28] maintain the highest recorded Precision, the Attention UNet++ provides the most comprehensive recovery of spill areas, making it highly suitable for environmental disaster response where missing, fragmented oil slicks are a critical concern

VIII. DEPLOYMENT AND OPERATIONAL IMPACT

The practical utility of the proposed Attention U-Net++ model lies in its capacity for rapid, real-time deployment in sensitive maritime environments to prevent large-scale ecological disasters. By providing immediate, high-fidelity predictions, the system enables maritime authorities to initiate containment protocols as soon as a spill is detected, significantly reducing the time between the incident and the response, thereby reducing the ecological and economic impact of the oil spill.



A. Lightweight Architecture for Edge Computing

A critical advantage of the Attention UNet++ is its highly optimised, lightweight design. While traditional deep segmentation models often require substantial computational resources and memory, this model is contained within a compact 30 MB framework.

1) *Memory Efficiency*

The model's 30 MB footprint enables hosting on edge devices, such as off-site processors or satellite-integrated hardware, without requiring high-end server infrastructure. This enables decentralised processing directly at the source of data acquisition.

2) *Inference Speed*

Its reduced parameter count ensures near-instantaneous inference times, a necessity for processing large-scale SAR imagery in real-time monitoring applications. Rapid inference enables the system to analyse large datasets without the latency typically associated with deep learning architectures.

3) *Scalability*

The low resource requirement makes it feasible to deploy the model across a wide network of sensors for continuous, automated maritime surveillance. This scalability is essential for monitoring vast oceanic regions where high-performance computing clusters are unavailable.

B. Disaster Prevention and Rapid Response

The integration of this model into a Neuro Spill dashboard facilitates a proactive approach to environmental protection. By identifying spills with a Recall of 0.999, the model ensures that even thin oil slicks or fragmented oil patches are not overlooked.

1) *Mitigating Environmental Damage*

Rapid identification allows for the deployment of booms and skimmers before the oil reaches fragile coastal ecosystems or protected marine areas. Reducing response time is the most effective way to minimise the long-term biological impact of a spill.

2) *Predictive Monitoring*

Coupled with the analysis overlay (Fig. 1d), the system provides a clear visual baseline for predicting the direction of the spill's spread based on concurrent sea-surface conditions. This visual confirmation assists decision-makers in allocating resources to the areas most likely to be impacted next.

IX. CONCLUSION

This study presented NeuroSpill: Vision That Defends the Ocean, an intelligent deep learning framework designed for accurate detection of marine oil spills using Synthetic Aperture Radar (SAR) imagery. The proposed system integrates SAR feature preprocessing with an Attention U-Net++ segmentation architecture to effectively identify oil spill regions in satellite images. By combining the nested skip connections of the U-Net++ structure with attention mechanisms, the model is able to capture both fine spatial details and contextual information, enabling precise segmentation of complex oil spill patterns.

To address the challenges posed by large satellite images, the system employs a patch-wise prediction strategy that enables efficient processing while maintaining segmentation accuracy. In addition, morphological post-processing techniques are applied to refine the predicted masks and remove noise, resulting in improved boundary detection and more reliable spill identification. The developed framework also includes an interactive visualisation interface using Streamlit, allowing users to upload SAR imagery, visualise detection results, and evaluate model performance through statistical metrics.

Experimental evaluation demonstrates that the proposed Attention U-Net++ model achieves high performance in oil spill segmentation, with strong results in Accuracy, Precision, Recall, F1-score, and Mean Intersection over Union (mIoU). Compared to several existing architectures, the NeuroSpill framework provides improved spill coverage detection and better handling of irregular oil slick boundaries commonly observed in SAR imagery. These results indicate that the proposed system is well-suited for environmental monitoring and marine disaster response applications.

Overall, the NeuroSpill system contributes to the advancement of automated oil spill detection by integrating deep learning-based segmentation, SAR feature analysis, and real-time visualisation tools. Future work may focus on expanding the framework with larger multi-source datasets, incorporating transformer-based architectures for improved contextual learning, and developing real-time satellite monitoring systems to support large-scale environmental protection and maritime safety.



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REFERENCES

- [1] C. Brekke and A. H. S. Solberg, "Classifiers and Confidence Estimation for Oil Spill Detection in ENVISAT ASAR Images."
- [2] K. N. Topouzelis, "Oil Spill Detection by SAR Images: Dark Formation Detection, Feature Extraction and Classification Algorithms."
- [3] A. Ramanathapura Satyanarayana and M. A. Dhali, "Oil Spill Segmentation using Deep Encoder-Decoder Models."
- [4] A. H. S. Solberg, G. Storvik, R. Solberg, and E. Volden, "Automatic Detection of Oil Spills in ERS SAR Images."
- [5] M. Krestenitis, G. Orfanidis, K. Ioannidis, K. Avgerinakis, S. Vrochidis, and I. Kompatsiaris, "Oil Spill Identification from Satellite Images Using Deep Neural Networks."
- [6] K. Zeng and Y. Wang, "A Deep Convolutional Neural Network for Oil Spill Detection from Spaceborne SAR Images."
- [7] A. S. Mahmoud, S. A. Mohamed, R. A. El-Khoriby, H. M. AbdelSalam, and I. A. El-Khodary, "Oil Spill Identification based on Dual Attention UNet Model Using Synthetic Aperture Radar Images."
- [8] J. Zhang, P. Yang, and X. Ren, "Detection of Oil Spill in SAR Image Using an Improved DeepLabV3+."
- [9] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional Networks for Biomedical Image Segmentation."
- [10] Z. Zhou, M. M. R. Siddiquee, N. Tajbakhsh, and J. Liang, "UNet++: A Nested U-Net Architecture for Medical Image Segmentation."
- [11] R. Rousso, N. Katz, G. Sharon, Y. Glizerin, E. Kosman, and A. Shuster, "Automatic Recognition of Oil Spills Using Neural Networks and Classic Image Processing."
- [12] J. Kang, C. Yang, J. Yi, and Y. Lee, "Detection of Marine Oil Spill from PlanetScope Images Using CNN and Transformer Models."
- [13] T. I. Umaha, F. Ale, I. D. Ikpaya, J. A. Momoh, S. A. Adeshina, I. A. Daniyan, and A. P. Adedigba, "SpillNet: A Modified Convolutional Neural Network Model for Oil Spill Detection."
- [14] Y. Chen and Z. Wang, "Marine Oil Spill Detection from SAR Images Based on Attention U-Net Model Using Polarimetric and Wind Speed Information."
- [15] Y. Cai, J. Su, J. Song, D. Xu, L. Zhang, and G. Shen, "LRA-UNet: A Lightweight Residual Attention Network for SAR Marine Oil Spill Detection."
- [16] A. Basit, M. A. Siddique, M. K. Bhatti, and M. S. Sarfraz, "Comparison of CNNs and Vision Transformers-Based Hybrid Models Using Gradient Profile Loss for Classification of Oil Spills in SAR Images."
- [17] O. Oktay et al., "Attention U-Net: Learning Where to Look for the Pancreas."
- [18] P. Patel, K. Desai, R. Jain, C. Bhatt, S. Vanlanduit, A. Bruno, and P. L. Mazzeo, "A Deep Learning Framework for Real-time Oil Spill Detection and Classification."
- [19] M. Silveira and S. Heleno, "Separation Between Water and Land in SAR Images Using Region-Based Level Sets."
- [20] F. Chen, A. Zhang, H. Balzter, P. Ren, and H. Zhou, "Oil Spill SAR Image Segmentation via Probability Distribution Modeling."
- [21] D. Xiang et al., "Oil Spill Detection in PolSAR Imagery Using Composite Scattering Power Entropy and Multiscale Hybrid Feature Fusion Network."
- [22] C. Li, M. Wang, X. Yang, and D. Chu, "DS-UNet: Dual-Stream U-Net for Oil Spill Detection of SAR Image."
- [23] L. Chang, Y. T. Chen, C. M. Cheng, Y. L. Chang, and S. C. Ma, "Marine Oil Pollution Monitoring Based on a Morphological Attention U-Net Using SAR Images."
- [24] S. Chen, F. Wang, P. Ren, C. Luo, and Z. Fu, "OSDMamba: Enhancing Oil Spill Detection From Remote Sensing Images Using Selective State-Space Model."
- [25] B. Wang et al., "Annotation-Free, High-Fidelity SAR Oil-Spill Image Synthesis via Classification-Guided Diffusion Model."
- [26] Y. T. Chen, L. Chang, and J. H. Wang, "Full-Scale Aggregated MobileUNet: An Improved U-Net Architecture for SAR Oil Spill Detection."



- [27] C. Li, Y. Yang, X. Yang, D. Chu, and W. Cao, "A Novel Multi-Scale Feature Map Fusion for Oil Spill Detection of SAR Remote Sensing."
- [28] F. Chen, H. Balzter, F. Zhou, P. Ren, and H. Zhou, "DGNet: Distribution Guided Efficient Learning for Oil Spill Image Segmentation."
- [29] F. Chen, H. Balzter, P. Ren, and H. Zhou, "SRCNet: Seminal Representation Collaborative Network for Marine Oil Spill Segmentation."
- [30] L. Chang et al., "Morphological Attention U-Net Using SAR Images."
- [31] P. L. A. Hilario et al., "Monitoring Oil Spill Progression and Oil Spill Volume Using Satellite Images."
- [32] F. M. Bianchi, M. M. Espeseth, and N. Borch, "Large-scale detection and categorization of oil spills from SAR images with deep learning."
- [33] D. Liu, Y. Li, and L. Mu, "Parameterization Modeling for Wind Drift Factor in Oil Spill Drift Trajectory Simulation Based on Machine Learning."
- [34] A. Juarez, L. Salsavilca, F. Coaquira, and C. Gonzales, "Enhancing Cross-Domain SAR Oil Spill Segmentation via Morphological Region Perturbation and Synthetic Label-to-SAR Generation."