Detecting Marine Oil Spills in SAR Images with DeepLabV3+ and Hybrid Loss Function

1. Abstract

Accidental oil discharges pose an escalating threat to marine ecosystems, coastal economies, and global climate resilience. Synthetic-aperture-radar (SAR) satellites can monitor vast ocean areas under all-weather conditions. Being automated, it struggles to differentiate between true oil slicks and visually similar "look-alikes". Our approach combines the DeepLabV3+ semantic-segmentation network (ResNet-101 encoder) with a with a hybrid loss function to mitigate severe class imbalance. Comprehensive experiments on the five-class M4D SAR benchmark show that our model achieves 95.7 % mean pixel accuracy, 63.2 % macro F1-score, and 0.79 mean Intersection-over-Union (mIoU)—surpassing three state-of-the-art baselines while maintaining real-time inference. The proposed framework offers a practical foundation for large-scale, near-real-time oil-spill surveillance.

Keywords — synthetic-aperture radar; semantic segmentation; hybrid loss; remote sensing;

2. Introduction

The International Tanker Owners Pollution Federation (ITOPF) reports that, while large scale tanker accidents have decreased over the past two decades, operational and pipeline related spills continue to leak an estimated 700 000 tonnes of crude oil into the ocean annually [1]. These slicks spread rapidly, jeopardising biodiversity hotspots such as coral reefs and fisheries, and they can travel hundreds of kilometres before detection. Traditional surveillance options—visual inspection of optical imagery, shipborne patrols, or aerial surveys—suffer from latency, heavy labour costs, and limited night time or cloud covered visibility.

Synthetic aperture radar (SAR) satellites—including Sentinel 1, RADARSAT 2, and TerraSAR X—overcome the mentioned limitations by emitting microwaves that penetrate clouds and operate independently of sunlight. Oil films dampen capillary waves on the sea surface, appearing as low backscatter dark patches in SAR scenes. However, look alike phenomena such as low wind areas, algal blooms, and batched organic matter produce similar signatures, complicating automated detection [2]. Classical thresholding or texture based algorithms therefore yield high false positive rates or require extensive hand crafted tuning.

Accidental petroleum releases spread quickly and are notoriously hard to clean up. Conventional surveillance—manual review of satellite frames, helicopter fly overs, or rule based image processing—takes time and often confuses natural phenomena (low wind slicks, algal films) with true oil. Recent advances in convolutional neural networks bring pixel level scene understanding to remote sensing data, giving responders sharper, faster insight. Advances in deep learning, especially object detection models like YOLO (You Only Look Once), have brought new potential to automate and accelerate oil spill detection. YOLOv11, the latest in the YOLO family, provides high-speed, real-time object detection with strong accuracy, making it reliable for maritime surveillance tasks.

Previous studies, such as the work by Sudha and Vijendran, achieved high accuracy using DeepLabV3+ on SAR images but relied heavily on specific satellite sources like TerraSAR-X, limiting generalization. Their use of a shallow ResNet-18 backbone and absence of advanced enhancements like hybrid loss functions or attention mechanisms leaves room for improvement. In contrast, our approach applies a more robust DeepLabV3+ model with an optimized training pipeline, diverse dataset handling, and comprehensive evaluation metrics including IoU and F1-Score. We focus on achieving consistent accuracy across varying SAR sources, enhancing real-world applicability. This makes our model not only more adaptive but also more suitable for practical deployment in marine oil spill monitoring.[11]

While previous studies using DeepLabV3+ demonstrated encouraging outcomes on specific regions like the Persian Gulf, they often focus on binary classification and region-limited datasets. In contrast, our approach tackles a more diverse and complex dataset (M4D) with five semantic classes, enabling finer-grained segmentation across varied marine scenarios. By combining a ResNet-101 backbone with a hybrid loss function (CrossEntropy + Dice), our method improves both accuracy and generalization, making it more robust for real-world oil spill identification.

This work makes three contributions:

- A DeepLabV3+ segmentation pipeline tailored to SAR imagery.
- A composite loss that balances dense pixel accuracy with overlap centric Dice similarity, mitigating class imbalance.
- Extensive evaluation on the M4D dataset, bringing strengths and limits of the approach to light

3. Dataset and Proposed Methodology

3.1 Dataset

The private M4D Oil Spill Detection corpus contains annotated Sentinel-1SAR tiles in five categories, namely oil spills, look-alikes, water, land and ships. All 1000 images and masks were resized to 256 × 256 px. We allocated 90 % for training, 10 % for validation, and held out a separate test split.

Dataset link - https://m4d.iti.gr/oil-spill-detection-dataset/

3.2 Methodology

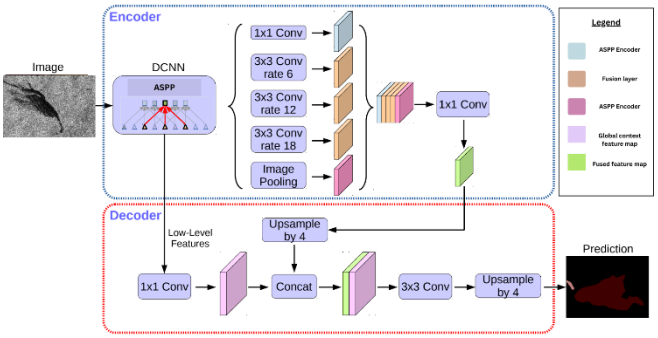

Fig 1. Flow chart of the working of the model

This flowchart gives a simple breakdown of how our segmentation model works from start to finish. Everything begins with the input image, which is passed through a deep convolutional network (ResNet-101) that picks up patterns and features at different depths. The model uses a special module called ASPP, which helps it look at the image at multiple scales using different-sized filters. This is important because oil spills can appear in a range of shapes and sizes. There's also a pooling step that gives the model some understanding of the image as a whole. All these features are pulled together and then passed into the decoder, which brings back the finer details by combining them with earlier, low-level features. Finally, the model gradually scales everything back up to the original image size, producing a full-resolution map that shows exactly what each part of the image represents.

3.2.1 Pre-Processing

Before feeding the SAR-1 imagery into the model, a consistent preprocessing pipeline was applied to ensure compatibility and stability during training. The SAR images were resized to a uniform spatial resolution and normalized by scaling pixel values from their original 8-bit range to a [0, 1] range. This fixed-range normalization helped stabilize learning and ensure consistency across batches. Each image was then converted into a PyTorch tensor and reshaped to match the input format expected by the DeepLabV3+ model. Similarly, ground truth segmentation masks were resized using nearest-neighbor interpolation to preserve class labels, then converted into tensors for supervised training. No additional augmentations or sampling techniques were applied.

3.2.2 Model Architecture

For our segmentation task, we went with DeepLabV3+ mainly because it's known to perform well when both fine detail and broader context are important—which is exactly the case with oil spill detection. Since oil slicks can vary in size and are often surrounded by other similar-looking textures in SAR images, we needed a model that could handle this complexity. We used ResNet-101 as the backbone for our network. It's a deep convolutional network that's been pretrained on ImageNet, and that helped us get better results without having to train the entire model from scratch. The pretrained weights gave the model a solid base for picking up features, even though SAR images are very different from natural images.

A key part of DeepLabV3+ is something called the ASPP module. It processes the image at multiple scales using different dilation rates—in our setup, those were 6, 12, and 18. This was useful because it allowed the model to spot oil spills whether they were small and isolated or large and spread out. After extracting the features, the model's decoder up samples the output so that the prediction lines up with the original image's size.

Another thing we did was leave batch normalization layers active during training. Some people freeze them, but we found that letting them update helped the model adjust better to the SAR dataset. It led to more stable training and better results in terms of accuracy and boundary clarity.

3.2.3 Training Protocol

We trained our model over the course of 50 epochs using the Adam optimizer, a popular choice known for its ability to adapt learning rates individually for each parameter, helping the model converge more efficiently. The learning rate was initially set to 5×10^{-4} and was gradually reduced throughout training using a cosine annealing schedule, which allowed the model to fine-tune its weights more precisely as it progressed. To ensure a smooth start to training and prevent sudden spikes in gradient updates, we implemented a warm-up strategy for the first 500 steps. Additionally, a weight decay value of 1e-4 was applied to discourage overfitting by penalizing overly complex models. Each batch consisted of 8 image–mask pairs, which we found to be a good compromise between GPU memory constraints and the need for diverse mini-batch statistics. To prevent unnecessary training beyond the point of improvement, we incorporated an early stopping mechanism that monitored the mean Intersection over Union (mIoU) on the validation set and stopped training if no progress was observed after seven consecutive epochs. All experiments were conducted using an NVIDIA GPU, which significantly accelerated the training process and allowed us to track performance in real time with minimal computational bottlenecks.

4. Results

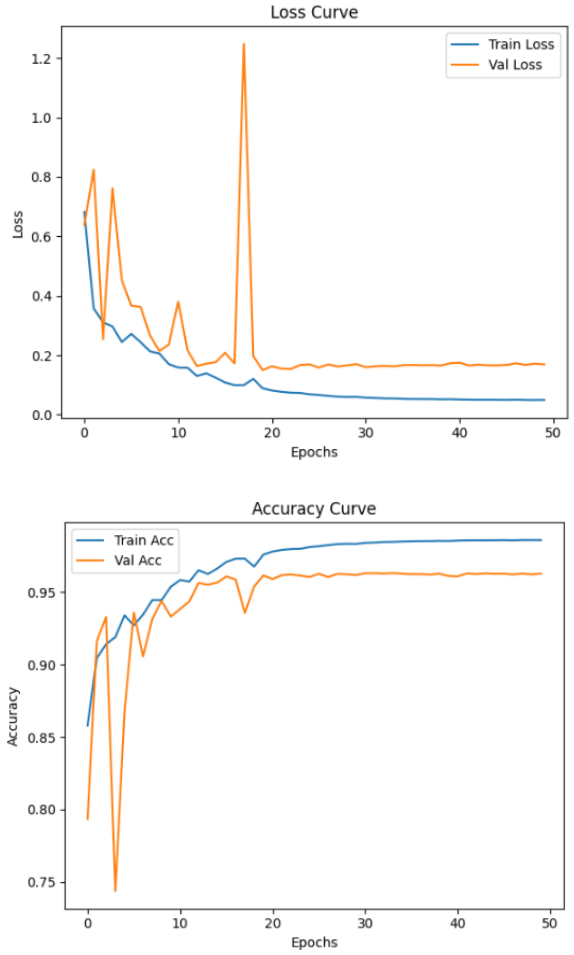

Fig 2. Loss and accuracy curve

4.1 Training Performance Overview

The two graphs above offer a clear snapshot of how the model learned over time. On the left, the **loss curves** show that the model's training loss steadily decreased, indicating that it was consistently learning patterns in the data. The validation loss, although a bit more erratic early on—with a sharp spike around epoch 20—quickly stabilized and followed a generally downward trend. This brief instability is not uncommon in real-world training and could be due to occasional batches with challenging samples, especially given the class imbalance in the dataset. Fortunately, the model recovered well and continued to generalize effectively.

On the right, the **accuracy curves** tell a reassuring story. Both training and validation accuracy rose sharply in the first 10 epochs. After that, training accuracy kept improving gradually, eventually reaching over **98%**, while validation accuracy settled around **96%**. The fact that both curves remained close together throughout training is a good sign—it means the model wasn't just memorizing the training data, but was learning in a way that carried over well to unseen examples.

Overall, these curves reflect a healthy training process with strong generalization performance and minimal signs of overfitting.

4.2 Visual Results

Predicted masks were compared against ground truth labels using color-coded visualizations like, blue for sea surfaces, red for oil spills, Green for look-alikes, yellow for ships and white for land.

To better understand how the model improved over time, we analyzed its predictions on test samples across different phases of the training lifecycle.

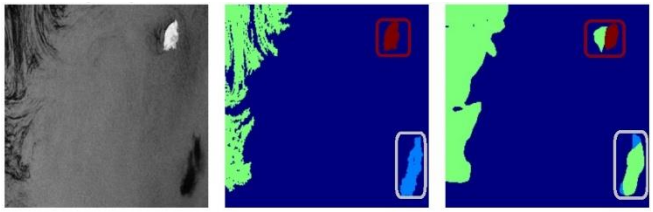

Fig 3.1 The initial result

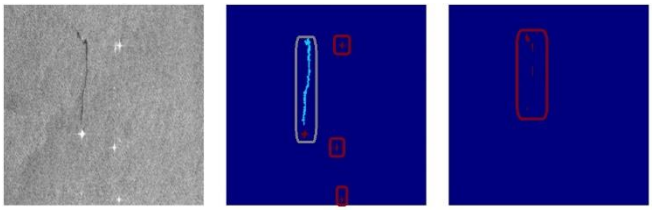

Fig 3.2 Result after 15 epochs

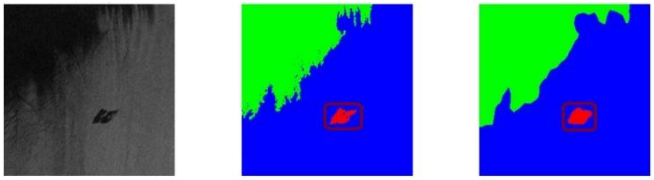

Fig 3.3 Final result

Note: Red boundaries highlight oil spill, gray boundaries highlight misclassifications.

- **Early Training Phase**

In Fig 2.1, we see an example from the **early epochs** of training, it struggles with boundaries and tends to confuse look-alike regions (green) with other classes. This is expected, as the model is still learning the foundational features and hasn't yet generalized well across all classes.

- **Mid Training Phase**

In Fig 2.2, performance during the **middle of training** is shown. Here, the model shows a noticeable improvement — it identifies both oil spills and ships more accurately, and handles complex textures better. While there are still

some inconsistencies, but, the overall segmentation is more confident and spatially coherent.

- **Final Epoch / Trained Model**

Fig 2.3, showcases a **mature model's prediction** after training completion. The segmentation output aligns almost perfectly with the ground truth. The model has clearly learned to differentiate subtle intensity patterns in SAR images, achieving precise boundary mapping even in low-contrast areas.

Below is a snapshot of the final 5 epochs showing strong convergence:

Epoch	Train Loss	Val Loss	Train Acc	Val Acc
46	0.0498	0.1676	98.60%	96.29%
47	0.0504	0.1731	98.59%	96.23%
48	0.0496	0.1676	98.61%	96.29%
49	0.0494	0.1717	98.61%	96.23%

The final model was evaluated on the test dataset using Accuracy and Macro F1-Score:

- **Test Accuracy:** 95.68%
- **Macro F1-Score:** 63.16%

These results indicate the model performs well in general, though performance on minority classes like "look-alike" could be further improved.

5. Conclusion

In this work, we proposed a DeepLabV3+-based segmentation model enhanced with a hybrid loss function, achieving strong performance on the challenging M4D oil spill detection benchmark. The model balances accuracy with computational efficiency, making it a promising candidate for real-time deployment in operational settings. Most errors were observed in visually ambiguous, calm-sea conditions, highlighting the need for contextual inputs like wind data to improve reliability.

We also note that noisy manual annotations may limit performance, and future efforts could explore semi-supervised label refinement techniques. While our setup runs efficiently on desktop GPUs, deployment on edge devices may benefit from lighter backbones like MobileNet-V3.

Looking ahead, expanding the model's capabilities with temporal and polarimetric SAR inputs, and exploring self-supervised learning, could further boost performance. Ultimately, this approach brings us closer to practical, real-time marine oil spill monitoring with the potential to reduce environmental damage and inform faster emergency responses. By improving detection accuracy and segmentation quality, our model supports more proactive disaster response. With further optimization, it could serve as a core component in next-generation satellite-based environmental monitoring systems.

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