Deep Learning-Based Semantic Segmentation for Accurate Marine Oil Spill Detection in SAR Imagery

Ms. Sayali S. Patil

Department of Computer Science and Engineering (Data Science), D.Y.Patil Agriculture & Technical University,Talsande, Kolhapur, Maharashtra, India

Email Id- sayali9528@gmail.com / sayali.patil@seti.edu.in

Mr. Rajwardhan S. Todkar

Department of Computer Science and Engineering (AIML), D.Y.Patil Agriculture & Technical University,Talsande,Kolhapur, Maharashtra, India

Email Id- rajwardhan.todkar@dyp-atu.edu.in

Abstract: Abstract Oil spills and other similar incidents in the marine ecosystem are a matter of ecological and economical great concern, which results in urgent need for fast and effective detection methods that minimize long-term damage. Traditional monitoring systems based on physical inspection or visual interpretations of remote sensing images are usually slow, manpower-consuming and incapable in violent s turbulence sea environments. With day-and-night, all-weather imaging, Synthetic Aperture Radar (SAR) is an ideal choice for large-scale ocean observational data. However, SAR analysis is difficult due to the fact that real oil spills often have similar visual features with look-alikes (e.g., calm sea surface, internal waves, biological slicks etc.).In order to alleviate these limitations, this paper presents an automated deep learning-based oil spill detection system by using hybrid semantic segmentation architecture on ResNet-18 as the encoder and DeepLabV3+ as the decoder. The pixel-wise classification numpy array allows an exactly precision separation around the oily areas bordering the water.In addition, indicators of oil spills such as the area affected and the spill's density are assessed to assist in environmental decision-making. The pipeline includes steps like preprocessing, segmentation, visualization, and the creation of reports to improve operational usability. The evaluation and reporting component developed using Random Forest model boosts reliability by offering results interpretation and a statistical summary. The proposed system enables real-time monitoring, emergency preparedness, and the sustainability of marine ecosystems, as it provides precise and scalable oversight of oil spills.

Keywords: Detection of Oil Spills, Pollution in Marine Environments, Synthetic Aperture Radar (SAR), Deep Learning Techniques, Semantic Segmentation Methods, ResNet-18 Architecture, DeepLabV3+ Framework, Classification at the Pixel Level, Remote Sensing Technology, Management of Disasters,

Feature Extraction Processes, Random Forest Algorithm, Monitoring the Environment, Estimation of Spill Areas, Density Assessment, Preprocessing of Images, Interpretation of SAR Data, Automated Detection Systems, Surveillance of Marine Areas, Visualization and Reporting Tools.

I. INTRODUCTION

Oil spills rank among the most detrimental forms of marine pollution, resulting in long-lasting adverse impacts on marine life, fishing industries, waterfowl, and coastal communities. The rapid expansion of offshore oil exploration, maritime transport, and industrial activities has significantly raised the likelihood of accidental leaks into oceanic waters. Traditional detection methods rely on human observation using aerial surveys or monitoring through optical satellite imagery, which is ineffective during poor weather, at night, or over extensive areas. As a result, environmental agencies face considerable challenges in the early identification of spills and in implementing timely response actions. The need for robust and automated monitoring has become increasingly critical to safeguard ecological health.

As advancements in remote sensing technology have progressed, Synthetic Aperture Radar (SAR) has emerged as an effective tool for ocean monitoring, capable of penetrating clouds, functioning in varying light conditions, and detecting changes in surface roughness. In SAR images, the dark areas usually represent oil spills due to the diminished surface waves. However, these low-backscatter regions can also arise from natural phenomena such as low wind zones, wave shadows, or biological slicks, making manual interpretation highly challenging. Therefore, it is essential to develop intelligent systems that can analyze complex images and distinguish between genuine oil spills and similar-looking features. The field of image processing and pattern recognition has been revolutionized by deep learning as it derives hierarchical features and provides the high-precision classification. Models of semantic segmentation can be used to detect pixels, and thus estimate the shape of the areas of oil influence. ResNet-18 is one of the architectures that have been used to effectively form an encoder backbone that is able to learn deep features, and DeepLabV3+ is also an architecture that contributes to better segmentation accuracy through various spatial pyramid pooling and enhanced decoder modules. It is this hybrid combination that provides the improved detection of the irregular boundaries of spills and reduces false predictions. Such model-based schemes are to be integrated to guarantee rapid and sound identifying, even in the intricate ocean scenes.

The suggested system adopts an entire pipeline that includes preprocessing, model-based segmentation, and post-processing analytics. SAR images uploaded are firstly normalized and resized to make them compatible with the model. The trained ResNet-18 + DeepLabV3 + architecture detects the polluted regions and produces the segmentation masks reflecting the pixels of the spills. The system also calculates vital aspects of oil spills including the total area covered by the spill and density concentration, which are essential in assessing the degree of environmental harm. Result visualization through overlays on the original SAR images assists the maritime authorities in having a clear picture of the spread of the spill. All in all, the introduction identifies the acute necessity of automated marine spills surveillance and underlines the importance of the combination of SAR data and deep learning tools in order to make the process more accurate. The suggested solution will cut down manual labour and enhance the accuracy of classification as well as real-time ocean surveillance on a large scale. The combination of smart analytics and reporting modules, in addition to the spill detection function, allows the system to be actively involved in the decision-support process of environmental response personnel. The study is a step in the right direction to establishing a dependable and scalable system of detecting oil spills as a means of safeguarding marine resources and timely response.

II. LITERATURE REVIEW

The remote sensing and machine learning are now considered fundamental components of active marine pollution surveillance in that satellites (especially Sentinel-1 Synthetic Aperture Radar, SAR) provide full-weather coverage of the ocean surface, both day and night. SAR is sensitive to surface roughness, and thus the capillary waves are damped in oil films producing deep contrasts which are dark patches, but deep contrasts are produced by natural look-alike phenomena (calm wind regions, algal blooms, wave shadows). Initial rule-based and classical image-processing algorithms - thresholding, texture analysis and object-based image analysis -were promising but failed to work effectively on the problems of false positives in complex scenes. The researchers in 20222025 then concentrated on deep learning semantic segmentation and encoder-decoder network to provide pixel-precise detection to different sea conditions and sensor modes. The focus of the research rapidly changed to no longer have patch classification and detection to end-to-end semantic segmentation which then has to give shape and area estimates needed to plan the response. As documented in supporting surveys and system papers below, the approach requires a significant amount of effort.<|human|>The The method is laborious, as will be seen in the supporting surveys and system papers below.

The recent works in the oil-spill literature involve architectures inspired by computer vision, such as U-Net variants, encoder-decoder networks based on ResNet backbones, and DeepLabV3+ as they can be characterized by a combination of feature richness and preservation of spatial detail. 20222024 Work focused on adapting encoders (ResNet- 18/50/101, MobileNetV2, Xception),attention modules (channel/position/dual-attention, scSE) to SAR backscatter properties. A number of studies evidenced that overfitting can be reduced with the use of lightweight backbones (MobileNetV2) or with attention layers that increase generalization to novel scenes and sensors. Multi-polarimetric inputs (VV , VH) and multi-source fusion (SAR + optical) were also tested by researchers in order to minimize the look-alike confusion. Recent papers have quantitative results showing improvements in their (IoU, precision, and recall) over older methods supporting the further adoption of encoder- decoder.

The quality of datasets, the constancy of annotation, and the alterations of domains are still problematic. A number of teams published or edited SAR oil-spill data and detected inconsistencies in labeling common collections (SOS, CleanSeaNet-based annotations). There is a crucial gap in cross-domain generalization models trained in one region frequently fail in another because of varying angles of incidence, sea conditions, and incidence-angle interactions. To fill this, there have been studies (20232025) on data augmentation approaches, domain adaptation, and cross-domain training, and some of them suggest new multi-class labels to explicitly represent look-alike classes (sea, oil, look-alike, ships, land). Articles also focus on the strict assessment based on the metrics of IoU, F1, and per-class; nevertheless, standard benchmarks and testbeds are under active enhancement.

Another focus is the operationalization - transitioning the research models into near-real-time monitoring. The researchers combined segmentation results with post-processing geo spatial to estimate spill area and density estimates and combined detection modules with alerting or reporting systems. The second stage decision has been proposed to be an interpretable model with hybrid solutions based on segmentation with Random Forest or classifiers that depend on the severity (minor/major). There were teams illustrating close-to-real time pipelines with Sentinel-1 data streams and report generation and also teams that examined multi-sensors fusion and ensemble approach to reduce false alarms. However, end-to-end deployments involve regular preprocess, incidence angle calibration, and binary map thresholding.

To conclude, the 2022-2025 literature demonstrates a rapid development of the semantic- segmentation deep learning models adapted to SAR data (the choice of encoder, attention modules, loss functions adjusted to class imbalance, etc.). Advances in datasets, consideration of look-alike classes, and work on cross-domain robustness and program pipelines have brought the field to practice. Nevertheless, prevalent limitations-dataset biases, generalization and real-world deployment constraints (e.g. false positives and sensor mode variations)- remain, and drive future research on domain adaptation, balanced large-scale datasets, and real-world explanations of analytics to authorities. The following in-depth paper summarizes provide tangible methods and numerical findings of recent studies. The following are a few of our 2022-2025 Studies Research Papers.

III. METHODOLOGY

- **Radar Signal Acquisition**

The maritime radar system traces the water on the surface of the sea in the first step and gathers the backscattered signals. The interaction of radar waves with clean water and oil- covered areas is different because of the difference in the roughness of the surface. These reflected echoes are recorded in real-time and represented as radar images or data frames. Signals obtained are then sent to the processing unit to undergo additional processing. This guarantees extensive coverage over a wide area even during bad weather or in low light areas.

- **Image Pre-Processing**

Obtained radar images usually entail the undesired noise and distortion due to waves, weather, and system interference. Filtering, normalization, and image enhancement of the pre-processing techniques are used to enhance the clarity. Such operations bring out key features, enhance contrast of oil and water around and minimize false targets. Prepared data also makes sure that modules that come after the preparation only concentrate on what is meaningful.

This is a phase where the processed radar images are examined in order to determine unique surface features. The common appearance of oil spills is in the form of dark patches with less intensity in terms of backscatter than in a normal seawater. Segmentation algorithms isolate these high-density suspicious low-intensity regions as opposed to the rest of the picture. The different textural and geometric features are opposed to comprehend the shape, spread and limits of the spill better.

- **Machine Learning / Deep Learning Classification**

The features that have been extracted are categorized with trained ML/DL models to ensure that a patch that is identified is actually oil. The model is conditioned using previous labeled data to learn the differences between the natural variations of the sea and the real spill patterns. Neural networks are advanced and enhance the detection rate and false alarms. This is done to make sure that right decision-making comes first before any action of alert and action.

- **Spill Detection and Location Mapping**

After the classification process is accomplished, the system identifies the spotted oil spill areas on a radar map using exact coordinates. The zones are indicated and measured in terms of size and severity. Such data allows the monitoring teams to evaluate the emergency response requirements. Visual mapping enhances situational awareness of coastal authorities and makes sure that the situation is intervened in time.

- **Alert Generation and Reporting**

The last procedure is to relay the detection alerts to the control center or the maritime safety systems. Notifications which are automated give information such as time, estimated spill area, and location. Future tracking and decision-support report and log generated in graphics. The speedy communication will guarantee the timely response to save the life of the marine organisms and to stop the massive contamination.

IV. PROPOSED FRAMEWORK

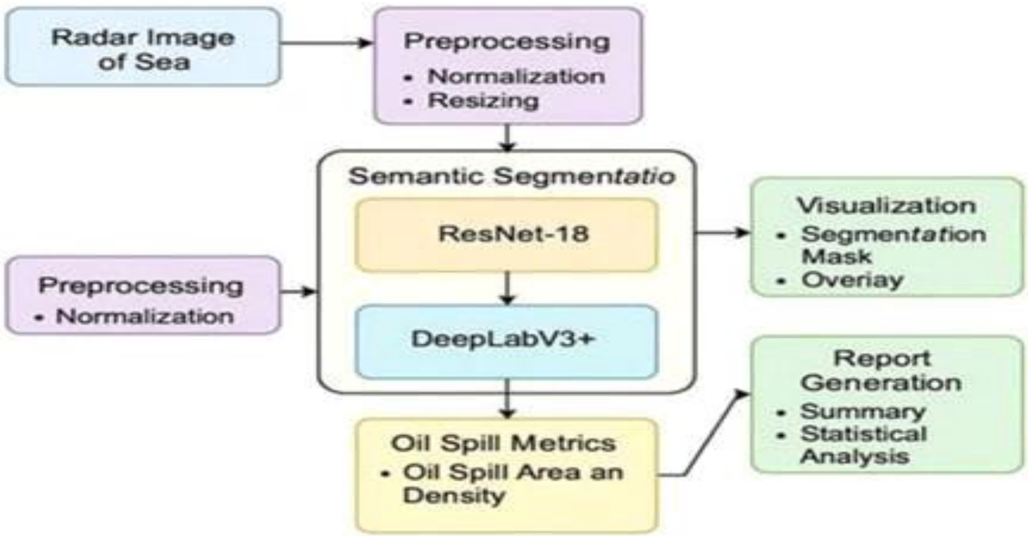

Fig.1.0 – Architecture Diagram

The proposed oil spill detection system works in such a way that it is started by the radar sea surface images. Synthetic Aperture Radar (SAR) is used since the system is used to capture the marine surface changes irrespective of the weather interference or light. These unprocessed radar images can be affected by noise, distortions, and other irrelevant variations which can impact on interpretation. As such, the system initially sends the input to a pre- processing phase whereby elementary modifications prepares the data to be analyzed. This makes sure that the received images can be used in subsequent processing and give meaningful pixel data to the model. Normalization and resizing of the received radar images take place in the first pre-processing block. Normalization modifies the intensity values and maximizes the contrast to provide clarity in the visible features that are needed to be detected. Resizing is done to make sure that every image fits into a common size needed by deep learning structures. In addition to this step, there is also another pre-processing route, which is to have consistency in the data set before the start of segmentation.

These joint operations allow minimizing fluctuations due to the noise in the environment or the conditions of the acquisition and enhance the accuracy of the outcome of the segmentation.

The base of the system intelligence is the semantic segmentation module constructed on the basis of ResNet-18 as the encoder and DeepLabV3+ as the decoder. ResNet-18 selects key features of the images with deep convolutional layers learning to obtain the distinctions of the textures that exist between oil spills and surrounding water. DeepLabV3+ is subsequently used to classify every pixel and yields a pixel-level segmentation mask, which contains possible spill regions and regular sea. Such architecture enables the system to manage complex detection problems such as spill look-alikes that frequently interfere with the operation of conventional classifiers.

After segmentation, visual representation of the detected oil spill areas is offered to allow the user to view the spills. The visualization block produces a mask that is divided into segments and superimposed on the original radar image. The spill boundaries and distribution on the affected surface are easily seen by the user. Moreover, The system calculates the significant spill metrics including spill area and pixel based density. These numerical data are effective indicators used to assess the extent of the incident, and take timely actions and respond to the emergencies.

The system also has an automated report generation process as the final output. It also presents observations, statistical measurements and segmentation performance in a systematic format that can be accessed by marine authorities or environmental agencies.

The system combines image pre-processing, deep learning-based segmentation, visualization tools, and report analytics into a single workflow, eliminating the time and effort spent on a manual inspection and minimizing human error. All in all, the block diagram is an entire oil spill monitoring pipeline that will assist in proper identification, quick analysis, and taking suitable measures to keep marine ecosystems out of spill disasters.

V. RESULTS AND DISCUSSION

Fig. 2.0 – Input SAR Image

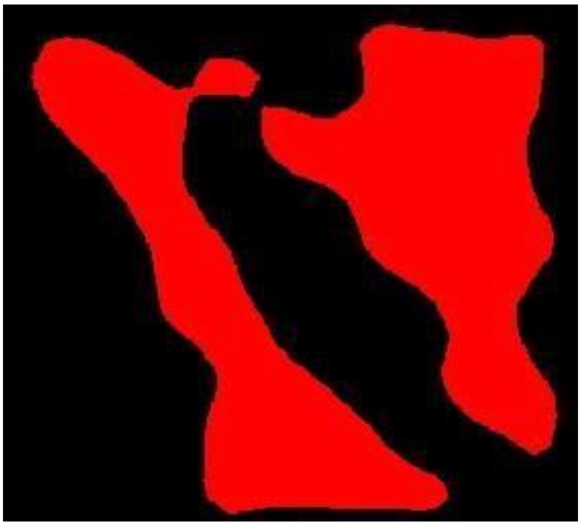

Fig. 3.0 – Predicted Oil Spill Segmentation Mask

Fig. 4.0 – Overlay of Segmentation Result on SAR Image

The following figures show the segmentation performance of the proposed system on SAR images.

ANALYSIS

Severity Level: Very High

Area Statistics

Class	Area (%)	Area (km²)
Background	59.11%	4.7673 km²
Oil Spill (Sheen / Rainbow / Truecolor)	40.89%	3.2979 km²

Table 1.1 – Area Distribution of Detected Regions

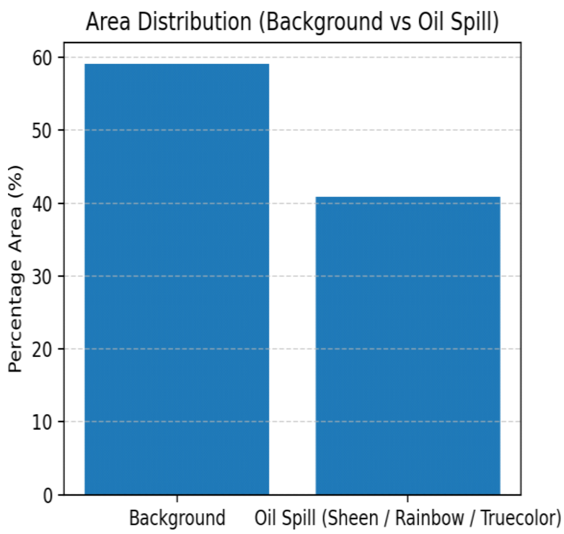

Fig. 5.0 – Bar Chart Showing Area Distribution of Background and Oil Spill

The analysis shows the proportion of oil spill regions relative to the background, helping in severity assessment.

VI. CONCLUSION

This project has indicated an effective and smart method of locating oil spills on the surfaces of the sea using radar technology. Radar sensors are used to detect the variations on the sea surface and the image processing is used to increase the visibility of suspicious areas. The machine learning models and the feature extraction classify accurately the oil-affected areas. The system also makes it possible to detect even in the bad weather and night-time conditions when the traditional monitoring fails.

The suggested methodology saves time on manual scanning, enhances more accurate responses, and enables massive area coverage. It has automated mapping and alert system that allows authorities to take up corrective actions immediately. It reduces false positives and enhances detection reliability, which is beneficial in safeguarding ocean ecosystems and coastal infrastructure. The combination of AI-based decision analysis and radar sensing makes the system very reliable to apply in practice.On the whole, this piece of writing becomes a powerful base of the modern solutions of environmental safety related to the oceans. The technology can be further developed into a real-time ocean surveillance network with the addition of other sensors, like predictive modelling. Not only will it assist in pollution control, but it will also save the sea life against dangerous effects. The results indicate the possibilities of the integration of radar technology and artificial intelligence to have a safer and cleaner marine environment.

VI. FUTURE WORK

The future research may aim at the implementation of high-resolution radar systems with the sophisticated deep learning models to increase the rates of detection. The system is able to detect even smaller traces of oil because it enhances the image sharpness and the separation of signals. The introduction of real-time data sharing in the Clouds can be considered to respond to the environment quickly. The implementation of satellite imagery and Drone surveillance coupled with radar detection can also be considered another progress. Such multi-sensor cross-checking will decrease the false alarms due to the changes of the sea surface. It will also enhance the geographical coverage when monitoring an emergency.

Predictive analytics can be a part of the future models that can estimate the direction, spread, and the environmental impact of an ongoing spill. The integration of the present-day detection and hazard prediction in The future will give early alerts to the coastal jurisdictions. This enhancement will aid the wiser decision-making and projecting of disasters. Also, the system can be improved to operate in fully autonomous marine vehicles toconduct constant watch in isolated areas of the sea. The solution will be more scalable, including energy-saving hardware and AI-based communication modules. These developments will aid in maintaining 24 hours monitoring without the involvement of human beings.

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