A.P. SHAH INSTITUTE OF TECHNOLOGY
DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING
(ARTIFICIAL INTELLIGENCE & MACHINE LEARNING)

Oil Spill Identification from Satellite Images Using Deep Neural Networks.

UN SDG Goal Alignment: 9,13,14

ACADEMIC YEAR 2025 - 2026

Goal Alignment with UN SDGs:

Encourages the use of AI and satellite technologies for sustainable environmental solutions.

Promotes technological innovation for environmental monitoring and disaster response.

Helps protect marine ecosystems by enabling early detection and mitigation of oil spills.

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Oil Spill Identification from Satellite Images Using Deep Neural Networks.

- Oil spills harm marine life and coastal ecosystems.
- Manual detection is slow and not scalable.
- Satellites provide wide, real-time ocean coverage.
- Deep learning detects spills accurately and fast.

Causes of Oil Spills:

- **Illegal Oil Dumping (MARPOL Violations)**

Ships sometimes illegally discharge oil or oily waste into the sea to avoid disposal costs.

These aren’t accidental — they are intentional, but not always large spills.

Hard to detect unless monitored by satellites or patrol aircraft.

- **Insurance Fraud**

There have been cases where ships are intentionally sabotaged or sunk, claiming an accidental oil spill to claim insurance.

- **Military or Political Deception**

Environmental sabotage using oil has been used as a war tactic. Example: During the Gulf War (1991), Iraq deliberately released millions of barrels of oil into the Persian Gulf to:

Disrupt US operations

Harm the Kuwaiti economy and environment

This is a classic example of a deliberate, weaponized oil spill.

Problem Statement:

To develop an accurate and efficient deep learning-based system that identifies oil spills from satellite images, enabling faster environmental response and minimizing the impact on marine ecosystems.

Objectives:

- To collect and preprocess satellite images for training and testing.
- To design and train a deep neural network for oil spill detection.
- To evaluate model performance using accuracy, precision, and recall metrics.
- To deploy the model for real-time oil spill monitoring and alerting.

Literature Survey:

Sr No.	Authors	Title	Summary	Limitations
1.	F. Del Frate, A. Petrocchi, J. Lichtenegger, G. Calabresi (2000)	Neural networks for oil spill detection using ERS-SAR data	Early application of multilayer perceptron neural networks on ERS-1/2 SAR imagery for oil spill classification.	Limited dataset; early computational methods; lacks transferability to modern sensors; no generalization validation.
2.	M. Fingas, B. Fieldhouse(2003)	Studies of the formation process of water-in-oil emulsions	Experimental study on oil-water emulsions' formation processes	No ML integration; laboratory-focused; lacks connection to remote sensing or automated detection.

Literature Survey:

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3.	M. Krestenitis, G. Orfanidis, K. Ioannidis, K. Avgerinakis, S. Vrochidis, I. Kompatsiaris (2019)	Oil Spill Identification from Satellite Images Using Deep Neural Networks	Benchmarked several deep learning architectures (DeepLabv3+, U-Net,	SAR “look-alike” confusion (ships, low wind zones); models not cross-comparable due to dataset variability.
4.	R. Al-Ruzouq, M. Barakat, A. Gibril, A. Shanableh, A. H. Saeed Al-Mansoori, M. A. Khalil (2020)	Sensors, Features, and Machine Learning for Oil Spill Detection and Monitoring: A Review	Comprehensive review of ML and feature-based methods (SVM, CNN, ANN, RF) using SAR, optical, and hyperspectral data. Emphasized multimodal fusion and sensor synergies.	Identified lack of standardized datasets, cross-sensor validation, and real-time fusion frameworks.

Literature Survey:

Sr No.	Authors	Title	Summary	Limitations
5.	F. M. Bianchi, M. M. Espeseth, N. Borch (2020)	Large-Scale Detection and Categorization of Oil Spills from SAR Images with Deep Learning	Developed a large SAR dataset and proposed a deep learning pipeline for segmentation	Focused only on SAR; still susceptible to look-alikes; lacks optical/hyperspectral validation.
6.	T. De Kerf, J. Gladines, S. Sels, S. Vanlanduit (2020)	Oil Spill Detection Using Machine Learning and Infrared Images	Used ResNet-based CNNs for infrared (IR) and SAR imagery classification;	Poor generalization across regions; small dataset;

Literature Survey:

Sr No.	Authors	Title	Summary	Limitations
7.	M. Fingas (2021)	Visual Appearance of Oil on the Sea	Descriptive study of how oil slicks appear visually depending on oil type, thickness, lighting, and sea conditions.	Non-ML approach; qualitative analysis; not directly linked to automated detection systems.
8.	K. Maharana, S. Mondal, B. Nemade (2022)	A review: Data preprocessing and data augmentation techniques	Reviewed data preprocessing and augmentation methods	General-purpose; lacks focus on remote sensing or oil spill–specific data augmentation.

Literature Survey:

Sr No.	Authors	Title	Summary	Limitations
9.	J. Zhang, P. Yang, X. Ren (2024)	Detection of Oil Spill in SAR Image Using an Improved DeepLabV3+	Enhanced DeepLabV3+ for SAR oil spill segmentation; improved feature extraction and boundary accuracy.	Focused solely on SAR; limited evaluation on real-world variability; needs multimodal integration.
10.	Zhen S., Qingshu Y., Nanyang Y., Siyu C., Jianhang Z., Jun Z., Shaojie S. (2024)	Utilizing Deep Learning Algorithms for Automated Oil Spill Detection in Medium-Resolution Optical Imagery	U-Net variants with CBAM attention applied to Sentinel-2 and Landsat data; improved segmentation for optical imagery.	Optical imagery affected by clouds, illumination; needs fusion with SAR for reliability.

Literature Survey:

Sr No.	Authors	Title	Summary	Limitations
11.	J. Kang, C. Yang, J. Yi, Y. Lee (2024)	Detection of Marine Oil Spill from PlanetScope Images Using CNN and Transformer Models	Enhanced DeepLabV3+ for SAR oil spill segmentation; improved feature extraction and boundary accuracy.	Focused solely on SAR; limited evaluation on real-world variability;
12.	K. Gkountakos, M. Melitou, K. Ioannidis, K. Demestichas, S. Vrochidis, I. Kompatsiaris (2025)	LADOS: Aerial Imagery Dataset for Oil Spill Detection, Classification, and Localization Using Semantic Segmentation	Introduced LADOS, a 3,388-image UAV RGB dataset (6-class masks: Oil, Emulsion, Sheen, Ship, Platform, Background).	Limited altitude/ geographic coverage; class imbalance; UAV-only (not satellite).

Literature Survey:

Sr No.	Authors	Title	Summary	Limitations
13.	Y. Zhang, J. Xing, W. Chen, et al. (2025)	A Novel YOLOv11-Driven Deep Learning Algorithm for UAV Multispectral Oil Spill Detection in Inland Lakes	YOLOv11 variant (ADHF + SimAM attention) for real-time multispectral UAV detection.	Not scalable to oceanic conditions; dataset limited to UAV scenes;
14.	M. Samkhaniani, A. Khoshand, S. Ezati (2025)	Deep Learning-Based Hyperspectral Oil Spill Detection for Marine Pollution Monitoring in the Gulf of Mexico	Applied U-Net and DeepLabv3 to PCA-reduced hyperspectral patches (HOSD dataset);	Hyperspectral data scarce and compute-intensive; complex preprocessing;

Literature Survey:

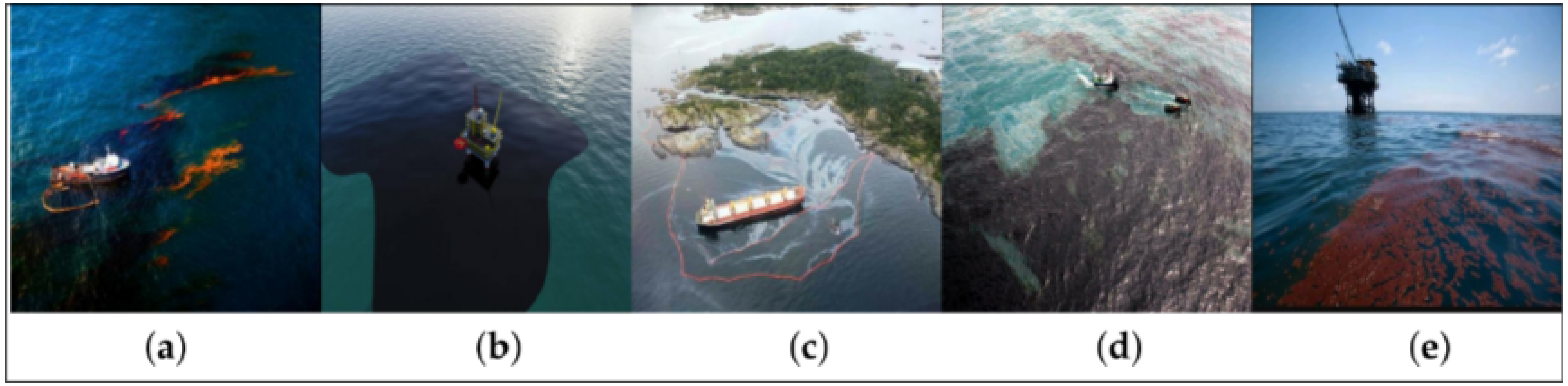
Sr No.	Authors	Title	Summary	Limitations
15.	J. Shi, T. Jiao, D. P. Ames, Z. Li (2025)	Improved Lightweight Marine Oil Spill Detection Algorithm of YOLOv8 (LSFE-YOLO)	Proposed LSFE-YOLO (YOLOv8s + FasterNet backbone + GN-LSC head + SE attention) for real-time SAR-based detection.	Only bounding-box detection (no segmentation);

Tech Stack:

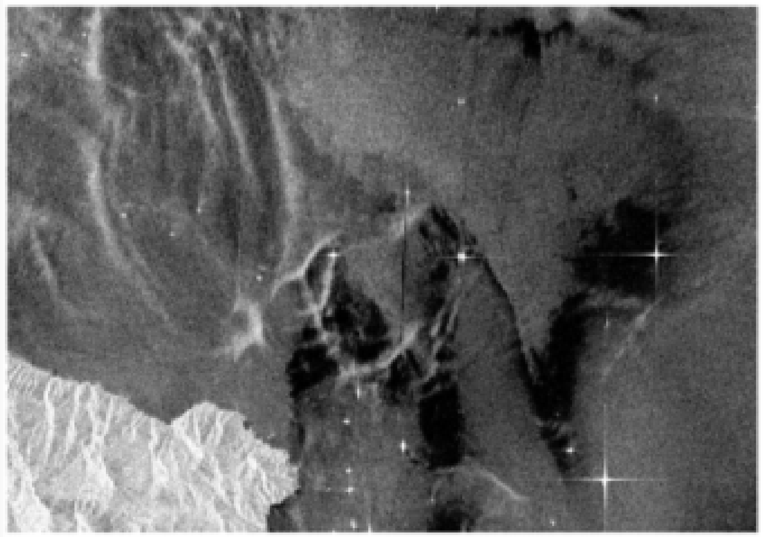
- Python (programming language)
- TensorFlow / Keras (deep learning frameworks)
- OpenCV (image preprocessing and manipulation)

- FastAPI (for backend API)
- React / Vite / Tailwind (for frontend)

Dataset:

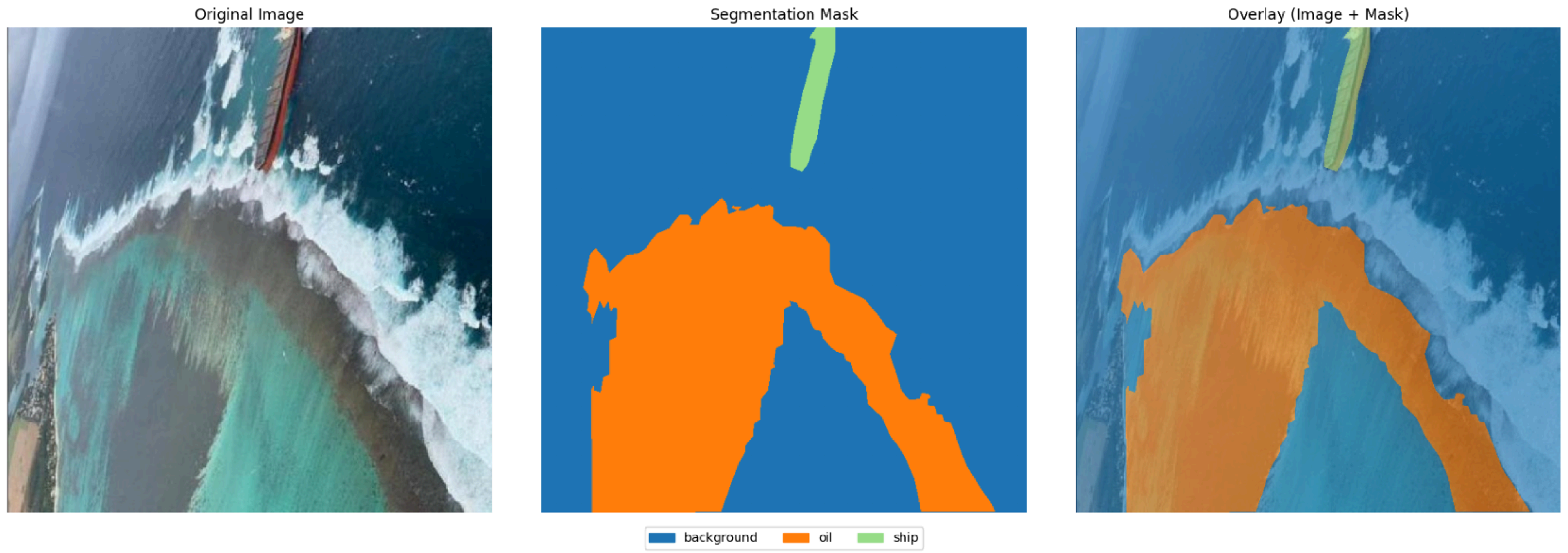


LADOS (aeria**L** im**A**gery **D**ataset for **O**il **S**pill detection)
(a) Oil, Emulsion and Ship (b) Oil and Oil-platform (c) Sheen and Oil (d) Oil, Sheen and Ship
(e) Emulsion and Oil-platform



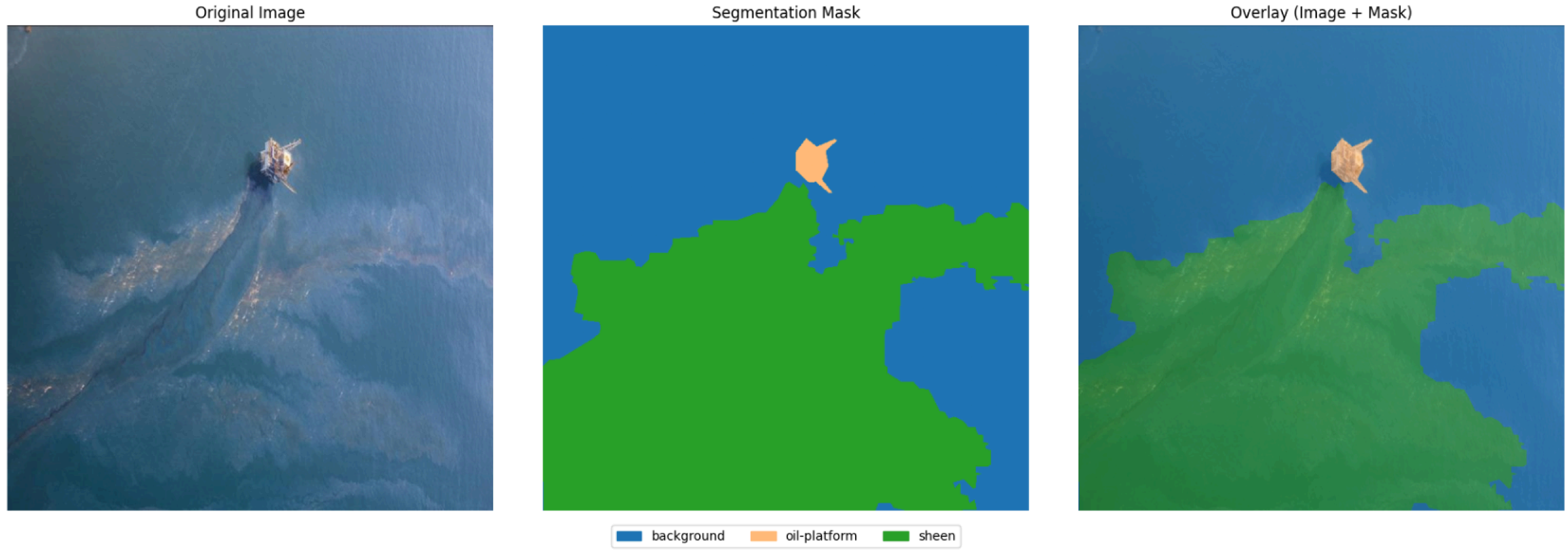
(a) Synthetic aperture radar (SAR) image.

Dataset:



Original Image
Segmentation Mask
Overlay (Image + Mask)
background
oil
ship

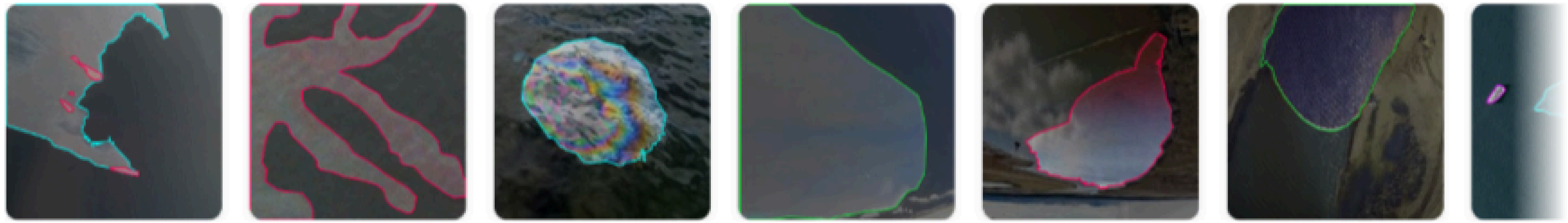
Dataset:


Original Image
Segmentation Mask
Overlay (Image + Mask)
background
oil-platform
sheen

Dataset:

3388 Total Images

View All Images →



Dataset Split

TRAIN SET 70%	VALID SET 20%	TEST SET 10%
2370 Images	675 Images	343 Images

Preprocessing

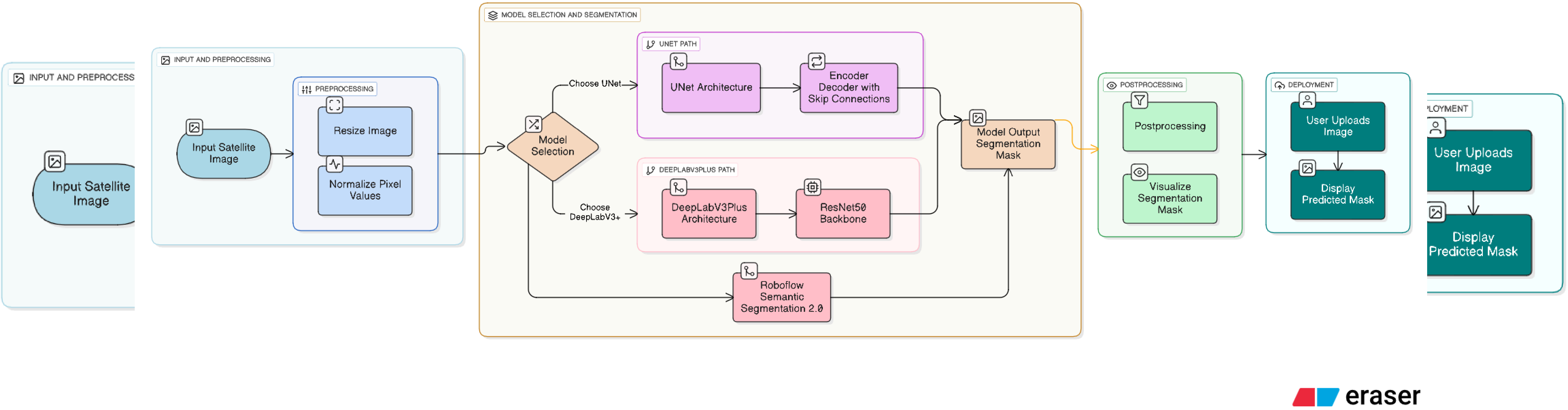
Auto-Orient: Applied

Resize: Stretch to 640x640

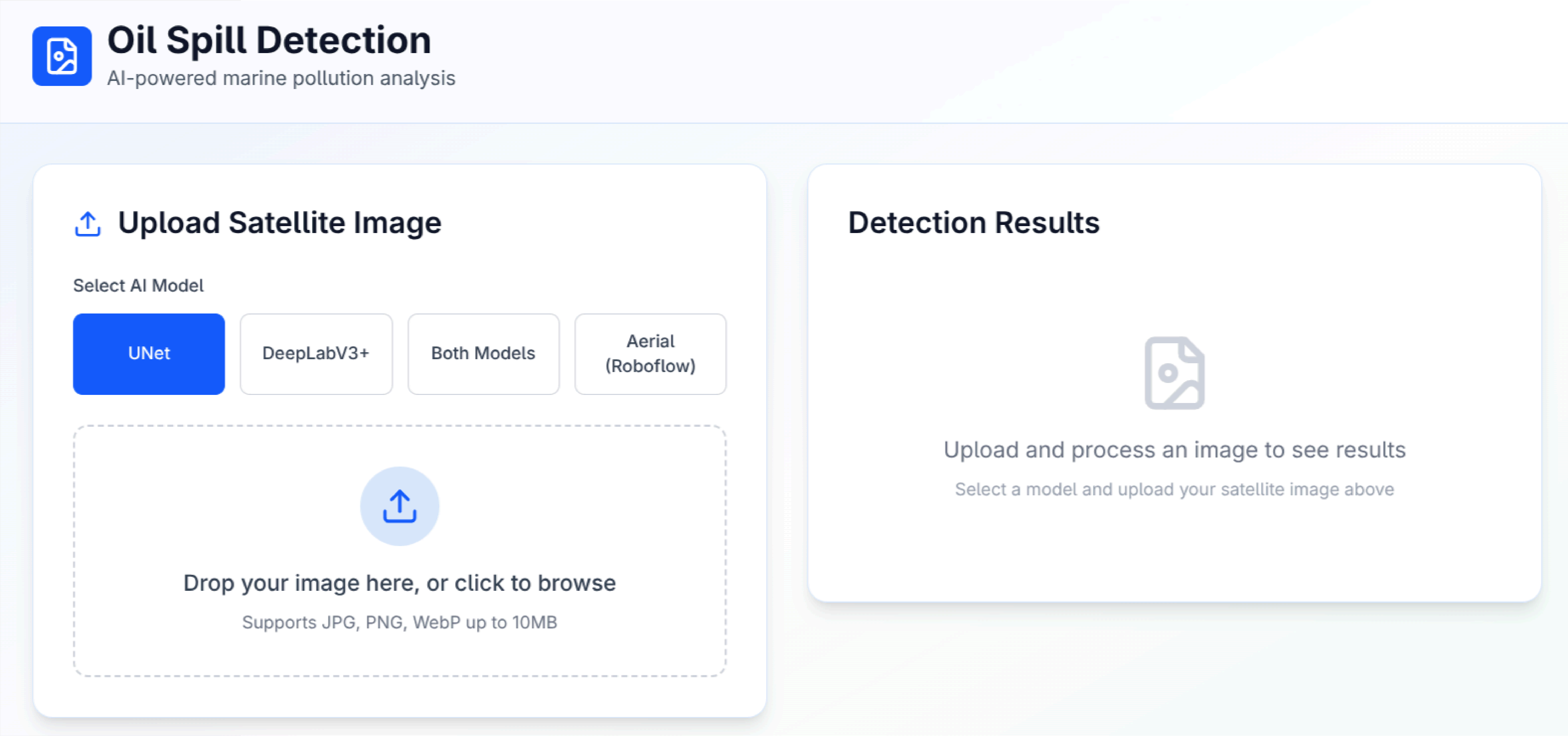
Augmentations

No augmentations were applied

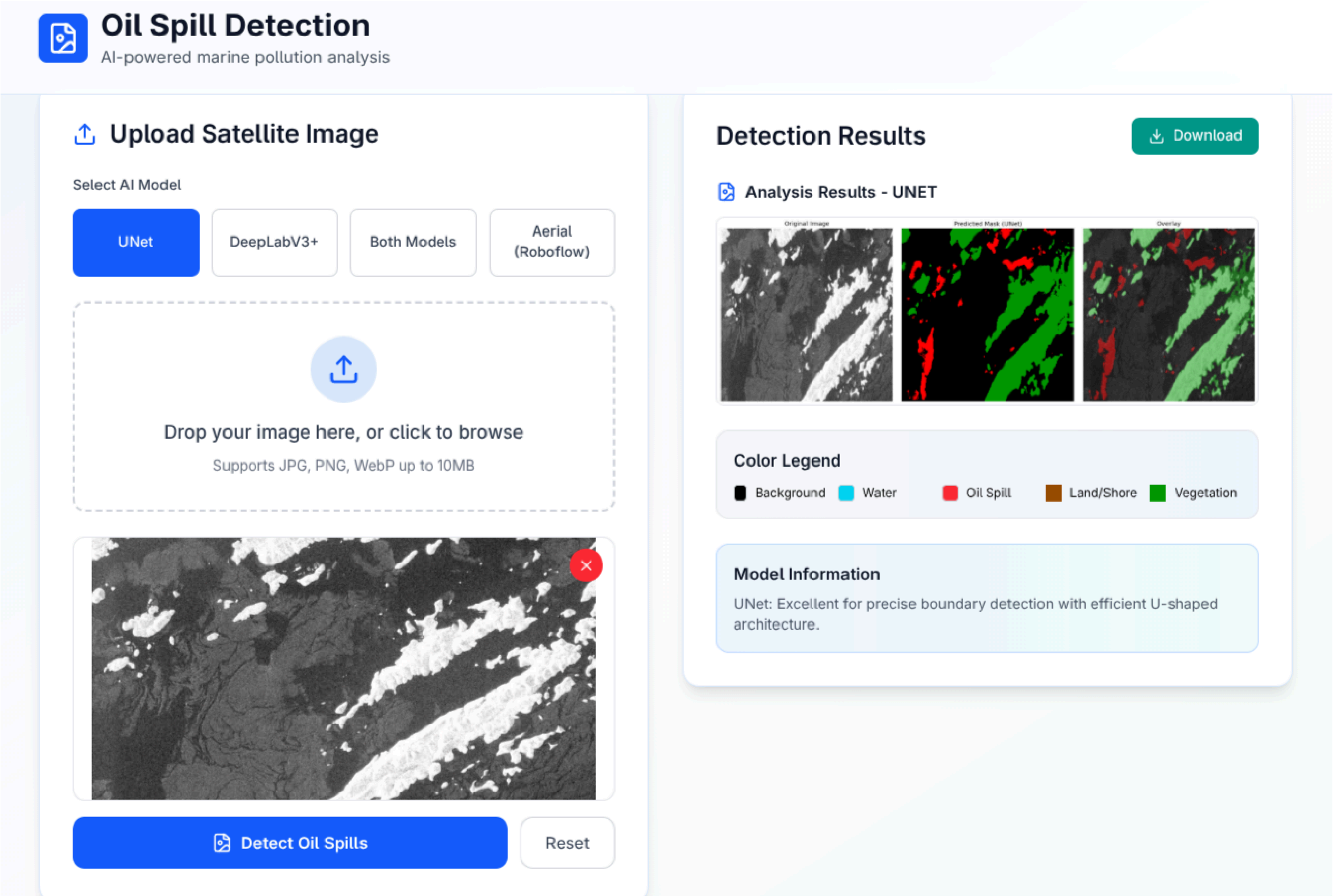
Diagram:


INPUT AND PREPROCESS
Input Satellite Image
INPUT AND PREPROCESSING
Input Satellite Image
PREPROCESSING
Resize Image
Normalize Pixel Values
MODEL SELECTION AND SEGMENTATION
Model Selection
Choose UNet
Choose DeepLabV3+
UNET PATH
UNet Architecture
Encoder Decoder with Skip Connections
DEEPLABV3PLUS PATH
DeepLabV3Plus Architecture
ResNet50 Backbone
Roboflow Semantic Segmentation 2.0
Model Output Segmentation Mask
POSTPROCESSING
Postprocessing
Visualize Segmentation Mask
DEPLOYMENT
User Uploads Image
Display Predicted Mask
LOYMENT
User Uploads Image
Display Predicted Mask
eraser

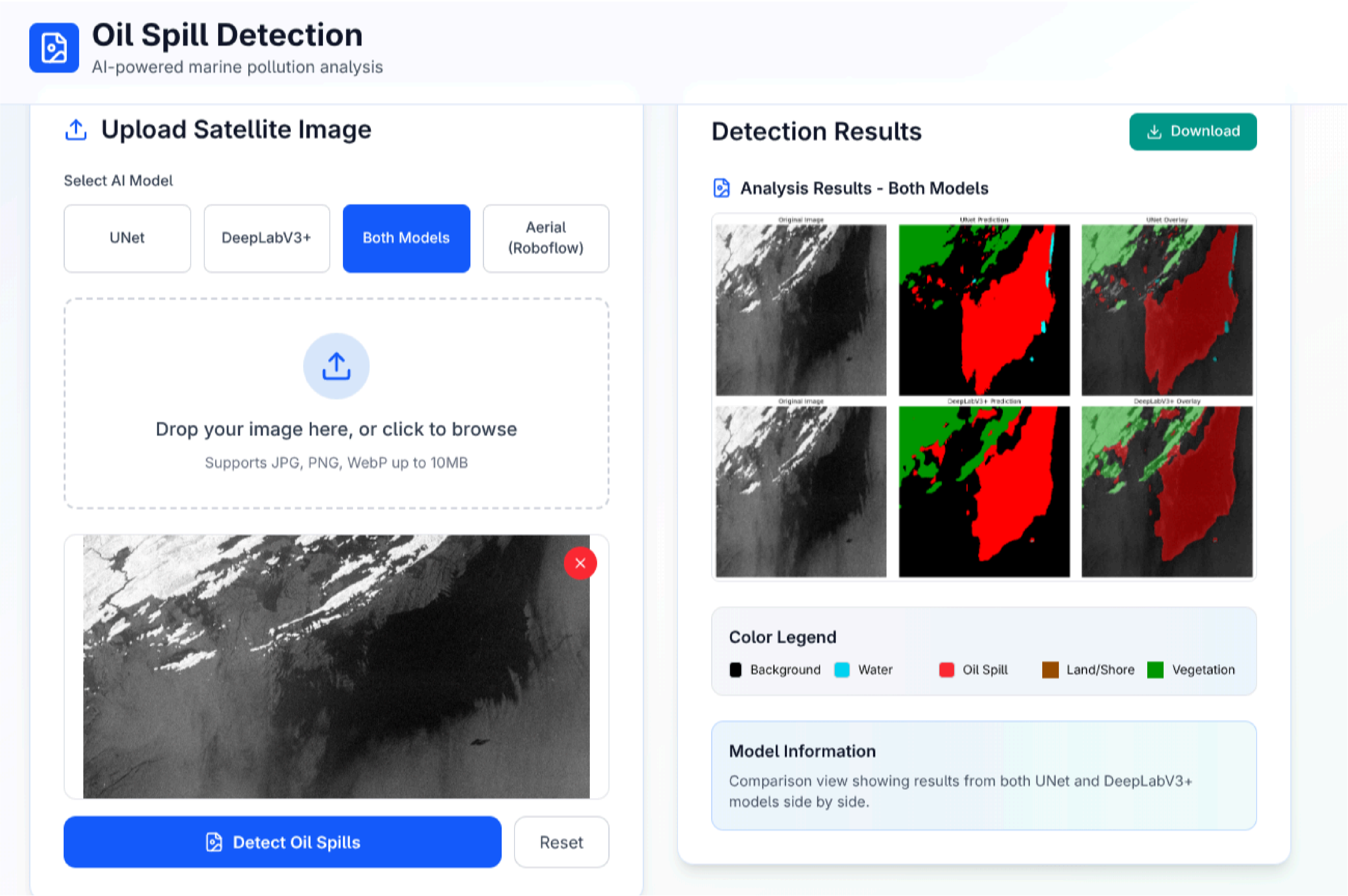
Implementation:



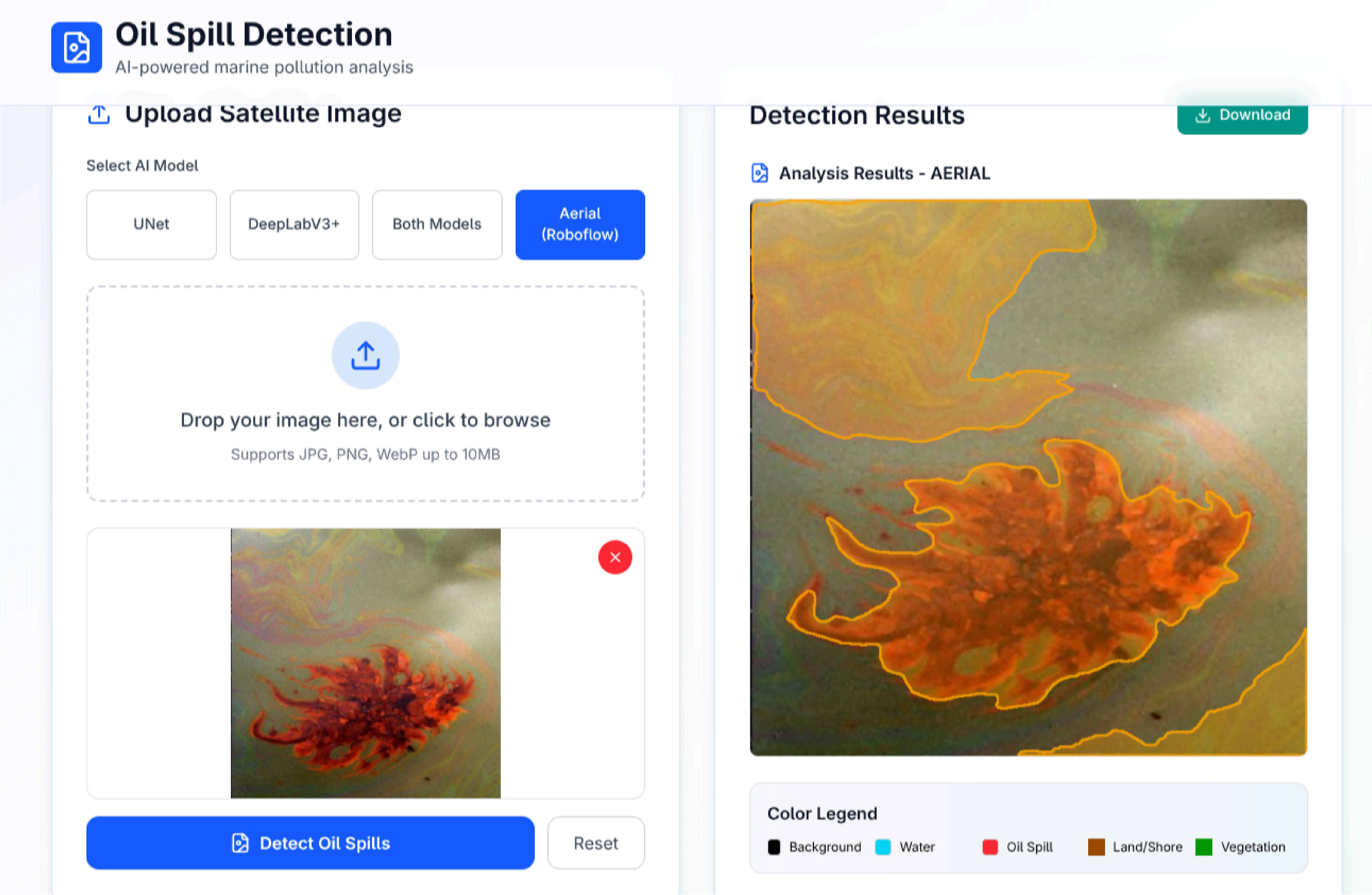
Implementation:



Implementation:



Implementation:



Conclusion

- Deep learning–based segmentation (U-Net, DeepLabv3+) shows strong potential for accurate oil spill detection.
- Aerial imagery: high-resolution, detailed classification.To deploy the model for real-time oil spill monitoring and alerting.
- SAR imagery: large-scale, all-weather monitoring.
- Combining both datasets improves robustness & generalization.

Future Scope

- Develop a Live API for exposing detection capabilities.
- Enable real-time oil spill monitoring from satellite & aerial streams.
- Integrate with early response systems to minimize ecological and economic damage.

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Neural networks for oil spill detection using ERS-SAR data.
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[14] Samkhaniani, M., Khoshand, A., & Ezati, S. **(2025).** Deep Learning-Based Hyperspectral Oil Spill Detection for Marine Pollution Monitoring in the Gulf of Mexico: A Step Marine Pollution Monitoring and Sdg 14 Compliance.
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