detecting floating debris: using machine learning with a focus on CHIME mission

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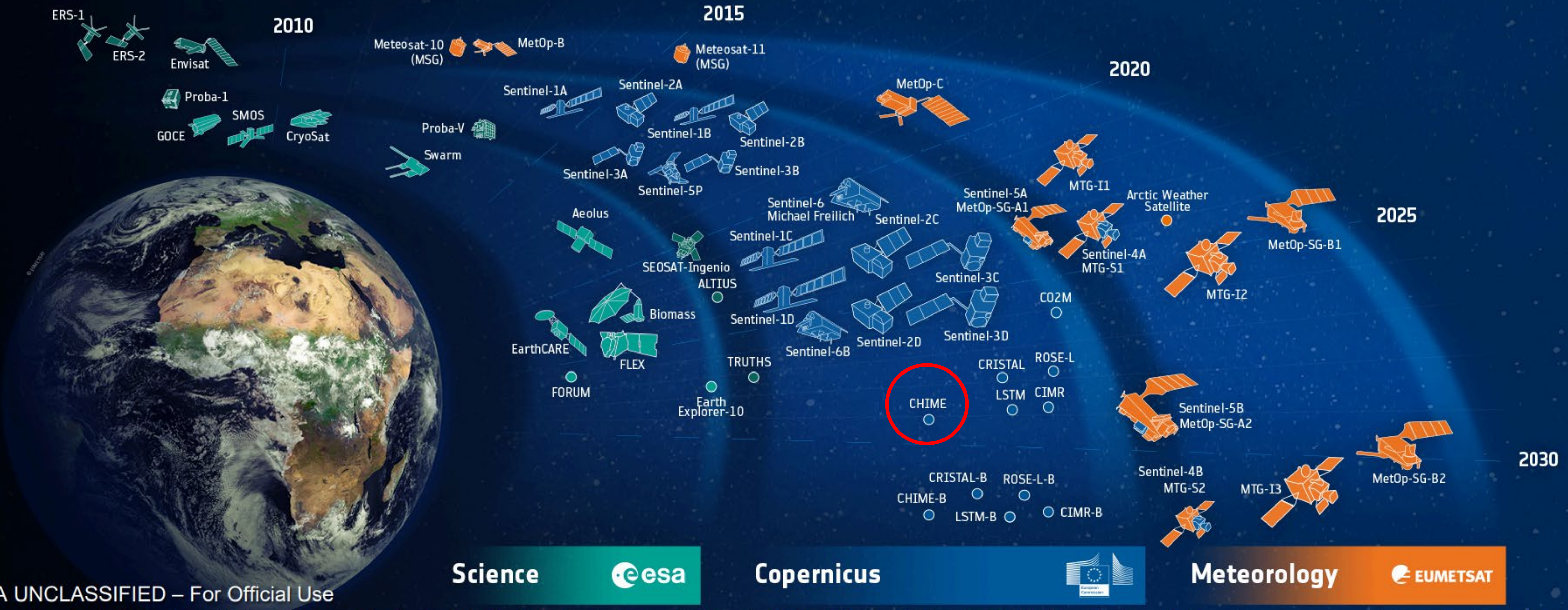
ESA-Developed Earth Observation Satellites

15 in operation
40 under development
13 under preparation



ESA UNCLASSIFIED – For Official Use

European Space Agency

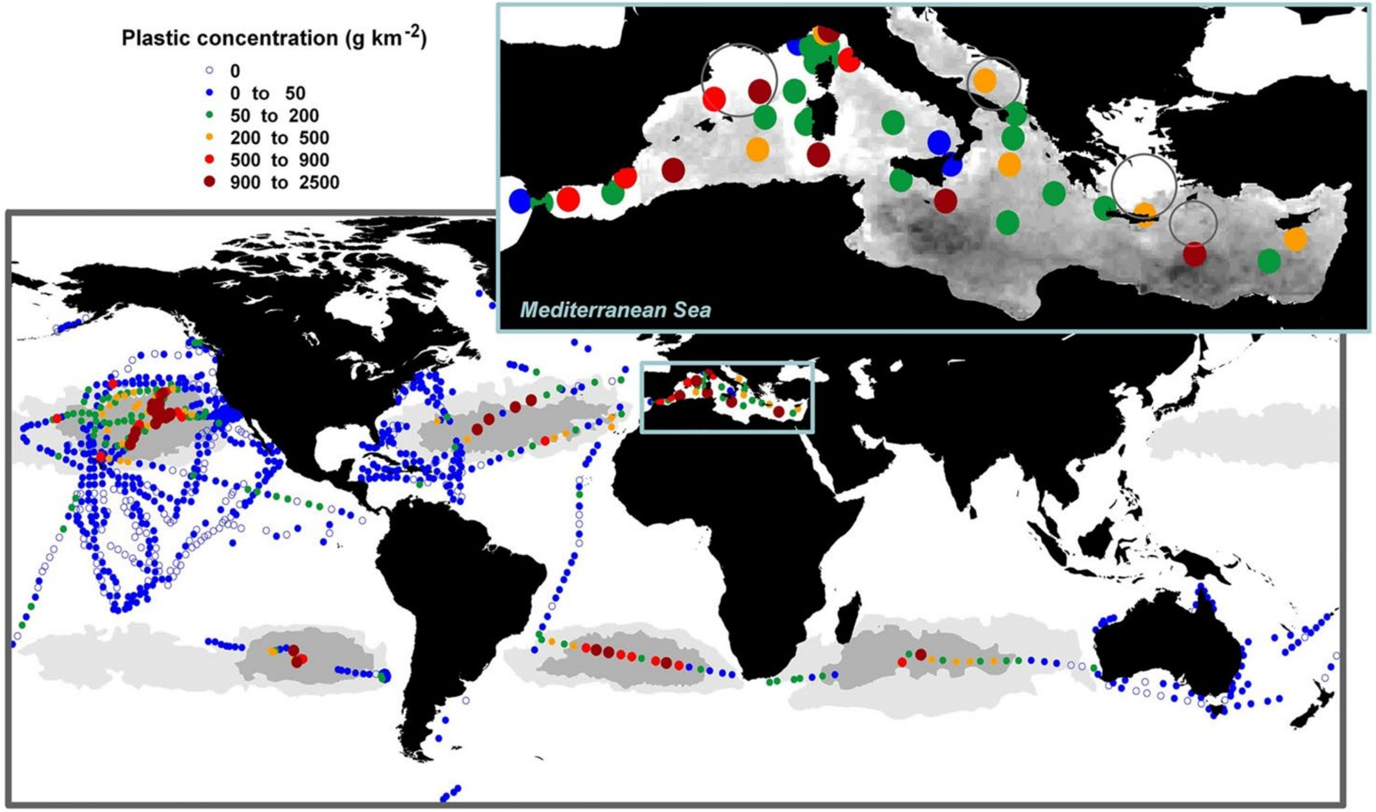
CHIME mission

- Hyperspectral Imaging:
  - Powerful remote sensing technology
  - Characterizes Earth surface materials
- Quantitative Variables:
  - Derived from spectral data
  - Support new Copernicus services
  - Focus on natural resource management
- Copernicus Services:
  - Enhance monitoring and policy implementation
  - Benefit various policy areas
- Optical Hyperspectral Remote Sensing:
  - Utilizes established spectroscopic techniques
  - Offers enhanced quantitative products

- Impact on Domains:
  - Agriculture, food security, raw materials
  - Biodiversity, environmental monitoring
  - Inland and coastal waters, forestry
- Relevance to EU Policies:
  - Addresses unmet needs
  - Potential for policy improvement
- Private Sector:
  - Opportunities for industry involvement and innovation

CHIME: mission extension

- CHIME team has identified an opportunity for adding an expansion for CHIME land monitoring mission
- explore the integration of an artificial intelligence (AI) unit on board
- process acquired data and selectively extract relevant information.
- Given the significance of detecting floating plastic debris, this application serves as a test case for evaluating AI on board.

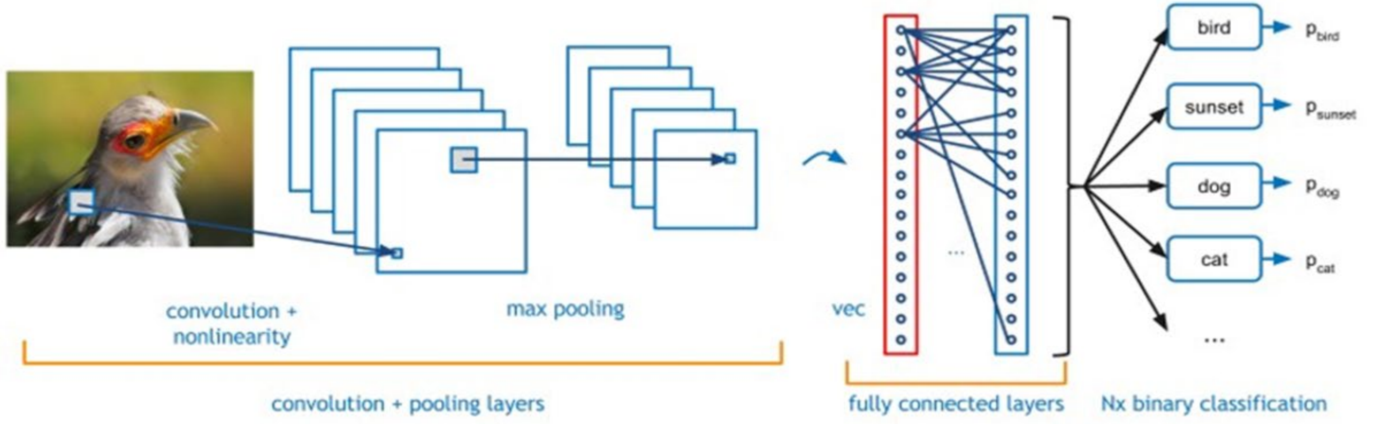


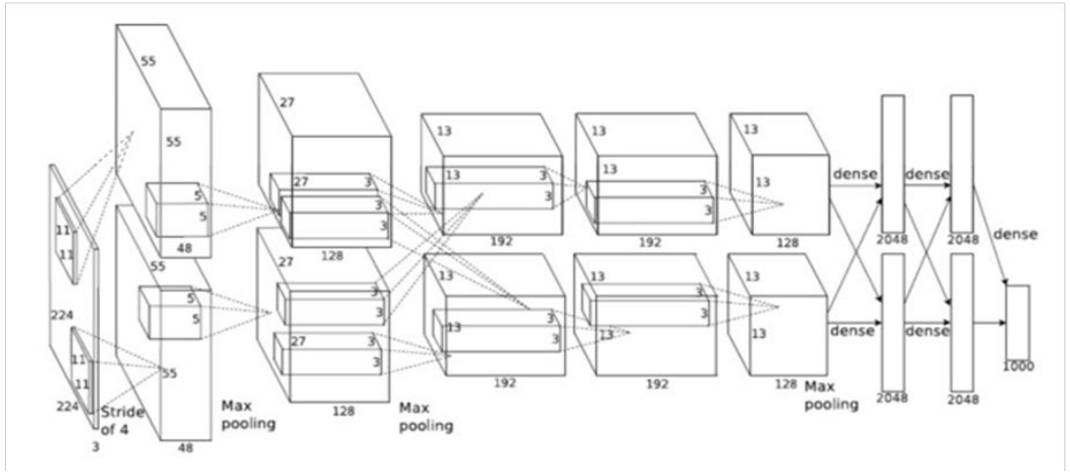
CHIME mission expansion

- ESA CHIME team and industry partners assessments
- Testing AI integration effectiveness
- Two scenarios:

First scenario: Separate unit for deep learning

- deep learning techniques
- Specifically: CNNs(LeNet, AlexNet, ResNet,etc.,)
- they are currently available and heavily optimized in the available development platforms for efficient inference
- Also, testing hybrid setups i.e., LSTM for segmentation of HS imagery



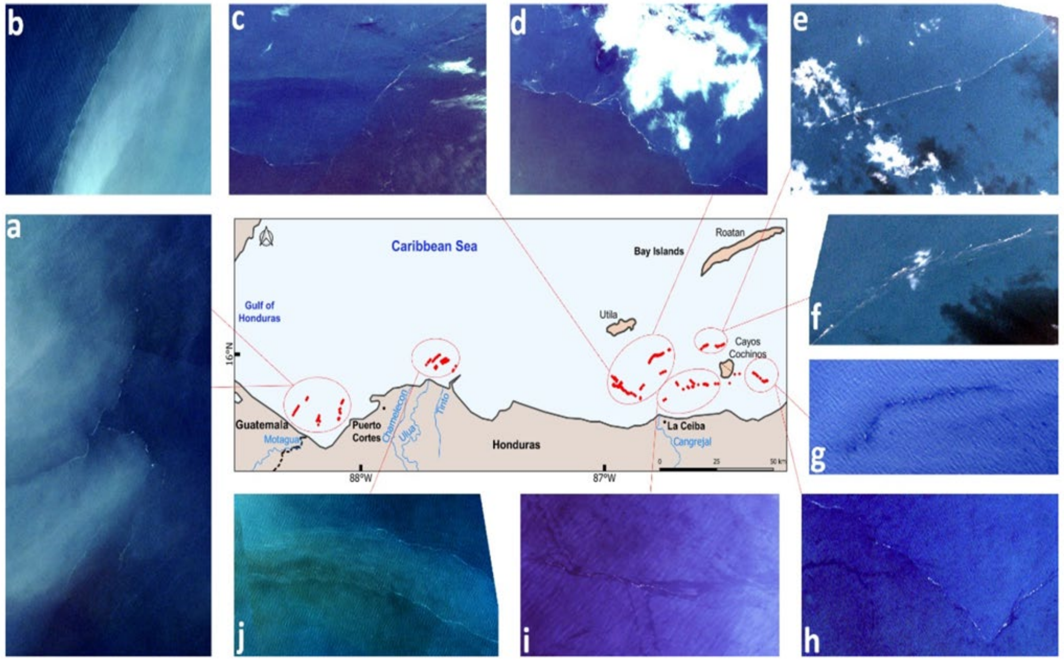


AlexNet CNN – Convolutional Neural Network

CHIME mission expansion: Deep learning scenario

Training dataset 1:

Planetscope



The detected plastic debris (red dots in the map) and snapshots of the corresponding satellite images at the Gulf of Honduras and Bay Islands during late September–October 2017.

- This dataset consists of 1370 bounding boxes of marine debris which were validated using peer-reviewed studies.
- An object detection deep learning model was trained on our curated dataset and initial results on Planetscope's optical imagery were obtained.
- Network architecture: CNN (Unet, ResNet)
- Spectral and spatial-spectral

Use the architectures of the investigated deep models—the spectral network (1D-CNN), alongside two spectral-spatial CNNs (2.5D-CNN and 3D-CNN, with 2.5D-CNN).

Although both spectral-spatial models operate on image patches, 2.5D-CNN convolutional kernels span the entire spectrum of B bands.

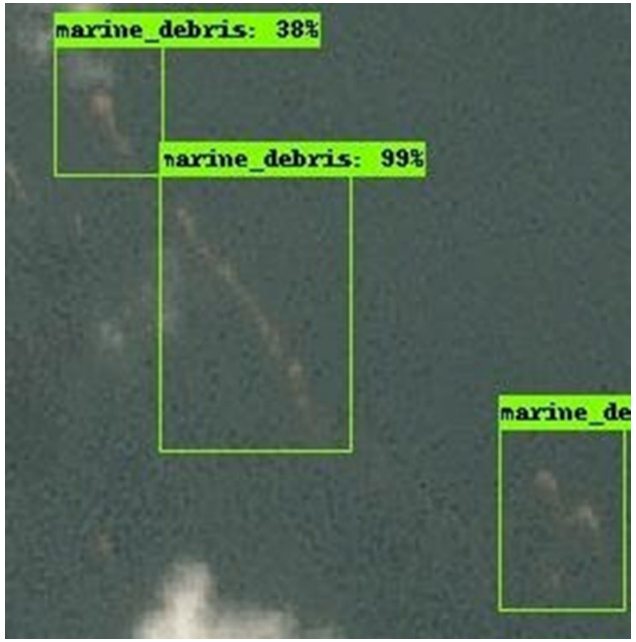
On the other hand, we utilize small (3×3×3) kernels in 3D-CNN to effectively capture local features that may be manifested in specific (often tiny) parts of the spectrum.

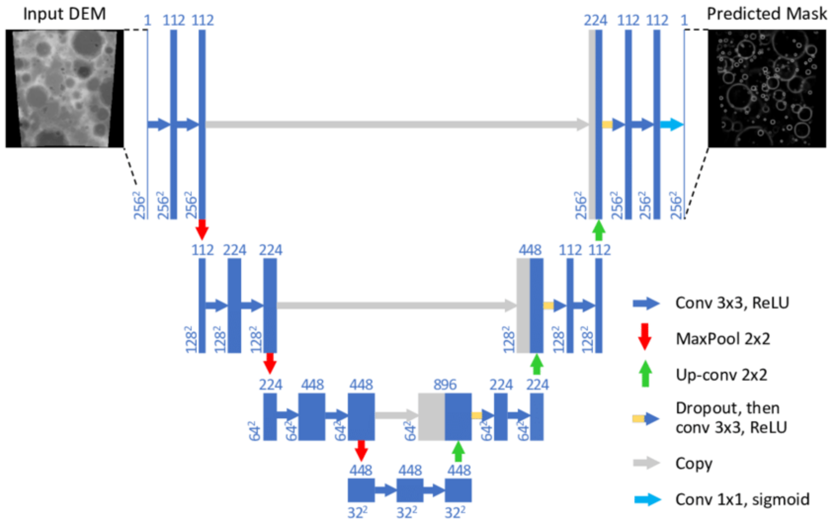
CHIME mission expansion: Deep learning scenario

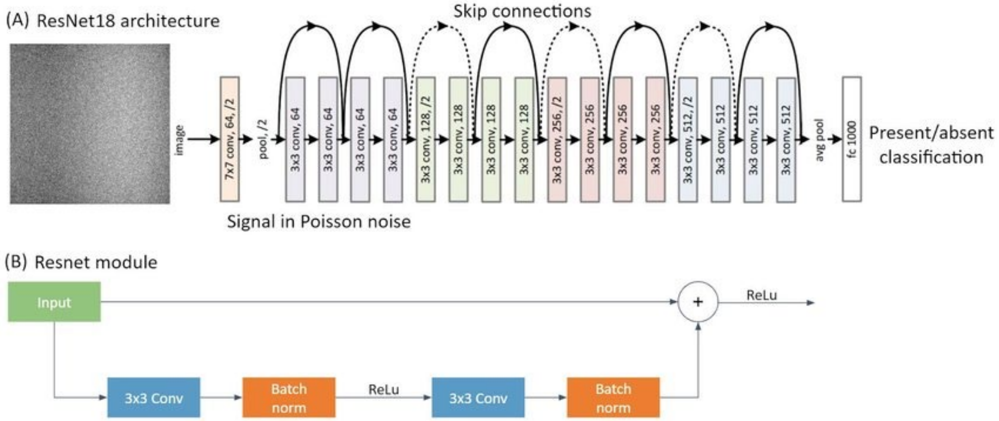
The images below display two examples of the detections from the model. The percentage represents a likelihood accuracy of the detection belonging to the class of marine debris.

ResNet

Unet





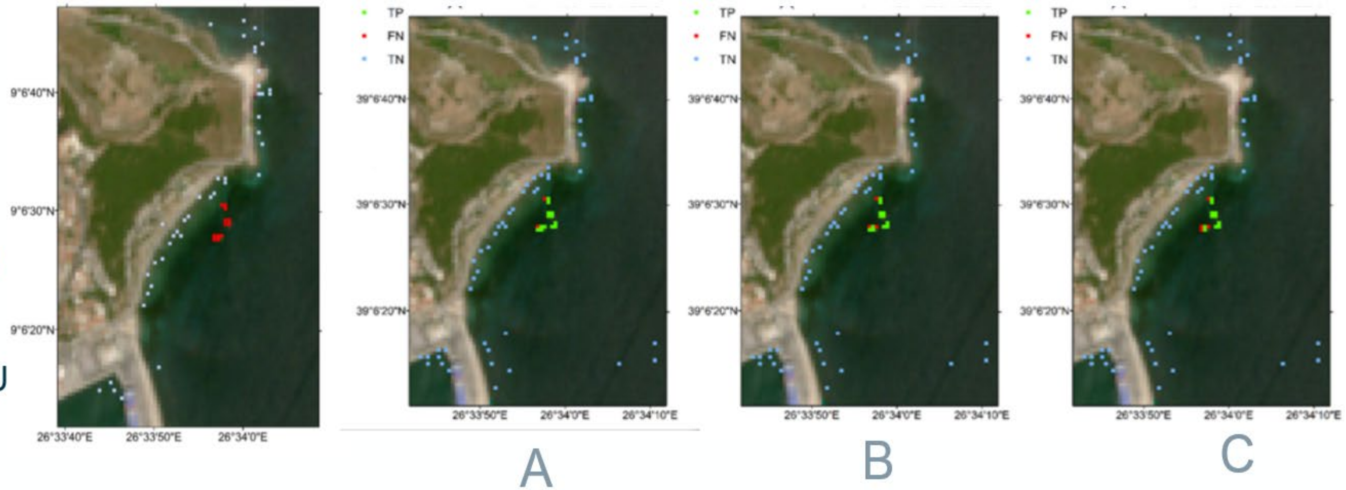


CHIME mission expansion: Machine learning on DPU scenario

esa

- In the second scenario, an additional support vector machine (SVM) with both linear and non-linear kernels was employed to detect floating debris.
- The performance of the Gaussian and Linear kernel-SVM was evaluated with the presence of manually induced clouds in cloud-free PRISMA data over Greece, which shares similarities with the future CHIME mission.

Training SVM
- Only floating plastic
- Different spectral bands and indices
- SVM with Gaussian Kernel showed promising results
- Yet to be adapted to the SVM available in the DPU



A	(i) Blue, (ii) Green, (iii) Red, (iv) RE2, (v) NIR, and (vi) SWIR1, and two indices (vii) FDI, and (viii) NDVI
B	(i) Red, (ii) RE2, (iii) NIR, and (iv) SWIR1, and two indices (v) FDI, and (vi) NDVI
C	(i) FDI and (ii) NDVI

Modelled	Observed		OA (%)
	Plastic	No Plastic	
Plastic	14	0	96.7
No Plastic	1	15	

CHIME mission expansion: Machine learning on DPU scenario

Trained a linear SVM on MARIDA Database (multi-spectral S2 images)

- 3 different datasets generated from « RAW » patches
  - Spectral indices
  - Texture
  - Spatial
- Dataset splits for each dataset
  - Train: 695 patches
  - Validation: 329 patches
  - Test: 360 patches

RESEARCH ARTICLE

MARIDA: A benchmark for Marine Debris detection from Sentinel-2 remote sensing data

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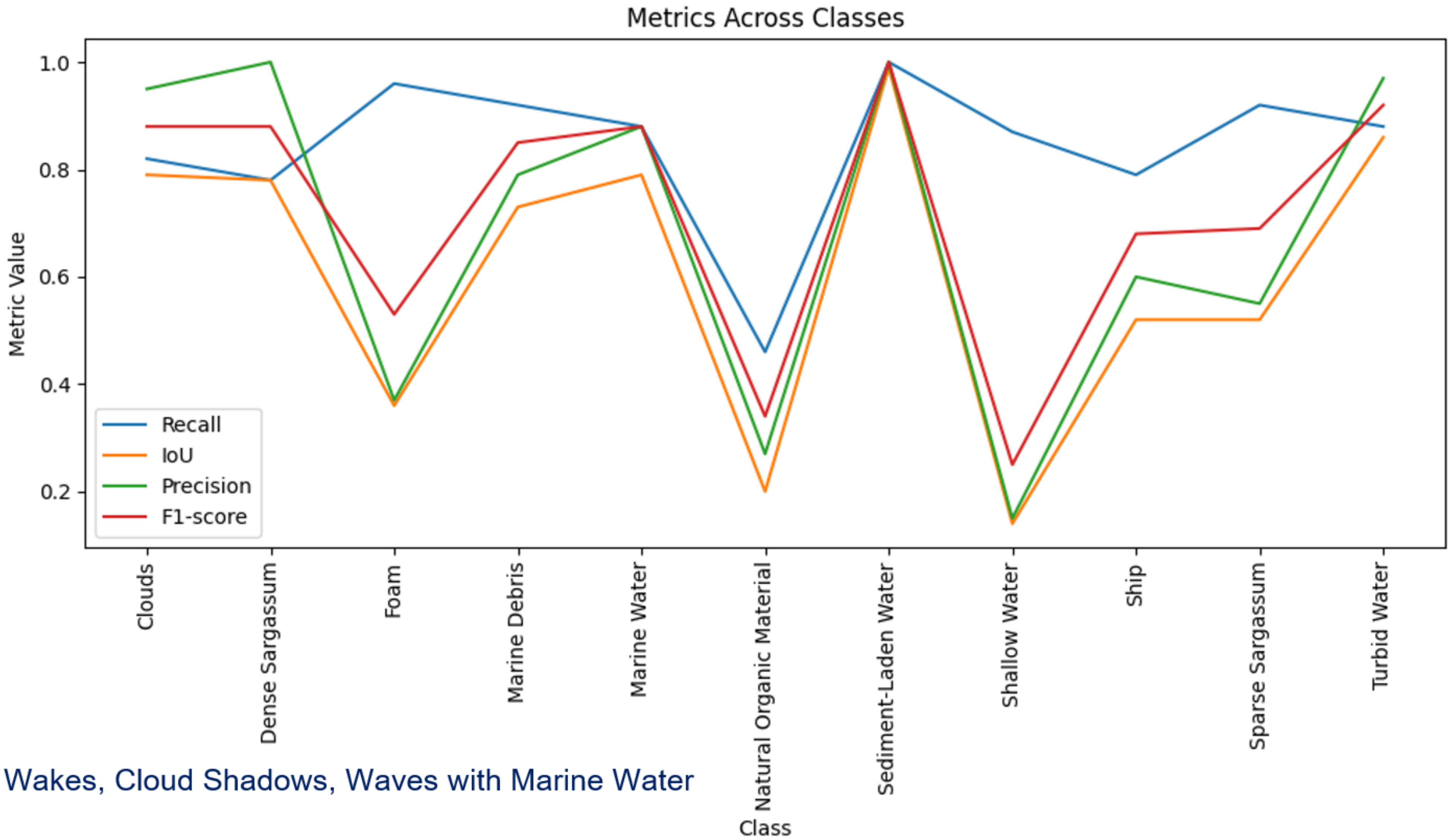
CHIME mission expansion: Machine learning on DPU scenario

1: 'Marine Debris',
2: 'Dense Sargassum',
3: 'Sparse Sargassum',
4: 'Natural Organic Material',
5: 'Ship',
6: 'Clouds',
7: 'Marine Water',
8: 'Sediment-Laden Water',
9: 'Foam',
10: 'Turbid Water',
11: 'Shallow Water',
12: 'Waves',
13: 'Cloud shadows',
14: 'Wakes',
15: 'Mixed Water'



Aggregated Mixed Water, Wakes, Cloud Shadows, Waves with Marine Water

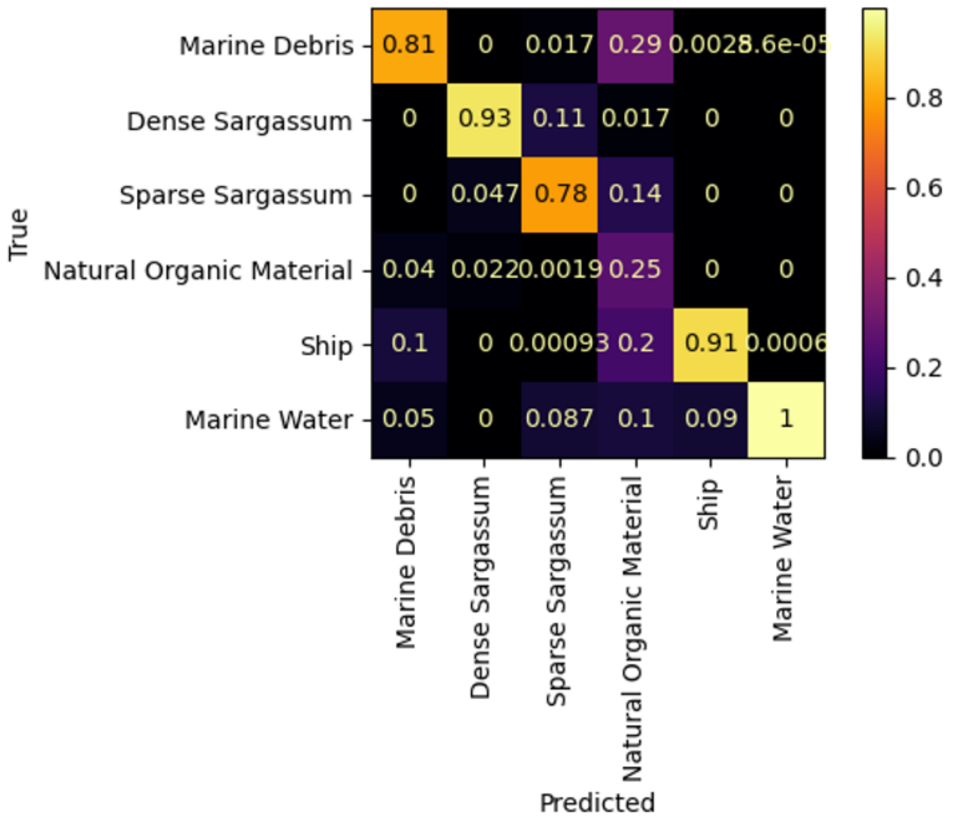
CHIME mission expansion: Machine learning on DPU scenario, aggregated features

/// Trained a linear MultiClass SVM on MARIDA Database (multi-spectral S2 images)

- Kept only features classes: Marine Debris, Dense Sargassum, Sparse Sargassum, Natural Organic Material, Ship
- Did not aggregate Marine Water with the other 5 classes as done per usual

Class	Precision	Recall	F1-score	Support
Dense Sarg	0.93	0.84	0.88	760
Marine Debris	0.81	0.90	0.85	381
Marine Water	1	0.99	0.99	23442
Natural Org Mat	0.25	0.31	0.28	49
Ship	0.91	0.94	0.92	1174
Sparse Sarg	0.78	0.95	0.86	881

Confusion matrix



CHIME mission expansion: Machine learning on DPU scenario, aggregated features

Trained a linear OneClass SVM on MARIDA Database (multi-spectral S2 images)

Features : Aggregated Marine Debris, Dense Sargassum, Sparse Sargassum, Natural Organic Material, Ship

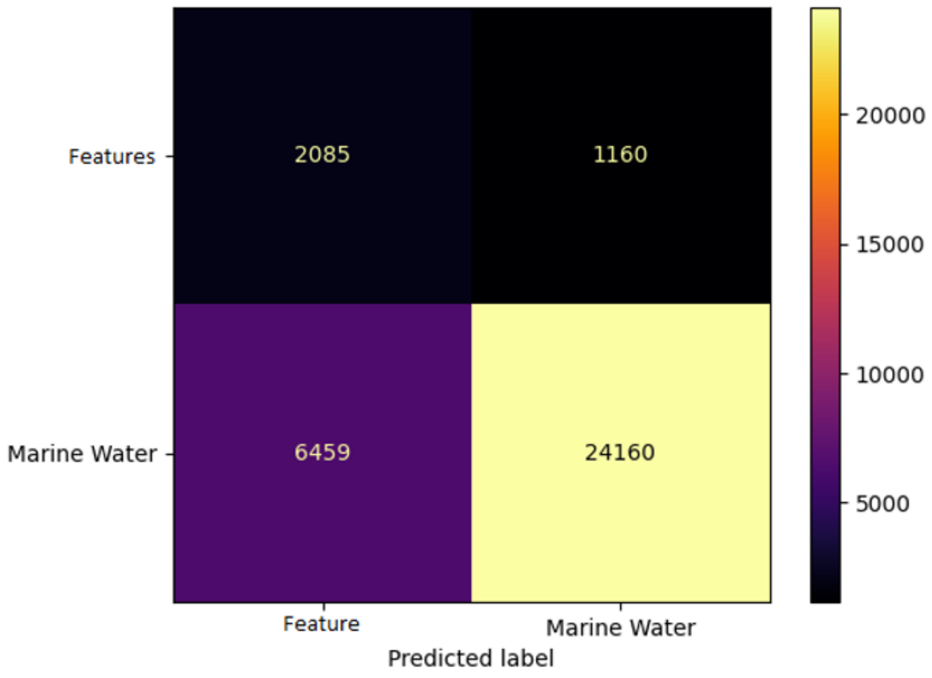
Marine water: Aggregated Mixed Water, Wakes, Cloud Shadows, Waves with Marine Water

Binary classification problem, closer to the on board target

	Precision	Recall	F1-score	Support
Features	0,24	0,64	0,35	3245
Marine Water	0,95	0,79	0,86	30619

64% of features detected
Among all feature detections, 24% of false positive
75% of water pixels compressed optimally

Confusion matrix



Continuing workplan

Targets

- Priority list of targets : floating plastic and organic, oil spills, ships, containers, ghost nets
- Size of objects: one pixel and larger (tbc, 1 pixel?)

Training dataset

- Important areas: small islands, sensitive areas i.e. coral reefs, fish farms, tourism
- ESA campaigns (MARIDA, reflectance library with VITO, UK study Plymouth)
- PRISMA dataset campaign (Mediterranean sea)
- EnMAP : oil spills
- HYPSO: future precise training dataset (fish farms airborne campaign, algae)
- Simulated dedicated dataset from end-to-end simulator

Fine tuning

- Morphologic filter
- Selection of bands: exploring spectral indices
- Optimisation of hyperparameters

Questions?