Feasibility Study of Real Time Oil Spill Tracking, Exploiting Dedicated AI On-Board Satellite

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Problem and motivations

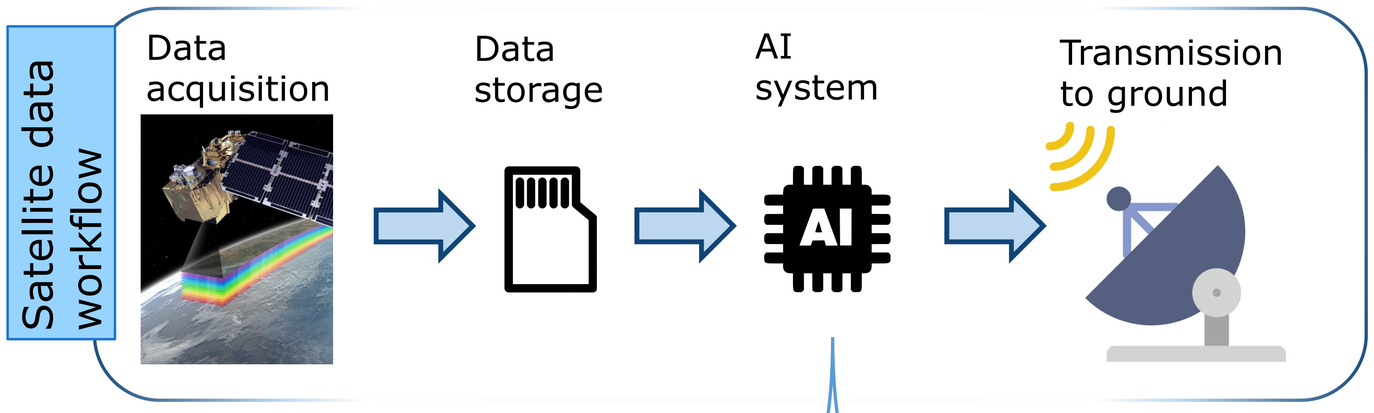
- **Oil spills** represent one of the **major threats** to **marine ecosystems;**
- The common **adopted data flow** need images to be **transmitted to the ground before analysing** process starts. This could **delay** the **identification of oil spills**;
- **Onboard identification** can: **reduce the latency** in identification of these phenomena; reduce **power consumption** by reducing the amount of data to be transmitted on ground; and reduce **storage needs** by avoiding to save useless images (sea only images).

Challenges

Common challenges when adopting **CNNs hardware accelerators:**

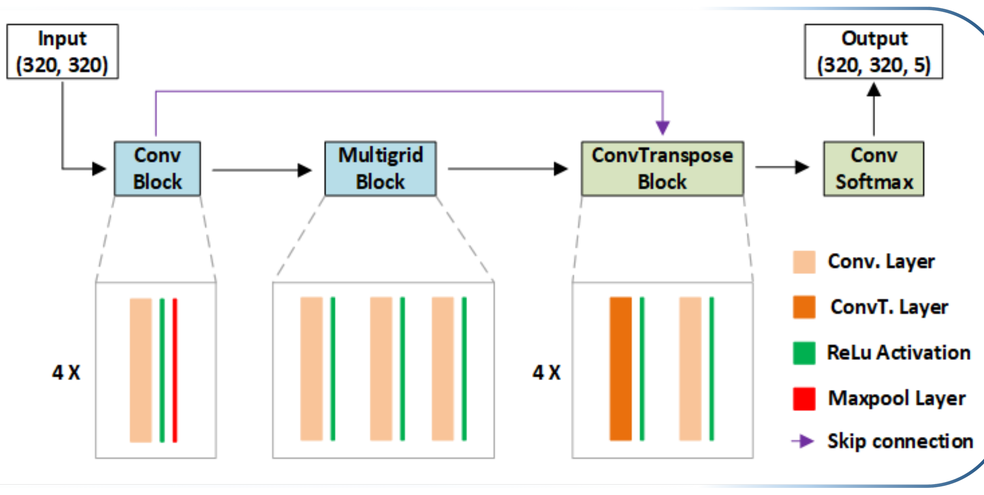
- Hardware accelerators usually features a **small amount of memory**;
- **Not every** type of **CNN's layer** is allowed to **run** on **every hardware** accelerator;
- **Development** of CNNs usually focus on best performance **neglecting hardware constraints** making state-of-the-art CNNs **not the best choice for resource constrained systems.**

Approach



- **Onboard processing** can be **unfeasible** for the **onboard CPU** of **low budget** nano- and micro-satellite **missions**;
- **Leveraging hardware accelerators** can be an **affordable** solution:
  - **COTS** for CNN acceleration **are available**;
  - They are **low cost**, **low power** solutions to bring CNN on resource constrained devices;
  - Some of them have **already passed** preliminary **radiation tests** and have been **used in LEO missions**.

- From a **SAR image** a **multiclass mask** is **generated**.
- Each **pixel** of the mask is **assigned** to one of the **following classes**:
  - Sea
  - Oil spill
  - Look-Alike
  - Ship
  - Land



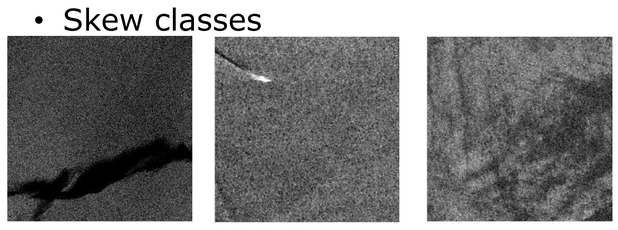
Dataset Description [1]

Pro:

- Known dataset, useful to share results of different methods
- Pre-processed to correct image artifact

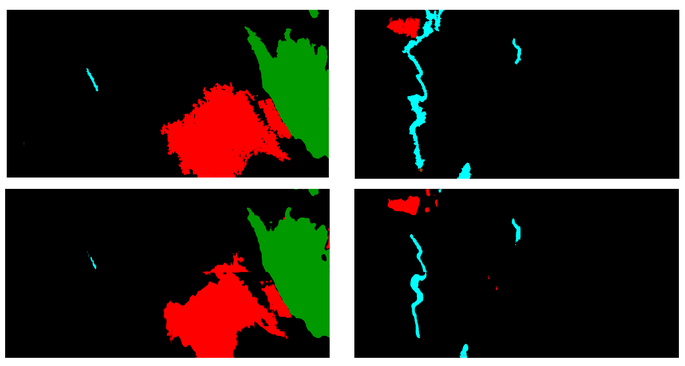
Cons:

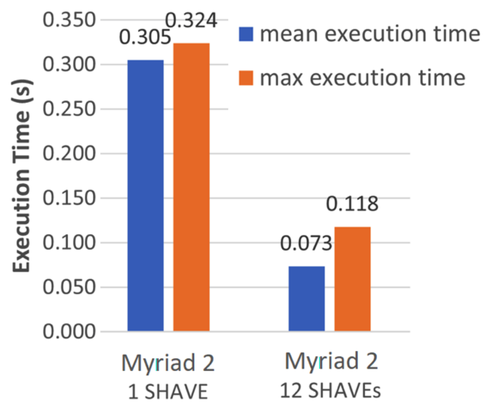
- Modest number of samples
- Skew classes

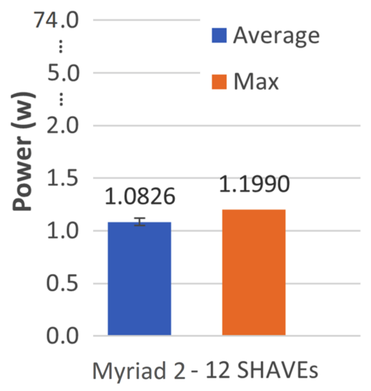


Results

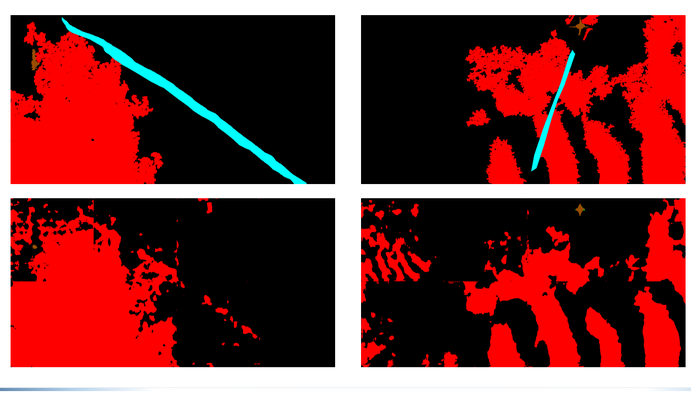
Good Classification Example







Bad Classification Example



	Single class IoU (%)					Mean IoU (%)	Inference Time on GPU (ms)	Memory allocated per inference (MB)	Number of parameters (K)
	Sea	Oil	Look-Alike	Ship	Land				
Deep-Lab V3 [1]	96.4	53.4	55.4	27.6	92.4	65	117	4901	2100
Proposed CNN	93.6	25.8	20	5.9	71.8	43.4	44	<128	9.7

Bibliography

[1] Krestenitis, M.; Orfanidis, G.; Ioannidis, K.; Avgerinakis, K.; Vrochidis, S.; Kompatsiaris, I. **Oil Spill Identification from Satellite Images Using Deep Neural Networks**. Remote Sens. 2019, 11, 1762.