Deep Learning for satellite imagery

Taghi Aliyev[1] , Lars Bromley[2], Federico Carminati[1], Nathan Lacroix[5], Sharada Mohanty[4], Walter Riviera[3], **Sofia Vallecorsa[1]**

[1] CERN-, [2] UNITAR, [3]Intel , [4] EPFL, [5] ETH
Sofia.Vallecorsa@cern.ch

The project

Motivation

UNITAR hosts the UN Operational Satellite Applications Centre (UNOSAT), which analyses satellite imagery to support disaster response and humanitarian operations. Because of the high level of precision required, manual analysis of a refugee settlement in a satellite image can take many hours (sometimes days).

Because of time and manpower constraints, UNOSAT can currently fullfill only 5-10% of UN requests.

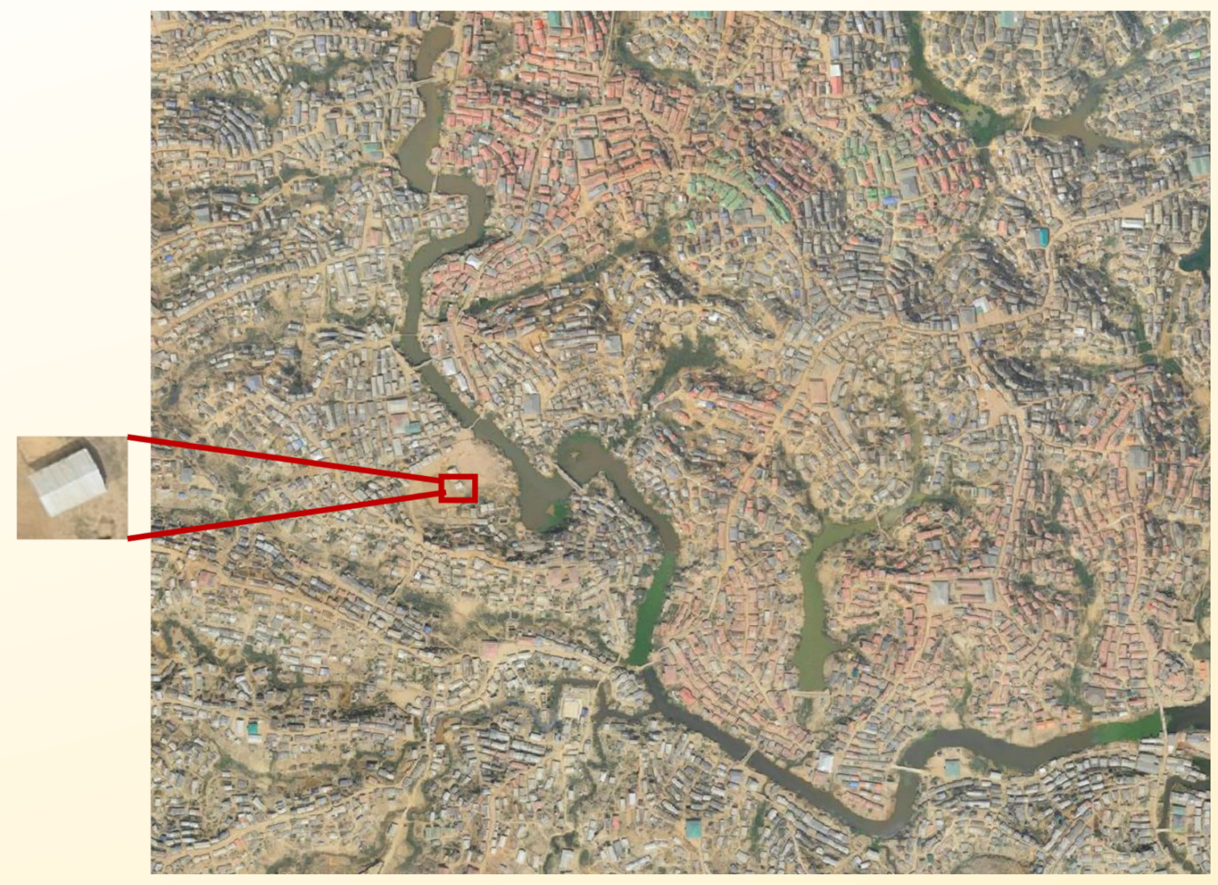
UNITAR is researching the use of **Artificial Intelligence and Deep Learning to improve efficiency and reduce** this amount of **time**, allowing an **effective deployment of field operations in critical humanitarian situations.**

Our project

A unique partnership between **CERN openlab, Intel, and UNITAR (United Nations Institute for Training and Research)** to use Deep Learning methods to improve the analysis of optical satellite imagery for humanitarian purposes.

Two main objectives:

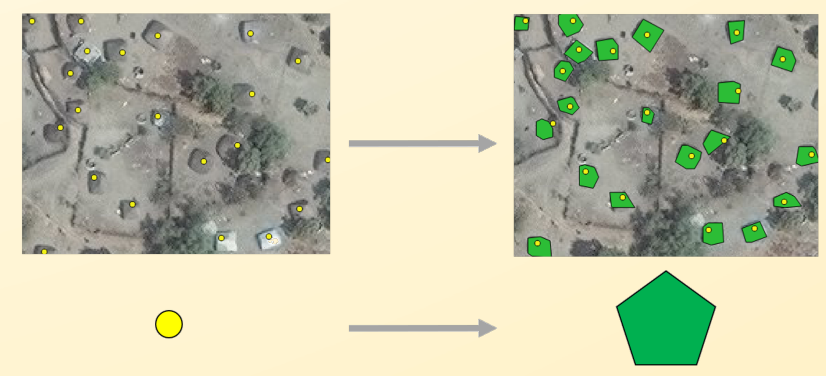
1. **Automatize** shelter counting in refugee camps images using **Deep Learning models**
2. **Use Generative Models to create spectrally valid simulated high-resolution satellite imagery** depicting humanitarian situations (refugee settlements, flood conditions or damaged infrastructure, …) to augment and diversify training samples.



A large variety of image quality and resolution, shelters in camps, environments

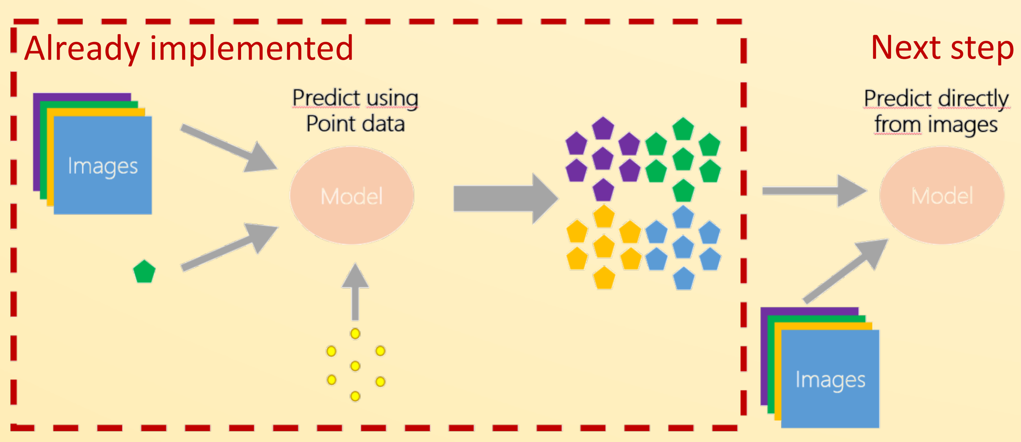
Current Status

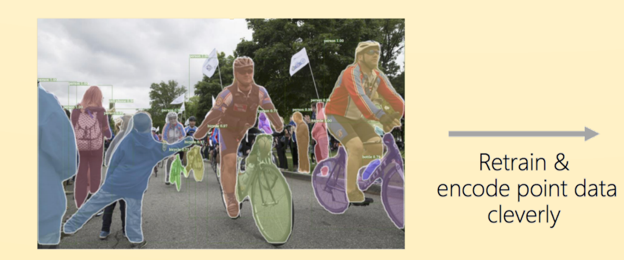
1. Convolutional Neural Networks CNN for counting shelters



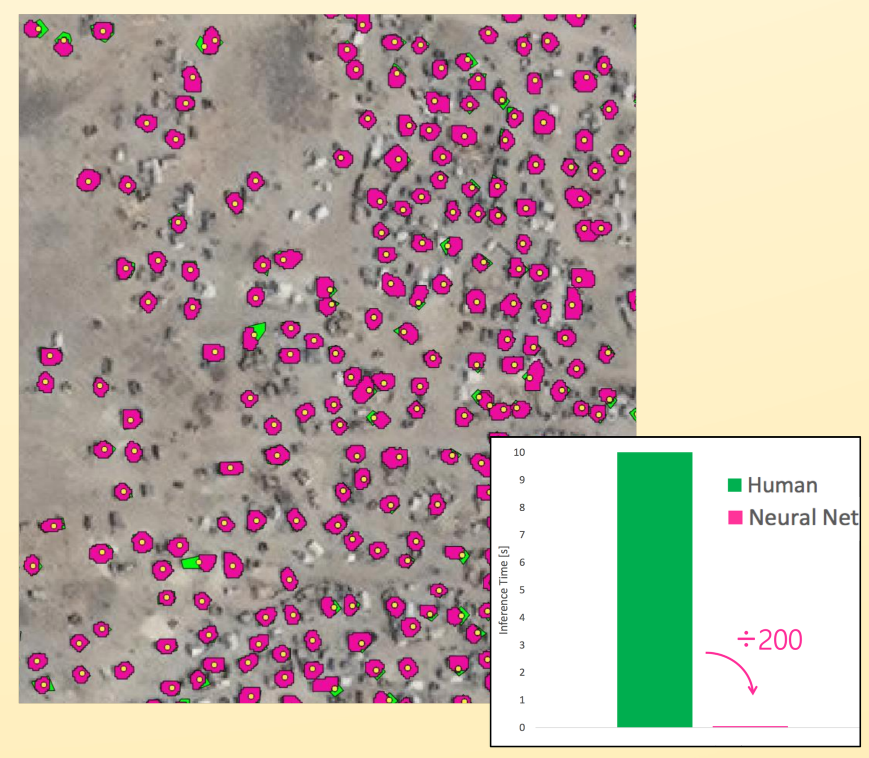
- UNITAR's standard approach uses **single points** to count tents: fast but not representative enough
- **Polygons** drawn around tents perimeter would represent more information: time consuming, only couple camps have been "polygonised"
- **Make more data usable by training a Region-based CNN[(1)] (RCNN) to draw polygons from point data**
- Apply **transfer learning** to FacebookAI Detectron framework[(2)]
- Average precision is 82%, Speedup is x200

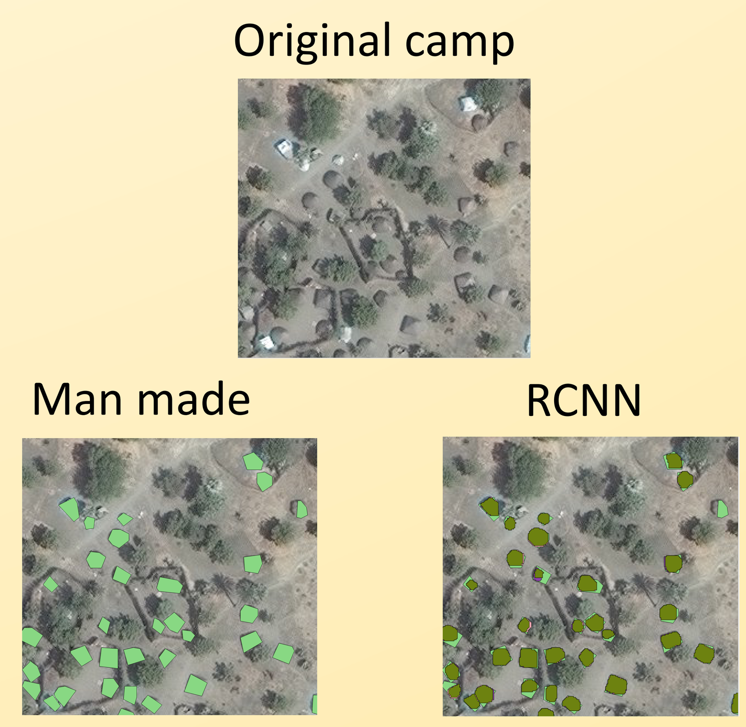
Results to be directly used by the UN Global Pulse office to enrich and refine their prediction tools by providing them with larger training and validation data sets





Detectron Framework (FacebookAI)





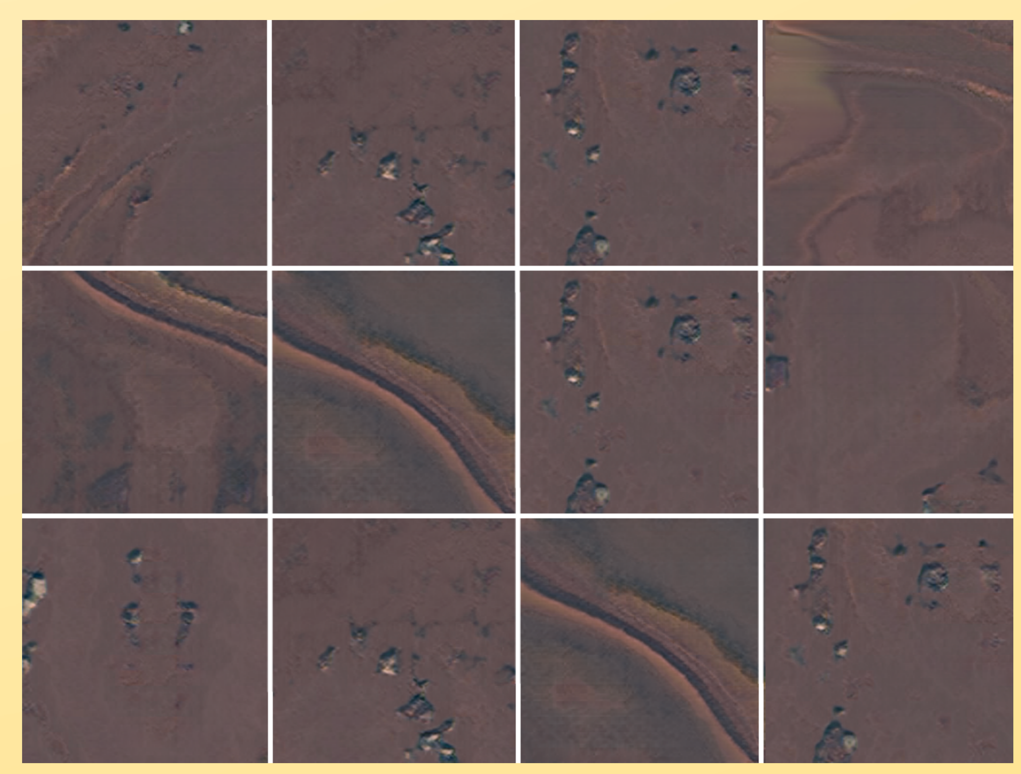
2. Generative Adversarial Networks[(3)] (GANs) for data augmentation

Training data availability is often a problem

- **High-resolution satellite imagery is very often licensed** in such a way that it can be difficult to share it across UNITAR, UN partners, and academic organizations, reducing the amount of image data available to train DL models.
- Interesting events are (luckily!) "rare" events.

The creation of realistic and spectrally accurate simulated images can enable and stimulate data sharing.

GAN generated tiles



First prototype based on progressive growing GANs[(4)]

RGB image of the Rukban Camp (Jordan) is segmented in 44060 256x256 tiles.

Progressive growing: model size grows through-out the training. Incremental approach allows the model to first learn large scale properties in the dataset, then shift to progressively finer data.

- Start with generating 4x4 pixels imagery, then 16x16 pixels, then double the size at each phase until reaching **256x256 pixels.**
- 1 **week** training on 2 NVIDIA Titan (Maxwell series) GPUs

One key aspect is the maximum size of the images that can be generated (real images are millions pixels wide): depends on software framework and hardware capabilities

Development

2019 Q2	2019 Q3	2019 Q4	2020 Q1
Prototype performance	Computing resources	Generalisation	Production

• Assess **accuracy** and **image fidelity**
  • Detailed study on different environments including desert, savannahs, and mountainous terrain
• Measure synthetic **sample variance**
	• Test and optimisation for **large scale training on Intel platforms**
	  • **Large memory** requirements
	  • Large datasets handling
	• Distributed training on Cloud/HPC
		• Exploration of the **maximum picture size** that can be generated while retaining the desired level of accuracy
		  • Test **conditional training** in order to patch tiles in a coherent image
		• Implementation and optimisation of a **multi-spectral GAN model**
			• Implementation of **auxiliary task to draw polygon** shapes on shelters in generated images
			• **Integration in the UNOSAT workflow**
			  • Production of synthetic datasets for different environments.
			  • **Evaluation of the existing procedures on synthetic vs real data**

This initial exploratory activity and results indicate that scaling up and expanding these efforts will facilitate a real burst of activity among researchers by providing an abundance of training data.

References

(1) https://arxiv.org/abs/1504.08083
(2) https://github.com/facebookresearch/Detectron
(3) Goodfellow et al. 2014
(4) karras et al. ICLR 2018.