Few-Shot Image Classification Challenge On-Board OPS-SAT

Dawa Derksen¹ dawa.derksen@esa.int Gabriele Meoni¹ gabriele.meoni@esa.int Gurvan Lecuyer¹ gurvan.lecuyer@esa.int

Anne Mergy² anne.mergy@esa.int $\begin{array}{c} \mbox{Marcus M}\mbox{artens}^2 \\ \mbox{marcus.maertens}\mbox{@esa.int} \end{array}$

Dario Izzo² dario.izzo@esa.int

Abstract

Artificial Intelligence on the edge is constrained to low-memory and low-energy environments, but has a high impact potential. We propose a data-centric competition to accelerate the deployment of on-board classification for Earth Observation satellites. To this end, we fix the model architecture *a priori* to be suitable for ground-to-satellite transmission and on-board inference. The competitors submit model parameters obtained via their training procedure using only a few labeled images taken from the European Space Agency satellite OPS-SAT, and are ranked according to classification accuracy on a larger hidden test set. Our final goals are to alleviate the need for large amounts of in-situ data for training on-board AI, and to reduce the number of pre-processing steps performed on-board. Our approach could be further extended to other domains, including guidance and control, astronomy and more.

1 Motivation

The impact of Artificial Intelligence (AI) will greatly increase as it is deployed more efficiently on the edge. An extreme application case is on-board spacecraft, where the hardware is strongly limited both in terms of energy consumption, memory capacity, and communications with the ground [8]. In the specific field of Earth Observation (EO), if successful, space-borne sensors with AI capabilities could provide automatic and rapid alerts of floods [15], wildfires [3], oil-spills [4], and other catastrophic events [18]. Further applications could include monitoring unlawful activities, e.g. deforestation [17, 10], illegal fishing [12] or floating debris dumping [21, 1]. Finally, many images captured by EO sensors are not of interest (e.g. clouds, noise), and can therefore be discarded, if they can be identified as undesirable [9, 8]. For these reasons, the motivation for on-board AI has increased much in the recent years, but its real-world deployment still faces many challenges, including data availability, low energy and memory budgets especially for CubeSat platforms [8].

Recent missions such as Φ -Sat-1 [14] and OPS-SAT [6, 7] demonstrate the capacity to perform onboard classification. However, most AI models, and particularly Deep Neural Networks, commonly demonstrate lower accuracy when faced with data that is significantly different from the training data [26, 11]. Figure 1 illustrates the data simulation, collection and annotation phases, which can be costly and time-consuming, especially when large amounts of labeled data are required to achieve sufficient accuracy. Satellite images are also generally pre-processed by applying sensor calibration and atmospheric corrections, to increase photo-consistency between training images and real images. When performed on-board, these additional steps increase the computational overhead and therefore limit the mission time.

35th Conference on Neural Information Processing Systems (NeurIPS 2021), Sydney, Australia.

¹Φ-Lab, European Space Agency, Largo Galileo Galilei, Frascati.

²Advanced Concepts Team, European Space Agency, Keplerlaan 1, Noordwijk.



Figure 1: Timeline of on-board AI satellite. We aim to reduce the need for data simulation (blue), collection (yellow), and annotation (brown) to limit costs and increase the mission lifetime (green).

Few-shot learning methods, in particular semi-supervised learning [13, 23, 25, 19], exploit scarce amounts of labeled data, in combination with large amounts of unlabeled data. However, the best approach for combining multiple image sources (both labeled and unlabeled), especially on unprocessed images, is not well established for Earth Observation, which motivates a challenge around this topic.

2 The challenge

We propose to conduct a public challenge on ESA's Kelvins platform (https://kelvins.esa.int) to encourage groups with diverse backgrounds to propose high-quality solutions within a limited time frame, in a competitive setting. Following the paradigm of data-centric AI, we fix the model architecture *a priori*. From our point of view, this is done to guarantee suitability for on-board application. First of all, by limiting the total model size, we ensure satisfaction of the satellite uplink requirements [22]. Secondly, a fixed architecture allows for hardware optimization, such as a tailored hardware accelerator on the Field Programmable Gate Array (FPGA) embarked on OPS-SAT [2]. In this regard, having a predetermined architecture ensures that the model operations are supported by the tools for edge inference, such as Vitis Xilinx [24] or TensorFlow-Lite [20]. Finally, it facilitates quantization, which can be crucial to enable the use of the state-of-the-art architectures while keeping a limited size. Specifically, using a fixed-point encoding can reduce the inference time, power consumption and complexity compared to floating-point solutions, when inferred on FPGAs [5].

In the data-centric paradigm, the competitors' task is to submit a trained model that fits within our specifications on the model architecture, that are linked to the specifics of mission design. To this end, they are encouraged to produce a data set and training procedure based on the few labeled and unlabeled images that we provide. The solutions are ranked by classification accuracy, computed on a large amount of hidden, manually annotated images from the satellite sensor.

3 Data source

The competition is based on images taken by the optical sensor of OPS-SAT [16], illustrated in Figure 2a. We firmly intend to use the outcome of this challenge for on-board tests and experiments on OPS-SAT. The automatic classification of OPS-SAT images using Machine Learning also poses several image/vision related challenges. First, because the spacecraft is in a tumbling mode, the scale of the observed land surfaces are not consistent, and these are often seen at a varying off-nadir angle. Secondly, no radiometric calibration step is performed to equalize the images. Finally, the signal to noise ratio can be low in certain areas, particularly where the off-nadir angle is elevated.

4 Conclusion

In this paper, we identified a lack of datasets and research regarding on-board AI for Earth Observation, and proposed a data-centric challenge to address key issues such as scarce training data and strong hardware limitations. If successful, the winning solutions will be considered for future missions with on-board AI capabilities.



(a) OPS-SAT, a 3U cubesat (30x10x10cm) during its solar panel test phase [16].



(b) An example of a pre-processed image from the OPS-SAT optical sensor.

Acknowledgments and Disclosure of Funding

This work has been done thanks to funding from the European Space Agency. We would like to thank Nicolas Longépé and Bertrand Le Saux from ESRIN's Φ -Lab for introducing us to the Data-Centric AI community, as well as David Evans and Vladimir Zelenevskiy from ESOC for providing valuable information, as well as the OPS-SAT images.

References

- Lauren Biermann, Daniel Clewley, Victor Martinez-Vicente, and Konstantinos Topouzelis. Finding plastic patches in coastal waters using optical satellite data. *Scientific reports*, 10(1):1–10, 2020.
- [2] Cyclone V FPGAs and SoC FPGAs. Available online at: "https://www.intel.com/ content/www/us/en/products/details/fpga/cyclone/v.html". Last accessed on 21/09/2021.
- [3] Maria Pia Del Rosso, Alessandro Sebastianelli, Dario Spiller, Pierre Philippe Mathieu, and Silvia Liberata Ullo. On-board volcanic eruption detection through CNNs and satellite multi-spectral imagery. *Remote Sensing*, 13(17):3479, Sep 2021.
- [4] Lorenzo Diana, Jia Xu, and Luca Fanucci. Oil spill identification from SAR images for low power embedded systems using CNN. *Remote Sensing*, 13(18), 2021.
- [5] Gianmarco Dinelli, Gabriele Meoni, Emilio Rapuano, Gionata Benelli, and Luca Fanucci. An fpga-based hardware accelerator for cnns using on-chip memories only: Design and benchmarking with intel movidius neural compute stick. *International Journal of Reconfigurable Computing*, 2019, 2019.
- [6] David Evans and Mario Merri. OPS-SAT: A ESA nanosatellite for accelerating innovation in satellite control. In *SpaceOps 2014 Conference*, page 1702, 2014.
- [7] Simone Fratini, Nicola Policella, Ricardo Silva, and Joao Guerreiro. On-board autonomy operations for OPS-SAT experiment. *Applied Intelligence*, pages 1–18, 2021.
- [8] Gianluca Furano, Gabriele Meoni, Aubrey Dunne, David Moloney, Veronique Ferlet-Cavrois, Antonis Tavoularis, Jonathan Byrne, Léonie Buckley, Mihalis Psarakis, Kay-Obbe Voss, et al. Towards the use of artificial intelligence on the edge in space systems: Challenges and opportunities. *IEEE Aerospace and Electronic Systems Magazine*, 35(12):44–56, 2020.
- [9] Gianluca Giuffrida, Lorenzo Diana, Francesco de Gioia, Gionata Benelli, Gabriele Meoni, Massimiliano Donati, and Luca Fanucci. CloudScout: A deep neural network for on-board cloud detection on hyperspectral images. *Remote Sensing*, 12(14):2205, Jul 2020.

- [10] Jeremy Irvin, Hao Sheng, Neel Ramachandran, Sonja Johnson-Yu, Sharon Zhou, Kyle Story, Rose Rustowicz, Cooper Elsworth, Kemen Austin, and Andrew Y Ng. ForestNET: Classifying drivers of deforestation in indonesia using deep learning on satellite imagery. arXiv preprint arXiv:2011.05479, 2020.
- [11] David Krueger, Ethan Caballero, Joern-Henrik Jacobsen, Amy Zhang, Jonathan Binas, Dinghuai Zhang, Remi Le Priol, and Aaron Courville. Out-of-distribution generalization via risk extrapolation (rex). In *International Conference on Machine Learning*, pages 5815–5826. PMLR, 2021.
- [12] Andrey A Kurekin, Benjamin R Loveday, Oliver Clements, Graham D Quartly, Peter I Miller, George Wiafe, and Kwame Adu Agyekum. Operational monitoring of illegal fishing in ghana through exploitation of satellite earth observation and ais data. *Remote Sensing*, 11(3):293, 2019.
- [13] Bing Liu, Xuchu Yu, Pengqiang Zhang, Xiong Tan, Anzhu Yu, and Zhixiang Xue. A semisupervised convolutional neural network for hyperspectral image classification. *Remote Sens. Lett.*, 8(9):839–848, 2017.
- [14] Gonzalo Mateo-Garcia, Silviu Oprea, Lewis Smith, Josh Veitch-Michaelis, Guy Schumann, Yarin Gal, Atılım Güneş Baydin, and Dietmar Backes. Flood detection on low cost orbital hardware. arXiv preprint arXiv:1910.03019, 2019.
- [15] Gonzalo Mateo-Garcia, Joshua Veitch-Michaelis, Lewis Smith, Silviu Vlad Oprea, Guy Schumann, Yarin Gal, Atılım Güneş Baydin, and Dietmar Backes. Towards global flood mapping onboard low cost satellites with machine learning. *Scientific Reports*, 11(1), Mar 2021.
- [16] OPS-SAT information page. Available online at: https://www.esa.int/Enabling_ Support/Operations/OPS-SAT. Last accessed on 22/09/2021.
- [17] Tara Slough, Jacob Kopas, and Johannes Urpelainen. Satellite-based deforestation alerts with training and incentives for patrolling facilitate community monitoring in the peruvian amazon. *Proceedings of the National Academy of Sciences*, 118(29), 2021.
- [18] Lorenzo Solari, Matteo Del Soldato, Federico Raspini, Anna Barra, Silvia Bianchini, Pierluigi Confuorto, Nicola Casagli, and Michele Crosetto. Review of satellite interferometry for landslide detection in italy. *Remote Sensing*, 12(8):1351, 2020.
- [19] Chao Tao, Ji Qi, Weipeng Lu, Hao Wang, and Haifeng Li. Remote sensing image scene classification with self-supervised paradigm under limited labeled samples. *IEEE Geosci. Remote Sens. Lett.*, 2020.
- [20] Deploy machine learning models on mobile and IoT devices. Available online at: https://www.tensorflow.org/lite/, note = "Last accessed on 27/09/2021".
- [21] Konstantinos Topouzelis, Dimitris Papageorgiou, Giuseppe Suaria, and Stefano Aliani. Floating marine litter detection algorithms and techniques using optical remote sensing data: A review. *Marine Pollution Bulletin*, 170:112675, 2021.
- [22] Li Wang, Shuaijun Liu, Weidong Wang, and Zhiyan Fan. Dynamic uplink transmission scheduling for satellite internet of things applications. *China Communications*, 17(10):241–248, 2020.
- [23] Hao Wu and Saurabh Prasad. Semi-supervised deep learning using pseudo labels for hyperspectral image classification. *IEEE Trans. Image Process.*, 27(3):1259–1270, 2017.
- [24] Xilinx vitis ai user guide. Available online at: https://www.xilinx.com/support/ documentation/sw_manuals/vitis_ai/1_3/ug1414-vitis-ai.pdf. Last accessed on 27/09/2021.
- [25] Kexin Zhang and Hua Yang. Semi-supervised multi-spectral land cover classification with multiattention and adaptive kernel. In 2020 IEEE International Conference on Image Processing (ICIP), pages 1881–1885. IEEE, 2020.
- [26] Xingxuan Zhang, Peng Cui, Renzhe Xu, Linjun Zhou, Yue He, and Zheyan Shen. Deep stable learning for out-of-distribution generalization. *CoRR*, abs/2104.07876, 2021.