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

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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 on-board 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.

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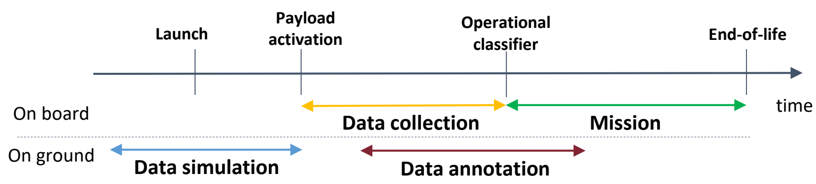


Figure 1: Timeline of on-board AI satellite. We aim to reduce the need for data simulation (blue), collection (yellow), and annotation (brown) to limit costs and increase the mission lifetime (green).

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].

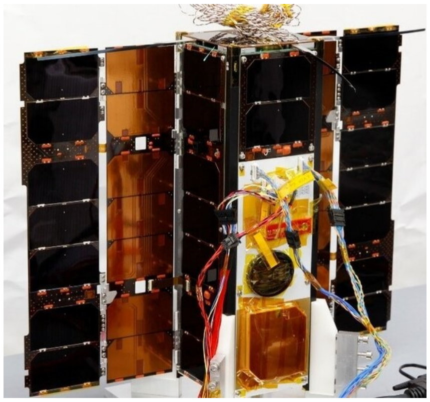
In the data-centric paradigm, the competitors' task is to submit a trained model that fits within our specifications on the model architecture, that are linked to the specifics of mission design. To this end, they are encouraged to produce a data set and training procedure based on the few labeled and 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

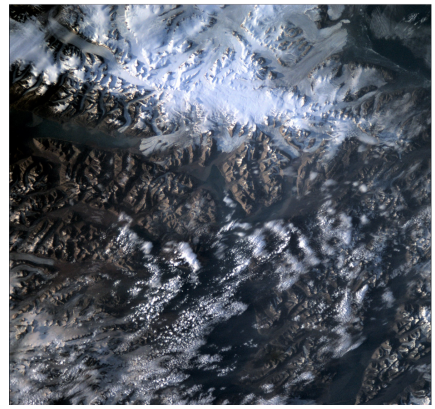
The competition is based on images taken by the optical sensor of OPS-SAT [16], illustrated in Figure 2a. We firmly intend to use the outcome of this challenge for on-board tests and experiments on OPS-SAT. The automatic classification of OPS-SAT images using Machine Learning also poses several image/vision 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.

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