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Semi-Supervised Learning for Automatic Improvement of Onboard Object Detection Models on Small Satellites

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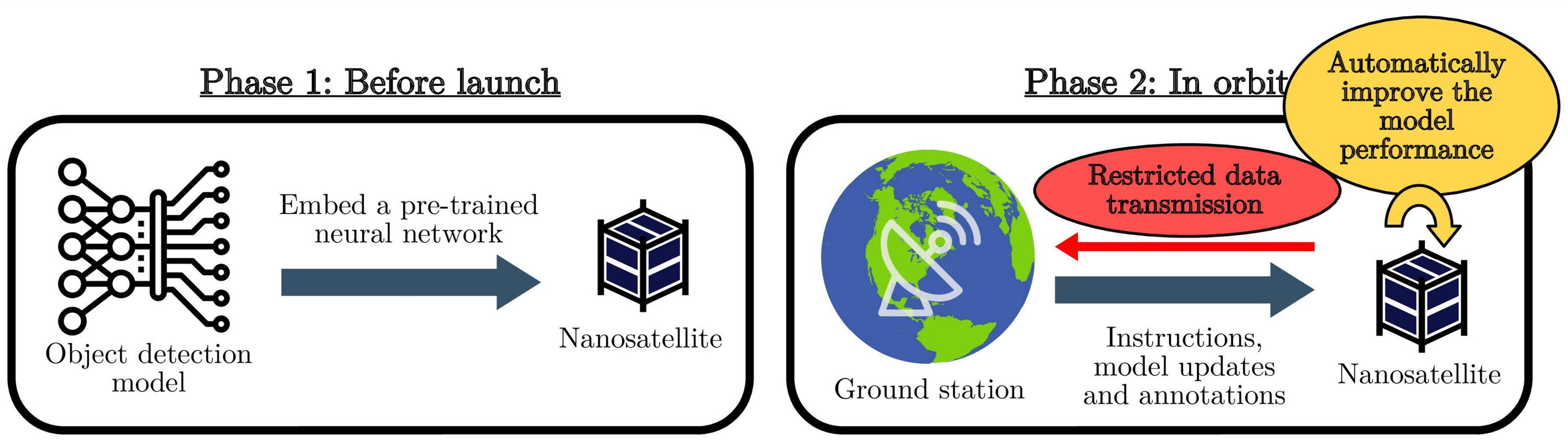
Introduction

- Nanosatellites and CubeSats offer a short development time and low production costs for Earth observation missions at the cost of having restricted power, size, and communication bandwidth
- Despite the limitations, it is possible to employ small edge computing platforms (*e.g.*, NVIDIA Jetson, Intel Movidius Myriad, and Google Coral) and neural network simplification strategies (SZE et al., 2017) to perform onboard image processing on nanosatellites and CubeSats
- An onboard ML model can process images captured by a satellite to select a few images of interest to be transmitted to the ground, reducing bandwidth usage and power consumption
- Current approaches of onboard image processing implement image classification for cloud detection (GIUFFRIDA et al., 2020) and image segmentation for flood mapping (MATEO-GARCIA et al., 2021)
- They have some limitations, such as using a static ML model, ignoring images not selected for downlinking, and potentially causing sample bias



The pipeline for self-improvement of object detection models in orbit.

Methods

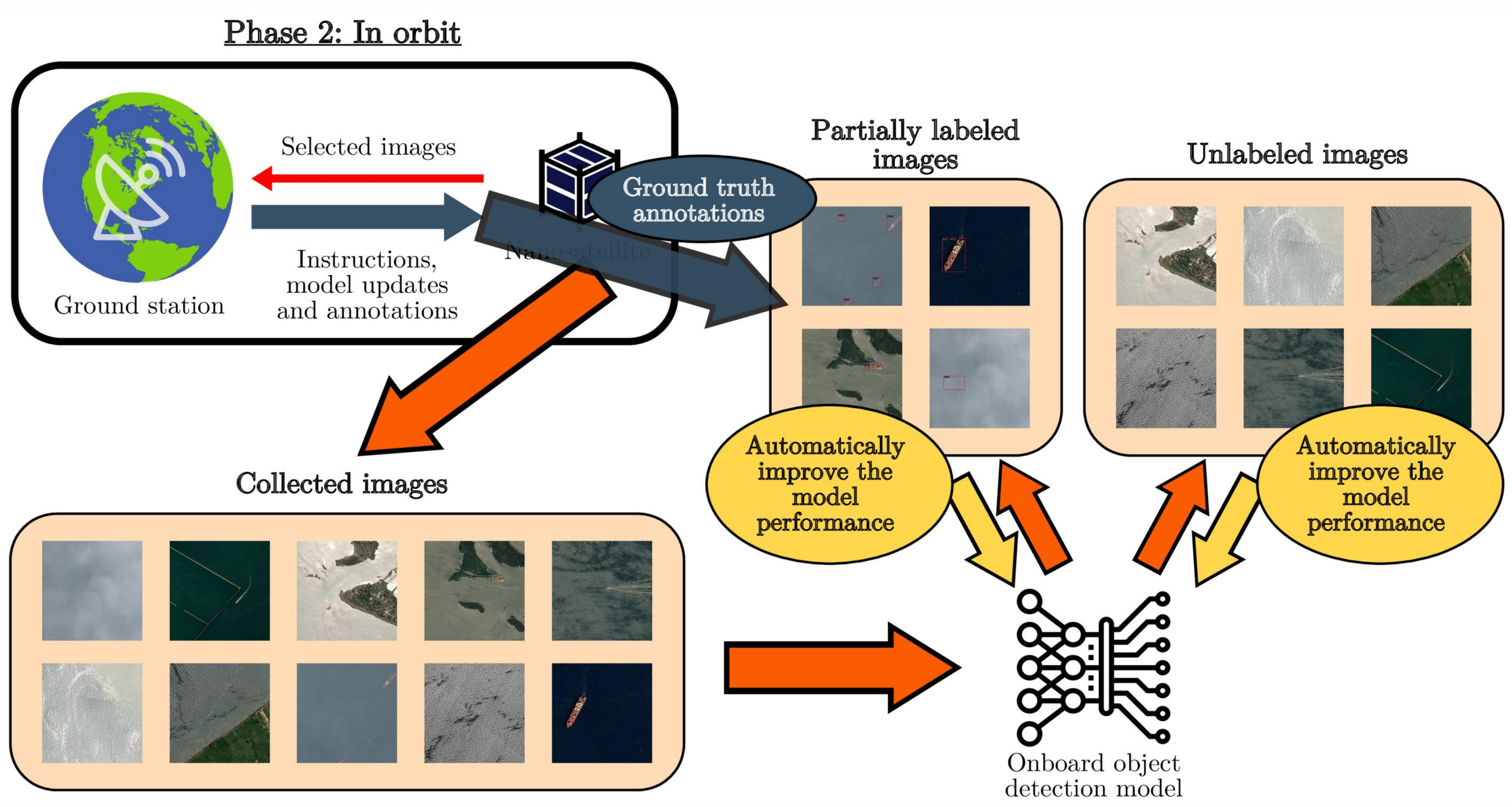
- Supervised learning is not a viable solution to improve the performance of an onboard model, since it requires using only labeled images, and labeling involves transmitting images to the ground and manually labeling them
- This research proposes to use the images captured by the satellite to automatically improve the performance of the onboard ML model
- We focus on object detection task and assume that a few labeled images can be acquired via active learning; the remaining images are unlabeled
- Therefore, we can apply semi-supervised object detection (SSOD) to use labeled and unlabeled images in order to improve the detection performance of the onboard model

Challenges

- Efficient training: performing onboard SSOD training is challenging due to the severe restrictions on the nanosatellite hardware
- Robust detection of small objects and minority categories: objects of interest are small and infrequent in images captured by nanosatellites
- Domain adaptation: access to labeled images of the target domain is limited and hinders adapting a pre-trained model

Objectives

- Develop SSOD methods that address the specific challenges of nanosatellite applications
- Demonstrate the effectiveness of our SSOD solutions with satellite imagery datasets and execute them on a CubeSat testbed



Proposed approach for using captured images to perform SSOD

References

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