Efficient Subnets for Scalable Onboard AI in Space

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Introduction

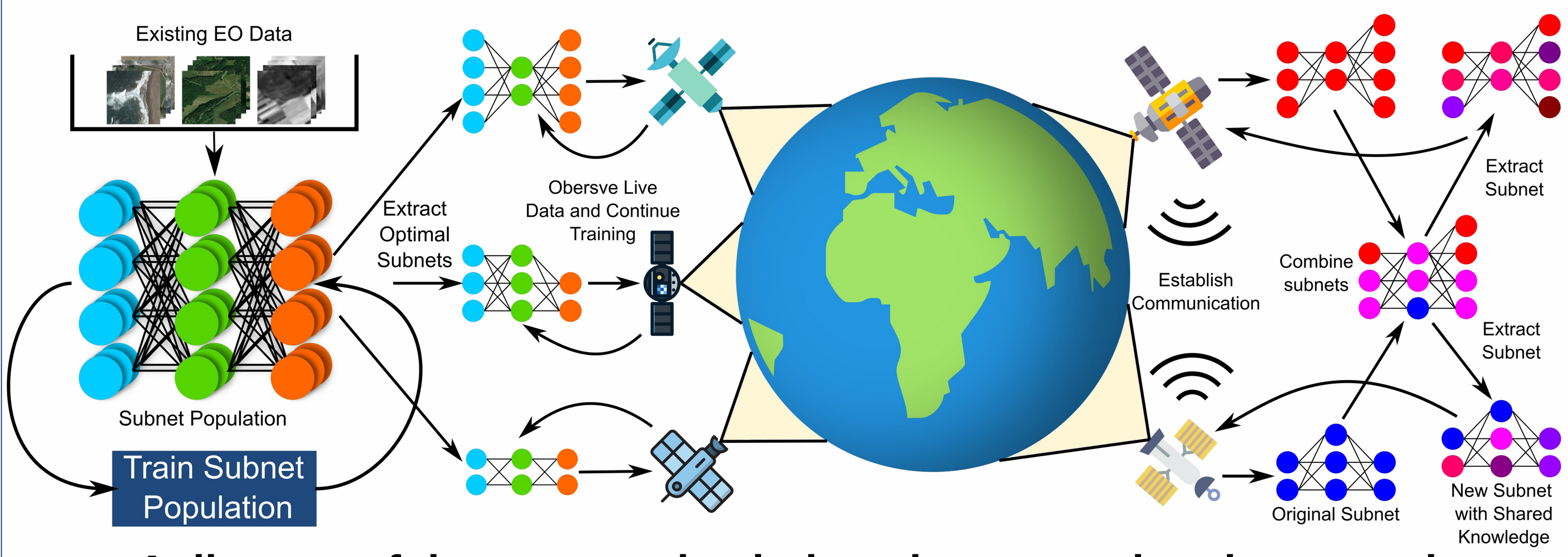
- **Artificial Intelligence** and **computer vision** can solve many challenging **Earth Observation** problems, such as flood detection [1] and semantic change segmentation [2].
- **Nanosatellites** have become the preferred platform, often launched in a **constellation** to allow for greater data capture.
- However, the use of **nanosatellite constellations** introduces several **challenges** for training AI models.
  1) **Limited data transfer** both between nanosatellites and between a nanosatellite and a ground station.
  2) **Training data heterogeneity** due to nanosatellites observing different geographical regions.
  3) **Limited onboard compute** hardware.
- How do we solve these **challenges** and enable state of the art **computer vision** solutions for **Earth Observation** task in a **nanosatellite constellation**?

Aims

- Enable the effective and practical use of **AI** models **onboard nanosatellites** in a **constellation**.
- Use recent advances in **computer vision** and **machine learning** to develop state of the art **Earth Observation** solutions.

Methods

- Our solution consists of three stages: **ground training**, **deployment** and **knowledge transfer**.
- In **ground training** we pretrain either a single network or subnet population (many networks) with all available and relevant data, limiting the onboard training time.
- In the **deployment** stage we search for and deploy optimal subnets to each nanosatellite.
- Lastly, we use Federated Learning [3] to coordinate the **knowledge transfer** of newly learnt knowledge between the subnets.



A diagram of the proposed solution, demonstrating the ground training, deployment and knowledge transfer.

References

[1] R. Hansch et al., "SpaceNet 8 - The Detection of Flooded Roads and Buildings," CVPR, 2022
[2] A. Toker et al., "DynamicEarthNet: Daily Multi-Spectral Satellite Dataset for Semantic Change Segmentation," CVPR 2022
[3] H. McMahan et al. "Communication-Efficient Learning of Deep Networks from Decentralized Data", NIPS 2016
[4] J. Shipard, A. Wiliem, and C. Fookes, "Does Interference Exist When Training a Once-for-All Network?," CVPRW, 2022
[5] J. Shipard et al. "Diversity is Definitely Needed: Improving Model-Agnostic Zero-shot Classification via Stable Diffusion," CVPRW, 2023
[6] Vaze et al. "Generalized Category Discovery", CVPR 2022
[7] Ouldnoughi et al. "CLIP-GCD: Simple Language Guided Generalized Category Discovery" Arxiv preprint, 2023
[8] Pu et al. "Federated Generalized Category Discovery", Arxiv preprint 2023

Results

Does Interference Exist When Training a Once-For-All Network? (CVPRW, 2022) [4]

Summary

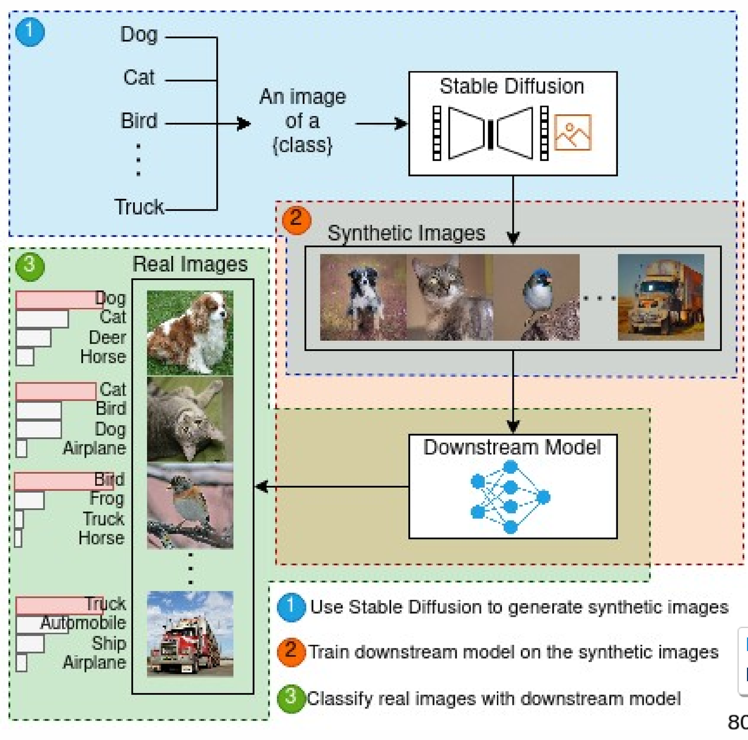
We found a faster, more efficient and better performing method for training a Once-For-All subnet population.

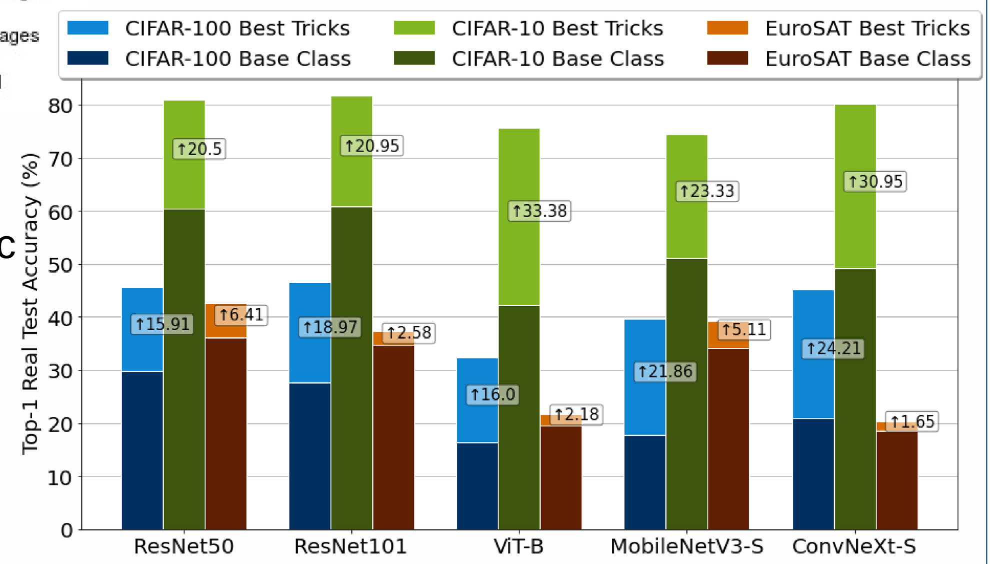
Paper

Diversity is Definitely Needed: Improving Model-Agnostic Zero-shot Classification via Stable Diffusion (CVPRW, 2023) [5]

Summary

We developed techniques for improving the quality of synthetic images from diffusion models such that they could generate training data for classification tasks with real images. This can be used to generate synthetic satellite training data.





Top Left: Overview of the entire method.
Top right: Real (top row) and synthetic (bottom row) satellite images.
Bottom right: Improved test accuracy on real datasets.

Paper

Federated Generalised Category Discovery with Vision Language Models (In progress)

Summary

We are currently working on developing a Federated Learning system capable of generalised category discovery from only natural language category descriptions.

Overview of Generalised Category Discovery Method

Preliminary results comparing against existing methods

Dataset	GCD[7]	CLIP-GCD[8]	Fed-GCD[9]	Ours
CIFAR10	91.5	96.6	84.8	78.1
CIFAR100	73.0	85.2	56.1	58.5
ImageNet-100	74.1	84.0	74.8	70.3
CUB-200	51.3	62.8	55.4	62.2
Stanford Cars	39.0	-	38.5	26.6
Herbarium19	35.4	-	-	15.8
Flowers	-	76.3	-	95.6
Oxford-Pet	-	-	82.7	79.1

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Cooperative Research Centres Program