Continual learning for satellite data analysis

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Introduction

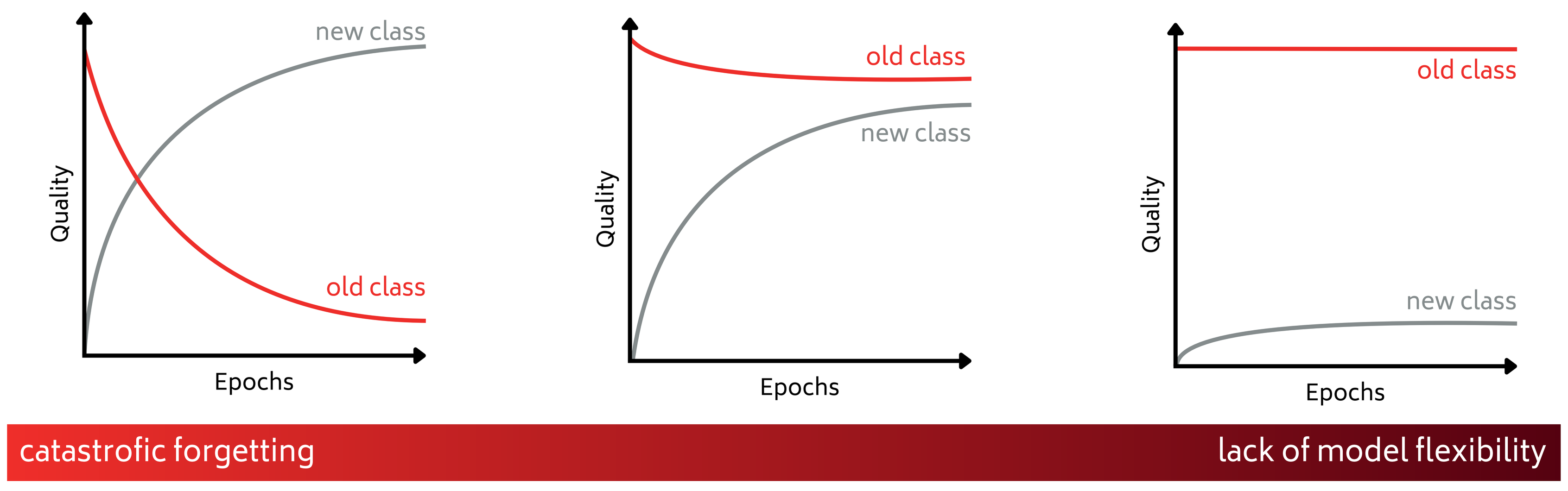
The world around us changes every day. Solutions and models that perform well today may become outdated or insufficient tomorrow in the face of new data and evolving requirements.
The concept of continual learning addresses this challenge by enabling models to systematically adapt to dynamically incoming data streams.
Space exploration is an area where continual learning demonstrates exceptional potential. Over the course of a mission, new factors may arise, both internal (e.g., sensor wear and tear) and external (e.g., novel disturbances), leading to the formation of previously unknown anomaly classes.

Continual Learning Overview

In the literature , three scenarios of continual learning are distinguished:

- Task-Incremental Learning (Task-IL): learning new tasks without forgetting previously learned ones.
- Domain-Incremental Learning (Domain-IL): adapting to new domains with a fixed set of tasks.
- Class-Incremental Learning (Class-IL): incorporating new classes into the model without forgetting existing ones.

CL faces a significant challenge in the form of catastrophic forgetting (CF). CF occurs when a model, while learning a new class, forgets how to recognize previously learned classes.



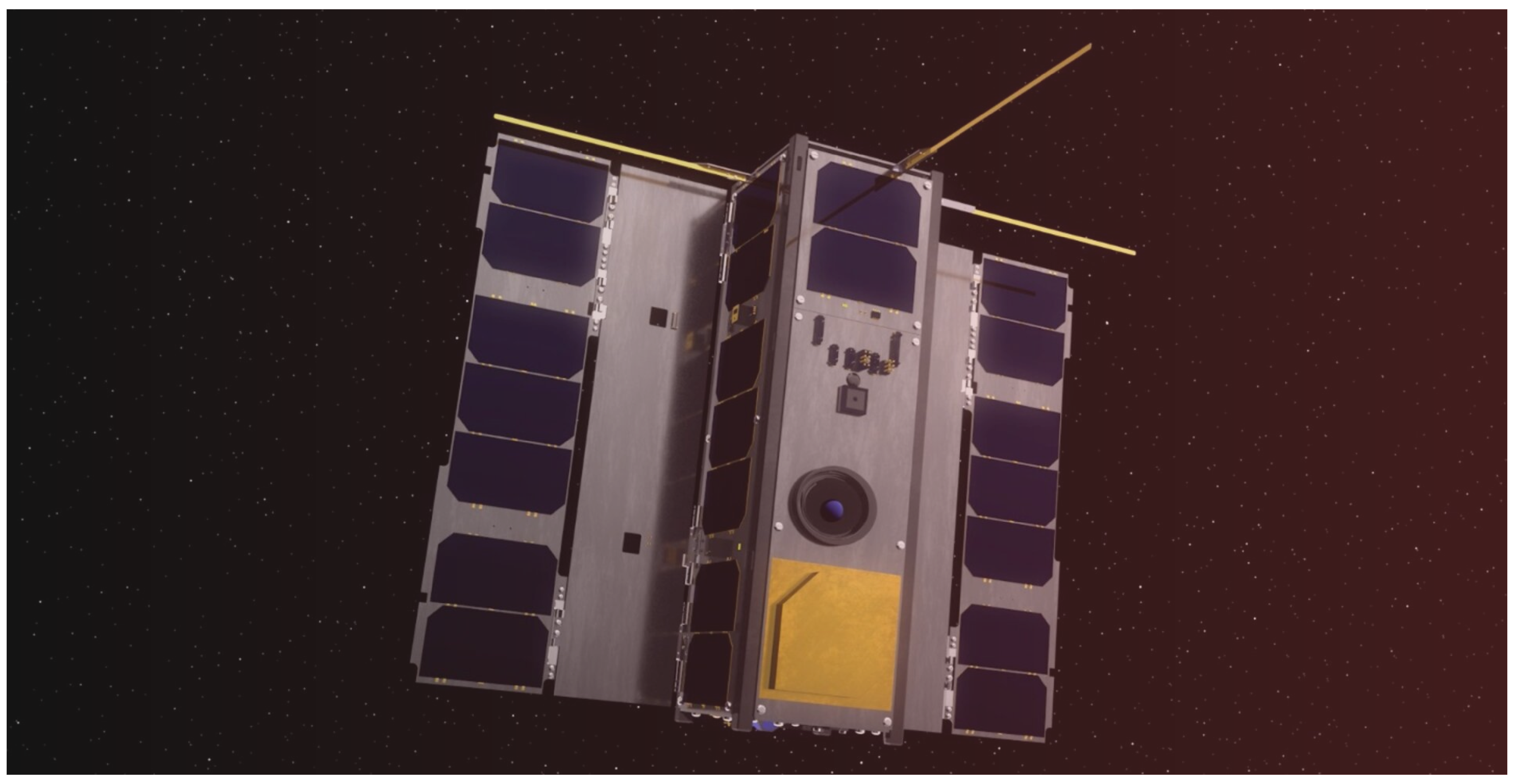


Figure 1. The ESA OPS-SAT frontal view. Image credits: European Space Agency.

Types of Satellite Data

1. Telemetry Data (shown at Figure 2) – internal data generated by the satellite to monitor its own status. Examples: system temperatures, battery levels, signal strength, sensor health.
2. Image Data – visual observations of Earth's surface, captured using various sensors.

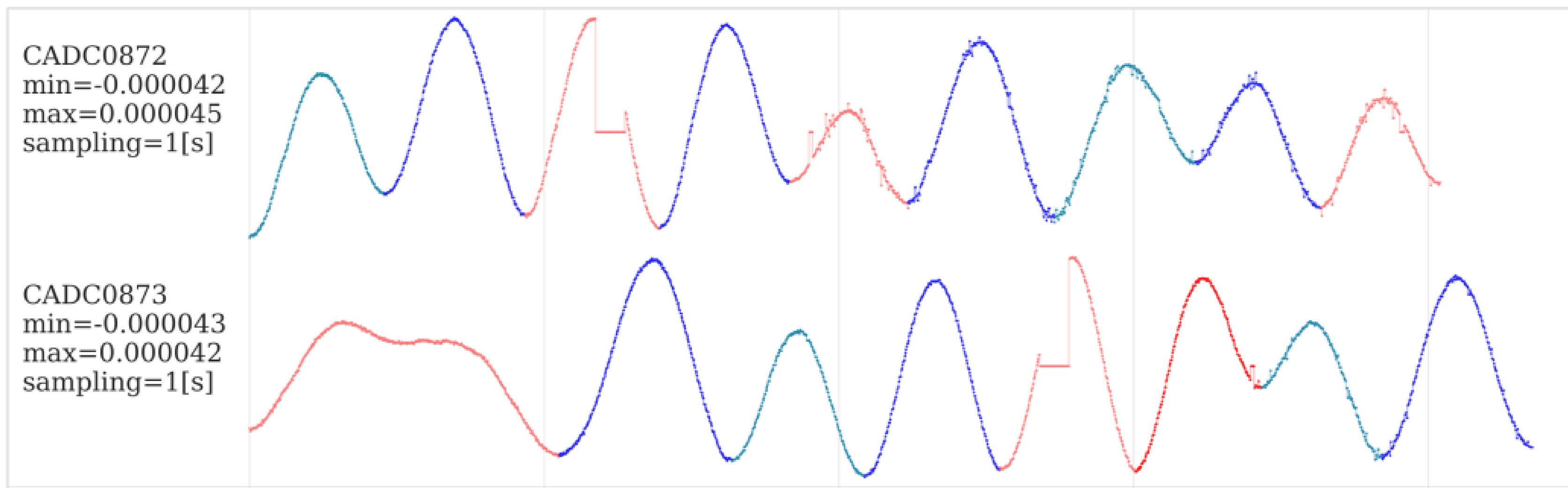


Figure 2. Examples of selected segments from OPS-SAT dataset.

Experimental Insights

The objective of the project was to replicate a realistic data stream scenario, where a model receives new data incrementally and must adapt without forgetting previous knowledge. The pipeline included:

1. Data stream simulation – the MNIST and OPS-SAT datasets were partitioned into sequential batches, each introducing new digit classes or distribution shifts to simulate incremental learning.
2. Training stage – continual learning strategies were applied, including a replay buffer for past examples and Elastic Weight Consolidation (EWC), which penalizes updates to weights important for previously learned classes.
3. Evaluation protocol – after each epoch, model accuracy was assessed on both current and past classes to track knowledge retention and adaptability.

Table 1. Metrics for each class for MNIST, capacity=6000.

class	accuracy	precision	recall	F1 score
0	0.983	1.000	0.983	0.991
1	0.978	1.000	0.978	0.989
2	0.946	1.000	0.946	0.972
3	0.929	1.000	0.929	0.963
4	0.889	1.000	0.889	0.941
5	0.923	1.000	0.923	0.960
6	0.963	1.000	0.963	0.981
7	0.896	1.000	0.896	0.945
8	0.888	1.000	0.888	0.941
9	0.980	1.000	0.980	0.990

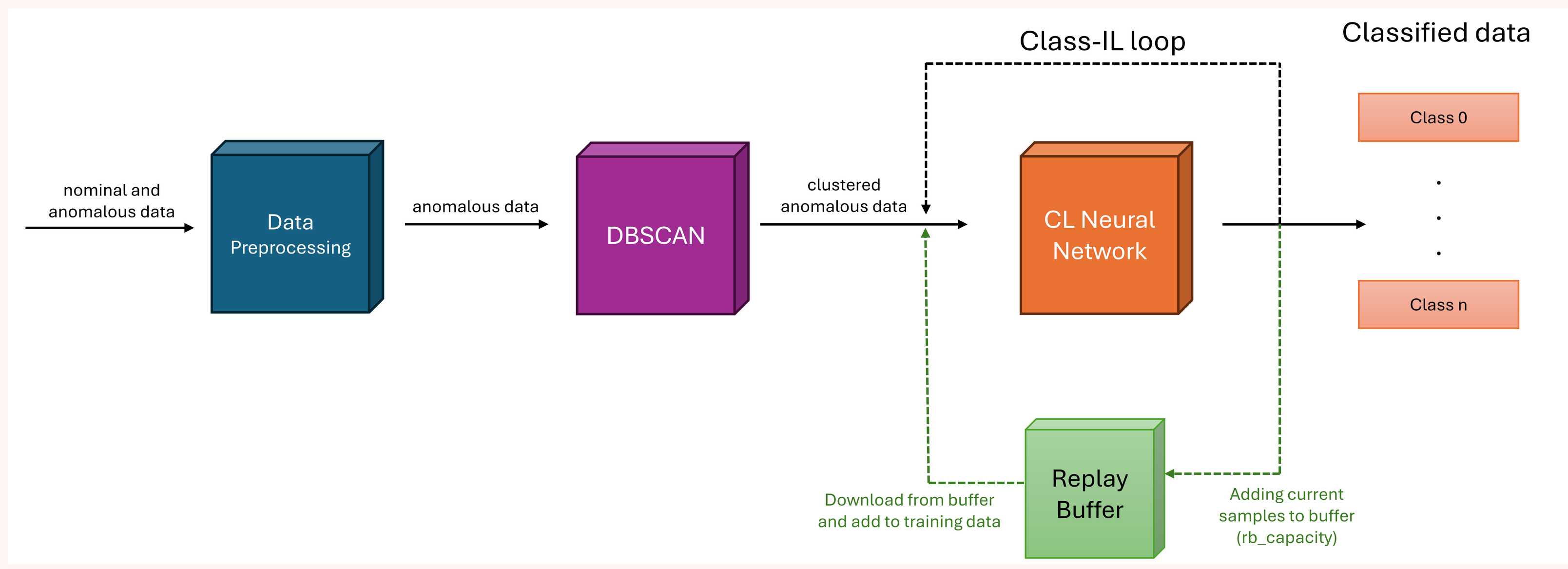


Figure 3. Structure of the project.

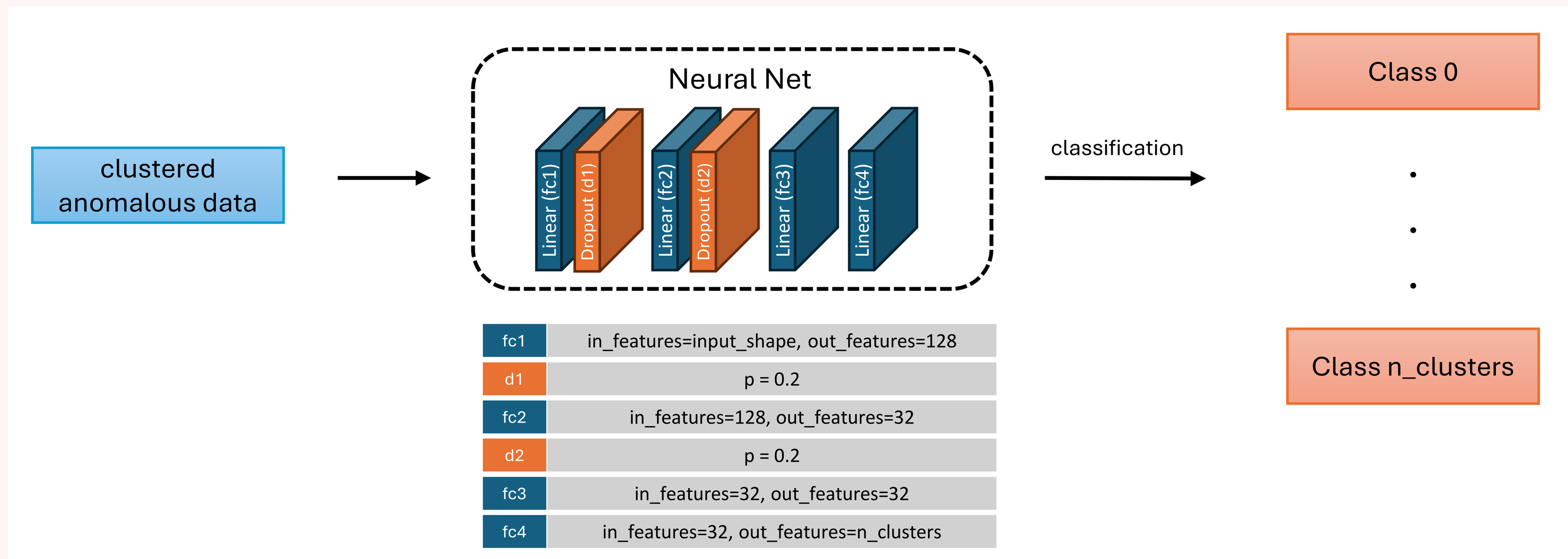


Figure 4. Structure of neural network.

Challenges & Future Directions

- Limited ground truth: Lack of labeled anomalies in real telemetry data
- Onboard constraints: Processing and memory limitations on the satellite
- Next steps:
  - Extend system to image data using continual learning CNNs
  - Deploy a lightweight version on embedded systems for in-orbit evaluation

References

Supervisor: Jakub Nalepa, PhD, DSc

[1] B. Ruszczak, K. Kotowski, D. Evans, and J. Nalepa. The ops-sat benchmark for detecting anomalies in satellite telemetry, 2024.

[2] D.-W. Zhou, Q.-W. Wang, Z.-H. Qi, H.-J. Ye, D.-C. Zhan, and Z. Liu. Class-incremental learning: A survey.