Towards Space Edge Computing and Onboard AI for Real-Time Teleoperations

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***Abstract*—This paper presents a summary of findings related to some current developments and emerging applications of the space edge-computing and onboard artificial intelligence (AI) as discussed at a workshop by the IEEE Future Directions Low-Earth Orbit Satellites and Systems (LEO SatS) Initiative. It focuses on the state-of-the-art AI techniques across various layers of the space communication link, benchmarking of deep-learning models and flight software applications evaluated on embedded processors on board the ISS, a mission for in-orbit experiments of AI and edge computing, and AI safety and security with applications in the context of Dataspaces and satellites for Earth observations.**

Keywords—edge computing; space-edge compute; artificial intelligence (AI); onboard AI; low-Earth orbit satellites; small satellites; nano satellites

I. Introduction

One of the emerging topics in satellite-systems research involves integrating computational and artificial intelligence (AI) capabilities directly within spacecraft or satellite systems (space-edge computing). This enables such systems to process data and make decisions locally, in real-time, without constant communication with ground-based systems. Such solutions may accelerate the convergence of terrestrial and non-terrestrial networks to implement real-time or near-real-time telecontrols.

Since the Sputnik moment in 1957, thousands of artificial satellites have been placed in orbits above the Earth. The geostationary (GEO) satellites orbit the Earth at 35,785 kilometers (km) above the equator with a 24-hour orbit. The medium-Earth orbit (MEO) satellites are located at 2,000 to 36,000 km with orbits between 2 and 8 hours, and the low-Earth orbit (LEO) at 160 to 2,000 km with orbits about 90 minutes long. The satellites have transformed global digital communications used for television, radio, phones (e.g., Telstar, Iridium, Globalstar, O3b), internet (Starlink, OneWeb), store-and-forward (CASSIOPE, Orbcomm), navigation (GPS, GLONASS, BeiDou), industry and military.

Of particular interest are the recent advances in LEO satellites and systems because they are closer to the terrestrial networks, with a much shorter latency time (around 25-88 ms, compared to 477-600 ms for GEO satellites, i.e., around 170 times shorter). Using optical inter-satellite laser communications with LEO satellites, even lower latencies than terrestrial fiber can be achieved because propagation in free space is 50% faster than fiber optical cables. Over the years, many large and expensive research-oriented systems have been placed there, including the International Space Station (ISS) at about 410 km, the Chinese Tiangong space station at about 340 km, and the Hubble Space Telescope orbits at about 540 km. They are designed to operate as stand-alone systems (extra-heavy sats with over 7,000 kg). Within the last decade, thousands of smaller satellites have been placed into orbit, including small sats (601 to 1,200 kg), minisats (201 to 600 kg), microsats (11 to 200 kg), nanosats (1 to 10 kg), picosats (0.1 to 1 kg), and femtosats (< 0.1 kg), the latter often developed by senior multidisciplinary college and university students as a part of their advanced experiential learning (e.g, [1]).

The short latency time is extremely attractive for possible real-time teleoperations (e.g., [2], [3]). However, since the field of view of each LEO satellite is small, constellations of such satellites have been implemented to operate and communicate among themselves using microwave bands (e.g., Ku 12-18 GHz, Ka 26.5–40 GHz, V 50-75 GHz, E 60-90 GHz) with phased-array beam-forming and digital processing technologies, and now optical inter-satellite links [4] to provide continuous coverage at many places on the planet.

To help in consolidating research and educational activities in this area, the LEO Satellites and Systems (SatS) Initiative was conceived in 2020 and started its operations under the IEEE

Future Directions in March 2021 [5]. This paper summarizes a recent LEO SatS workshop about some current developments and emerging applications of the space edge-computing and onboard AI. In the following sections, we provide a focus on (i) machine learning (ML) for mega satellite networks, (ii) benchmarking deep learning models on edge processors onboard the ISS, (iii) benchmarking flight software applications on the Snapdragon processor on-board the ISS, (iv) the OPS-SAT Space Lab as space to experiment with edge computing and on-board AI, and (v) exploring the synergy between Gaia-X and satellites for data-driven earth observation.

II. ML FOR MEGA SATELLITE NETWORKS

A. *Mega Satellite Networks*

Since the early commercial use of satellite communications in the 1960s, the technology has evolved significantly. However, the underlying bent-pipe architecture has persisted for more than five decades. In this setup, the satellite acts as a simple analog relay that receives uplink signals from ground stations and transmits them back to the same or different coverage spots. This approach results in poor spectral efficiency as radio resources are occupied throughout the entire coverage area. To overcome this limitation, high-throughput satellites (HTS) have emerged, providing hundreds of smaller coverage spots where spectral resources can be spatially reassigned. This breakthrough architecture has greatly increased spectral efficiency, resulting in hundreds of times higher throughput. Thus, it has made it economically and technically viable to provide coverage to remote and hard-to-reach limited regions.

Traditionally, most satellite communication services, including HTS, were provided by geosynchronous equatorial orbits (GEO), with a few exceptions, such as the Iridium and GlobalStar constellations that aimed to offer global or near-global mobile satellite services (land mobile satellite service - LMS) with voice and narrowband data connections. Until recently, global wideband satellite connectivity has been either too costly or slow compared to the highly reliable terrestrial fiber network. This limitation was primarily due to the prohibitive costs of satellite development and launch. However, with the significant reduction in these costs in recent years, the path to achieving true global satellite connectivity has now opened. Several major players, such as Starlink, OneWeb, and Amazon, currently deploy thousands of satellites in Low Earth Orbit (LEO). Fig. 1 provides an overview of the current status of these two constellations showing the staggering number of satellites.

Such large constellations can be called mega, massive, or dense, distinguishing them from the much smaller, older LMS networks. Mega satellite networks offer several key advantages, including: (i) Significantly reduced latency compared to GEO orbits. (ii) Higher spectral efficiency due to smaller coverage spots, resulting in higher throughput. (iii) Reduced free space path loss, leading to smaller and more cost-effective ground terminals and satellites. (iv) The potential to provide lower delays than fiber networks when utilizing intersatellite links (ISL). (v) Redundancy and resilience due to the large number of satellites and overlapping coverage spots. (vi) Global or near-global coverage, depending on the configuration of the orbits. However, the deployment of such a massive number of satellites also brings forth numerous challenges.

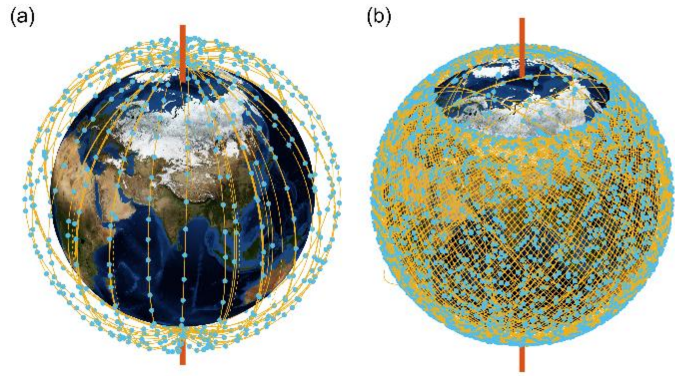

Fig. 1. Example of two mega satellite constellations as of mid-2023, (a) OneWeb 636 satellites in Walker-star configuration, (b) StarLink 4,275 satellites primereley in Walker-delta confguration.

B. *Challenges in Mega Satellite Networks*

Spectrum availability: Spectrum scarcity is already a concern with current satellite systems, and mega satellite networks will exacerbate this challenge. The sheer scale of these networks will push spectrum availability to a whole new level, posing challenges for current and future operators.

Radio channel fluctuations: To address spectrum scarcity, exploring higher frequency bands, including terahertz (THz) and wireless optical links, is a potential solution. However, operating in these bands introduces increased atmospheric impact, both in terms of severity and variability, which can affect signal quality and reliability.

Interference: Cross-satellite interference and interference from other satellite constellations or terrestrial sources can have a detrimental impact on signal quality and overall network performance.

Intersatellite connection: although promising, are not yet widely implemented in current mega satellite networks due to the technical complexities involved. Challenges include determining the appropriate physical interface (optical, millimeter-wave, or terahertz) and implementing the required online processing for efficient routing.

Jitter and topology optimization: Mega satellite networks exhibit a high level of complexity and dynamic topology. Optimizing routing paths involves considering various factors, such as minimizing delay and reducing overall energy consumption. Fig. 2 illustrates a low-density mega constellation with two possible routes based on desired costs.

Network modelling: The increasing complexity of mega satellite networks makes it challenging to establish the

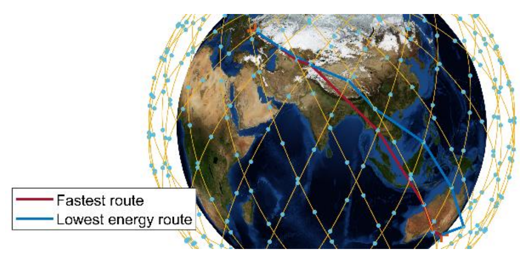

Fig. 2. Example of two possible ISL routes for different cost consideration (delay and energy).

tractability of network parameters against performance metrics. New analytics and simulation tools [6] are required to address the unique characteristics of satellite networks, which differ significantly from terrestrial cellular systems.

Network security: Securing mega satellite networks against unauthorized access, cyberattacks, spoofing, and signal jamming is a critical challenge. The broadcast nature of satellite communications adds complexity to implementing robust security measures, requiring diligent efforts.

Integration with terrestrial networks: Is necessary to provide a consistent user experience when transitioning between urban and remote regions. In addition to technical challenges, regulatory and standardization efforts are crucial to address interoperability and ensure smooth integration.

Onboard processing: Mega satellite networks entail vast network complexity which make current digital onboard processing architectures inefficient in terms of energy consumption. Developing more efficient onboard processing methods becomes essential to optimize energy usage and enhance overall network performance.

C. *Addressing Challenges with ML*

Addressing the challenges in mega satellite networks requires a combination of regulatory frameworks, collaboration among satellite operators, researchers, and industry stakeholders, as well as advancements in technology. AI methods can play a crucial role in tackling these challenges, such as:

Radio channel forecasting: ML can be utilized to predict the status of radio channels [7], enabling satellite-user links to switch frequencies or even satellites in response to atmospheric impairments, thereby mitigating their impact on communication quality.

Spectrum sensing and classification: Cognitive sharing techniques can improve spectrum utilization. ML algorithms can assist in detecting [8] and classifying traffic from other users, enabling efficient sharing of available spectral resources.

Frame detection under interference: AI techniques can enhance the detection of radio signals under unknown interference [9], which is particularly valuable in scenarios where traditional methods fail. By leveraging AI algorithms, the identification of signals in the presence of interference from other systems becomes more efficient.

Traffic forecasting and topology optimization: AI, especially recurrent neural networks (RNNs), can provide reliable predictions of temporal behavior. Applied to satellite networks, these tools can generate spatio-temporal-spectral predictions as satellites traverse different geographic areas with varying traffic demands, facilitating efficient topology optimization.

Spoof detection and physical layer security: AI is effective in detecting irregular patterns in network traffic and identifying intrinsic fingerprints in radio signals from devices [10]. This capability aids in detecting spoof attacks and enhancing the security of satellite networks.

Additionally, there are numerous other potential applications for AI in mega satellite networks, including end-to-end AI-enabled radio communications for automated channel coding, satellite operations and management, beamforming, and radio resource allocation and traffic management. By harnessing the power of AI, mega satellite networks can overcome challenges, optimize performance, and deliver enhanced services to users [11]. Continued research and development in AI methods specifically tailored to the unique characteristics of satellite networks will contribute to the success and advancement of mega satellite constellation.

III. Benchmarking Deep Learning Models and Running Memory Checkers on Edge Processors Onboard the ISS

As seen from the previous section, future space missions will greatly benefit from the ability to process data directly on board utilizing AI-based approaches. This, in particular, applies to, e.g., remote sensing missions, where processing imagery directly onboard allows for autonomous data collection, targeted downloads, or onboard alert generation. Current space processors such as the Rad750, however, have limited compute compared with modern edge processors. We benchmark two commercial-off-the-shelf processors: the Movidius Myriad X and the Qualcomm Snapdragon 855 [12]. Both offer direct hardware acceleration for deep neural networks, although they are not radiation hardened.

Models ported include image classification, segmentation, and spectral unmixing. Model inference is run both on the ground, and remotely on Hewlett Packard Enterprise’s Spaceborne Computer-2 [13] onboard the International Space Station (ISS). Although the processors are shielded by the ISS itself and the orbit does not go over Earth’s polar regions, the radiation is greater than on Earth. To further quantify potential radiation effects, we also run memory checkers onboard. To date, we have found no difference in output between ground and ISS runs, and no errors from memory checkers.

In the next section, we discuss one Jet Propulsion Laboratory (JPL) model in detail. Following that, we summarize our results for a range of JPL models as well as some standard pre-trained networks for image classification. For more details, please see [14] and [15].

A. *UAVSAR Model for Image Segmentation*

We benchmark an image segmentation model used to detected flooded regions in UAVSAR imagery of Houston TX, USA, after flooding by Hurricane Harvey [16]. This model has a UNET-6 [17] architecture and outputs six possible classes. These classes are then compressed into a binary value: flooded/non-flooded. Fig. 3 shows model output obtained when run on the MacBook Reference and the Myriad X. Light green denotes open water, dark blue denotes flooded vegetation, and remaining colors denote non-flooded regions. Results on the Myriad X are nearly indistinguishable from the reference, although there is some discrepancy, which we list in Table I. Models must be quantized to half-precision floating point to run on the Myriad, and to fixed point to run on the Snapdragon Digital Signal Processor (DSP) or Neural Processing Unit (NPU), which leads to this quantization discrepancy (note that

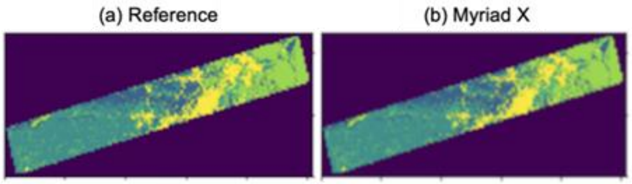

Fig. 3. SAR Image Segmentation Results.

TABLE I. UAVSAR FLOOD MAPPING BENCHMARKS

Processor	Full Class. Discrepancy (pixels)	Binary Class. Discrepancy (pixels)	Speedup from Snapdragon CPU
Snapdragon CPU	0.0%	0.0%	--
Snapdragon GPU	0.0%	0.0%	8x
Snapdragon DSP/NPU	0.7%	0.4%	20x
Myriad X	1.6%	0.7%	8x

these discrepancies are not pixel classification errors, rather differences from MacBook runs). All discrepancies are small.

Runtime compared with Snapdragon CPU is also shown in Table I. The Snapdragon NPU provides a 20x speedup over the Snapdragon CPU, and the Myriad X runtime is similar to the Snapdragon GPU. Models have been run 21 times on the Snapdragon and 9 times on the Myriad X, with no differences from ground runs.

B. *Model Summary*

JPL models benchmarked are summarized in Table II. Since transfer learning with pre-trained networks is a common technique, we also report on standard Keras models for image classification: MobileNet, Xception, InceptV3, ResNet50, InceptResNetV2, VGG16, VGG19 [21]. Whether a model can be ported depends on the network architecture; the NavCam model could not be ported to the Myriad X and was not able to be pre-quantized for the Snapdragon DSP/NPU.

TABLE II. JPL MODELS

Model	Type	Network Structure	Port to Myriad X?	Port to Snapdragon DSP/NPU?
HiRISE [18]	Mars Reconnaissance Orbiter Image Classifier	AlexNet	yes	yes
NavCam [19]	MSL Rover Navigation Image Segmentation	DeepLabV3	no – incompatible layers	only DSP, runtime quantization only
UAVSAR [16]	L-band SAR Earth Image Segmentation	UNET-6	yes	yes
Unmixing [20]	Spectral Imagery from NASA CORAL mission	Deep Conditional Dirichlet Model	yes	yes

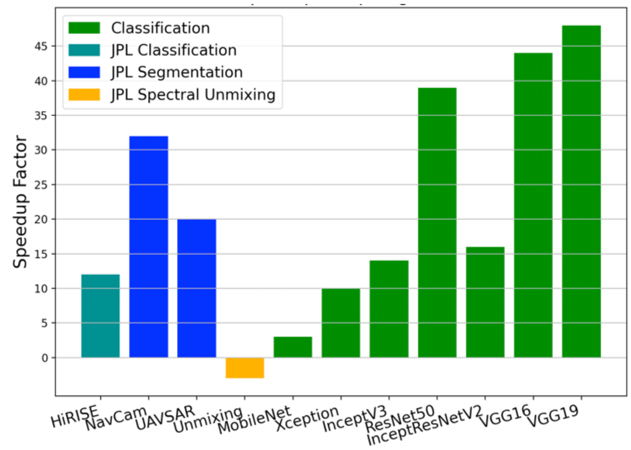

Fig. 4. Snapdragon DSP/NPU vs CPU Speedup

The discrepancy introduced through quantization and sporting of our JPL models was usually quite low (<5%), except where runtime quantization was used (NavCam). The quantization discrepancy for the standard classification models was 1-16% for the Myriad X and Snapdragon NPU, except for MobileNet which had 100% discrepancy on the NPU (likely due to large model weight fluctuations, which makes quantization difficult [22]). We found that the Myriad X and Snapdragon NPU provide speed improvement over the Snapdragon CPU in all models except single pixel models (typically >10x for the NPU). In Fig. 4, we show the speedup obtained using the Snapdragon DSP/NPU over the CPU. The standard classification models are ordered by number of network parameters, and we see the speedup typically increases as network size increases.

All models have been run multiple times onboard, and to date, we have found no differences between ground and ISS runs.

IV. BENCHMARKING FLIGHT SOFTWARE APPLICATIONS ON THE SNAPDRAGON PROCESSOR ONBOARD THE ISS

More powerful onboard computing will be necessary to meet future space mission objectives. Deep space missions have limited contact with ground operations teams due to limited numbers of Earth-based ground communications stations and geometric constraints. Onboard autonomy can address this by distilling down the large amounts of instrument data and responding to science events and changes from predicted execution.

In Section III, we discussed benchmarking deep learning image processing models on a Qualcomm Snapdragon SoC hosted by HPE's Spaceborne Computer-2 (SBC-2) [13] onboard the ISS**.** In this section, we benchmark various other algorithms, including instrument processing, mission planning, and targeting remote sensing applications, to highlight the potential of using embedded Commercial-Off-The-Shelf (COTS) processors for future space missions. The Snapdragon delivers significant computing in small Size Weight and Power (SWaP) packaging and offers hardware acceleration in the form of graphics processing units (GPU) and digital signal processors (DSP).

All applications are benchmarked on a ground-based Snapdragon and onboard the ISS. When possible, they are also benchmarked on the HPE SBC-2 CPU and other flight hardware such as the GR740/Sabertooth [23] and RAD750 [24] on the ground [25].

A. *Instrument Processing Applications*

We benchmark a variety of instrument processing applications shown in Table III. This step is often the most computationally demanding onboard spacecraft operation.

A good application to compare the performance of the Snapdragon against both the Sabertooth and RAD750 is the Sequential Maximum Angle Convex Cone (SMACC) spectral endmember extraction application [26]. Running single threaded on the Snapdragon ARM CPU we measured a 25.6x speedup in runtime from the Sabertooth to the Snapdragon and a 59x speedup from the RAD750 to the Snapdragon.

A big advantage to using the Snapdragon is having access to hardware acceleration such as a GPU. The Thermal and Cryosphere decision trees application shows how powerful this acceleration can be [27][28]. We found a 25.8x speedup from the Sabertooth to the Snapdragon CPU and a 41.9x speedup from the Sabertooth to the Snapdragon GPU.

B. *Targeting Remote Sensing Applications*

The targeting remote sensing applications focus on the "Dynamic Targeting" concept in which a lookahead sensor is used to identify targets (e.g. convective storms) or avoidances (e.g., clouds) to inform targeting and configuration of a primary sensor. The Dynamic Targeting [29] application was run on the SBC-2 CPU, the Snapdragon ARM CPU, Sabertooth, and RAD750. The achieved performance is presented in Table IV. There was a 75x speedup from the Sabertooth to the Snapdragon and a 140x speedup from the RAD750 to the Snapdragon CPU.

C. *Mission Planning Applications*

We benchmark a range of mission planning applications involving satellite planning, scheduling the Mars Perseverance Rover, and scheduling Europa lander Mission Concept activities.As shown in Table V, the Snapdragon demonstrates significant speedup over traditional flight hardware in the MEXEC application. This application takes a "task network" and generates conflict free plans and monitors the execution of those plans [30]. The test recorded a 57.5x speedup from the Sabertooth to the Snapdragon ARM CPU.

V. OPS-SAT SPACE LAB: THE PERFECT SPACE TO EXPERIMENT WITH EDGE COMPUTING & ONBOARD AI

In 2019, ESA launched a unique mission that, for the first time, offered the chance for any Space Agency, European company, research, or educational institute to run their software or firmware experiments, in space, at no cost. Its objective was simple: allow in-flight experimentation on critical operations processes which are normally off-limit and thereby accelerate innovation in the domain. ESA handles the risk of testing experimental software in space allowing the experimenters to concentrate on generating value as quickly as possible. They called the service OPS-SAT Space Lab [31].

TABLE III. INSTRUMENT PROCESSION APPLICATION PERFORMANCE

Application	Components Used	Language	SBC-2 Runtime	Snapdragon Runtime	Sabertooth Runtime	RAD750 Runtime
OWLS	CPU(ST)	Python	12.76s	22.5s	-	-
NEAS	CPU(ST)	C++	-	494s	-	-
Thermal Emission Random Decision Forest (RDF)	CPU(ST)	C	.034ms	.057s	.29s	.43s
Normalized Difference index (NDI)	CPU(ST)	C++	-	56s	-	-
SAM Spectral Algorithm	CPU(ST)	C++	1.63s	1.7s	6.44s	-
MF Spectral Algorithm	CPU(ST)	C++	1.6s	2.4s	6.18s	-
Decision Trees (Thermal + Cryosphere)	CPU(ST)	C++	CPU: .00068ms	CPU: .012ms GPU: .0074ms	CPU: .31ms	-
Synthetic Aperture Radar (SAR) Image Formation	CPU(ST) + GPU	C++	-	217s	-	-
Match Filters (Cuprite)	CPU(ST)	C++	-	850s	-	-
Match Filters (Lunar)	CPU(ST)	C++	-	108.4s	-	-
Hyperspectral Compression	CPU(ST), GPU, DSP	C	-	CPU:14.12ns GPU:6.5ns DSP:184.5ns	-	-
SMACC	CPU(ST)	C	0.027ms	0.039ms	1ms	2.3ms
SMICES Classification	CPU(ST)	Python, C	-	-	-	-
- RDF			0.34s	.05s	1.65s	1.13s
- MLP			0.62s	0.55s	21.4s	26.47s
- SVM			0.01s	1316s	-	-
- Bayes			0.05s	0.27s	7.76	5.27s
Salience Detector	CPU(ST)	Python, C	-	23s	-	-
Landing Vision System	CPU(ST)	C	-	COARSE: 2.46s FINE: 2s	-	-
HOWFS	CPU(ST)	Python	12.8s	2.2h, 1.8h,	-	-
Europa Lander Stereo Vision	CPU(ST)	C	-	19s-15.6m	-	-

TABLE IV. TARGETING REMOTE SENSING APPLICATION PERFORMANCE

Application	Components Used	Language	SBC-2 Runtime	Snapdragon Runtime	Sabertooth Runtime	RAD750 Runtime
Dynamic Targeting	CPU(ST)	C++	.39ms	20ms	1,500ms	2,800ms
SMICES Targeting	CPU(ST)	Python	37,000ms	53,600ms	-	-
Cloud Avoidance	CPU(ST)	Rust	-	-	-	-
- adaptive grids			53.3ms	199.2ms	-	-
- mixed grids			3.9ms	13.7ms	-	-
- fixed grids			.724ms	9.7ms	-	-
- greedy			32.3ms	49.7ms	-	-

TABLE V. MISSION PLANNING APPLICATION PERFORMANCE

Application	Components Used	Language	SBC-2 Runtime	Snapdragon Runtime	Sabertooth Runtime	RAD750 Runtime
MEXEC (Europa Lander)	CPU(ST)	C	1.07s	1.6s	92s	-
Copilot (M2020)	CPU(MT)	C++	-	0.63s	-	-
CLASP (ECOSTRESS)	CPU(ST)	C++	1,133s	1,400s	-	-

The idea was very successful, and the number of users continuously grew. There are now over 250 experiments covering every aspect of mission control and type of organization. To keep things fast and light, ESA does not sign contracts with experimenters or ask for payment. The registration only takes a few minutes and then the experimenter is given their own directory on the mission control system and the spacecraft, plus access to an experimenter portal [32] with all the technical information. The fastest turnaround time from registration to the delivery of results was 72 hours. Space Agencies such as ESA, CNES, DLR, NASA, and JAXA, large primes such as ADS, THALES, and OHB, government organizations such as the EU Commission, educational institutions such as MIT and Oxford University and a multitude of start-ups, research institutes and new entrants are all OPS-SAT Space Lab users.

The risk is partially mitigated by having a space segment that is effectively two spacecraft in the same box. The first mission uses a 3U box i.e., 30cm x 10cm x 10cm. One spacecraft, called the bus, is based on standard cubesat subsystems, and its main role is to monitor the other experimental spacecraft. At the center of the latter is a control processor with an 800 MHz processor and a reconfigurable FPGA. This is powerful enough to run normal software (e.g., Java and Python), meaning experimenters do not need embedded software skills to control this satellite e.g., take pictures, change the attitude, communicate with the ground, etc. ESA has developed a preloaded Java framework that allows experimenters to control the spacecraft by loading software in an “App” like way, further expanding the reach. The experimental processor runs Linux and experimenters can take advantage of preloaded packages e.g., Python, or load and install their own, within reason. On the ground side, the mission control system has been opened to allow experimenters to perform their own command and control of the spacecraft by simply connecting up to ESOC over the internet when it passes over Darmstadt, Germany.

A. *SmartCam*

The first experiment to use AI on OPS-SAT was called SmartCam [33]. It was originally created to resolve an operational problem when commissioning the onboard camera. Since the attitude control system couldn’t always guarantee accurate pointing, the mission was downlinking a disproportionate number of bad images (black space, over-exposed, or blurry). We wanted to discard these “bad images” from being downlinked to save bandwidth. A member of the flight control team started working on this problem and found that image classification is a very common ML use case. Since a wealth of downloaded thumbnails could be used as training data, developing an image classifier seemed like the natural solution. A group of existing open-source ML frameworks were tested, and the final selection was Tensor Flow Lite. This decision was partly influenced by the low memory and low storage footprint it required. With only 9 MB for the model file and 6 MB for the model inference binary file, uplinking it was not a problem.

The model gave predictions with ~95% balanced accuracy for each label shown in Fig. 5. What was quite remarkable was that a single engineer proposed, developed, tested, uplinked, and successfully operated it on the spacecraft within a timespan of less than two weeks. It was almost immediately incorporated into routine operations. The app was later expanded to enable additional image classification with unsupervised learning using k-means clustering. SmartCam's image classification pipeline was also made "openable" by allowing other experimenters to build their own apps on top of this infrastructure [34].

B. *Further examples*

Building on the success of SmartCam the most common experiment type on OPS-SAT involves some sort of AI. Sometimes this is implemented as firmware in the FPGA or in software and is usually based on Tensor Flow Lite. While it is impossible to list them all here, we have highlighted those that ESA funded in a recent Discovery-funded Open Space Innovation Platform (OSIP) Campaign [35].

Mission Control Services, Canada deployed a low-level implementation of the OPS-SAT SmartCam model using a Field Programmable Gate Array (FPGA) and compared it against a high-level CPU model using Tensor Flow Lite. Experiments showed that the FPGA implementation reproduced the precision and accuracy of the high-level model, while running at a slower speed. Adatica, Spain, developed the proof of concept of an attitude control system based on AI for a spacecraft, as an alternative of the current state-of-the-art systems based on model-based approaches. The system commanded reaction wheels to actively control and modify the attitude, so that its optical camera kept framed and focused on an Earth feature (island) that had been previously detected by the system itself without the aid of any other instrument installed on the spacecraft. Agenium, France, performed forest detection (segmentation problem) using AI deployed on the FPGA. A simplified DNN was pre-trained on Sentinel 2 images over Slovenia and these images were processed to simulate OPS SAT images. Then real OPS SAT images were used with the transfer learning method. A Binary Deep Neural Network using convolution was ported onto the FPGA. Airbus Defence and Space, UK, used reinforcement learning in an online fashion to continuously improve the attitude control performance of a space system and adapt to its environment. Its role is to compute an appropriate torque command based on the measured attitude. Vision Space, Germany, provided a Software as a Service app providing onboard ML capabilities to the experimenters of the ESA OPS-SAT platform. It focuses on abstracting complex ML operations to spare the users the difficulties of provisioning data sets, training models, and performing inference on new data. It can also be used onboard by multiple experimenters in parallel. OHB Hellas / FORTH, Greece, developed and deployed an AI-based (3DWDSR), multi-frame super-resolution algorithm to achieve a notable improvement in image quality starting with a set of low-resolution images.

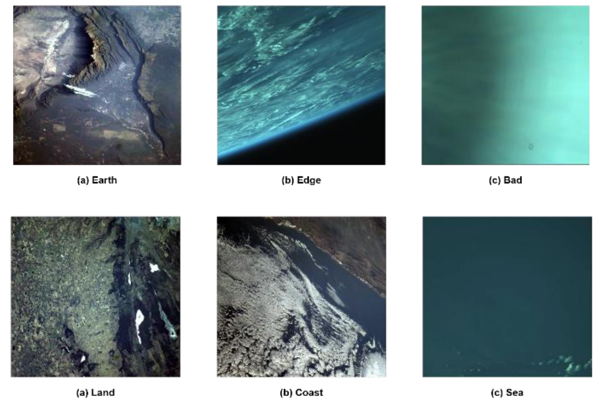

Fig. 5. SmartCam Top Level Image Classes.

C. *Future Work*

The OPS-SAT Space Lab is now working with ESA ARTES Scylight on a follow-up mission called OPS-SAT VOLT. The prime is Craft Prospect, UK, and the mission is due for launch in 2025. It will be a 16U cubesat with propulsion allowing for optical and quantum domain communications experiments.

VI. Exploring the Synergy between Gaia-X and Satellites for Data-driven Earth Observation

As we have seen, advanced data processing capabilities are a key enabler at both the spacecraft and the satellite-mission level. But moving towards a broader scope of today's digital era, data has become the lifeblood of numerous applications and business models. The concept of a Data Space (DS) [36] has emerged as a solution to enable the trusted implementation of data-based applications and business models, providing stakeholders with a high degree of flexibility and sovereignty.

A. Gaia-X: An Introduction

Gaia-X is an initiative led by European stakeholders with the goal of establishing a federated, secure, and sovereign data infrastructure – a DS. It aims to create value by enabling new data-based applications, business models, and stakeholder collaboration. Gaia-X provides standardized technical interfaces, protocols, and governance mechanisms to enable secure data sharing, interoperability, and collaboration while ensuring data sovereignty and promoting innovation in the digital economy [37] [38]. By embracing the principles of value creation, self-determination, and efficiency, Gaia-X fosters an ecosystem where data can be shared, accessed, and utilized in a controlled and reliable manner. [39]

B. Key Features

Key features of DS have been identified in, e.g., [40]. In a compact way, those can be summarized as:

Decentralization: A DS avoids centralized structures and concepts in favor of decentralized solutions. This decentralized approach enhances agility, scalability, and resilience within the ecosystem, allowing for efficient collaboration and innovation.

Federation and Interoperability: Interactions between actors within a DS, as well as across DS boundaries, are encouraged through federation and interoperability. This promotes seamless data sharing, integration, and collaboration, facilitating the realization of data-driven applications that span multiple domains and stakeholders.

Sovereignty: Sovereignty is a fundamental principle of a DS. It ensures that individuals and organizations maintain control over their data and its use at all times. By empowering data owners with the ability to define access rights and usage policies, a DS guarantees data sovereignty and privacy. [41]

Trust: Trust is a critical aspect of any DS. To build trust, robust technologies, control mechanisms, and unique digital identities are employed to authenticate and authorize data access and usage.

Transparency: A DS promotes transparency through digital identities and the traceability of data-based operations. By providing clear visibility into data provenance, usage, and processing, transparency strengthens trust among stakeholders and enables accountability.

C. How Data Spaces and Gaia-X foster Earth Observation

By combining the principles and infrastructure provided by Gaia-X with the concept of DS, stakeholders in Earth observation can benefit from enhanced data sharing, collaboration, and innovation while ensuring data sovereignty, trust, and transparency. [42]

Data Sharing and Collaboration: Earth observation involves collecting vast amounts of data from satellites, sensors, and other sources. DS enable secure and controlled data sharing among different stakeholders, such as satellite operators, research institutions, government agencies, and commercial entities. By establishing federated DS within the Gaia-X infrastructure, these stakeholders can collaborate more efficiently, exchange data securely, and leverage each other's expertise and resources to tackle complex Earth observation challenges.

Interoperability and Integration: DS, in conjunction with Gaia-X, promote interoperability by enabling seamless integration of diverse data sources and services. With DS, stakeholders can integrate different data streams and services, enabling comprehensive analysis and decision-making based on a holistic view of Earth's systems.

Advanced Analytics and AI: By leveraging the computational capabilities and advanced analytics within Gaia-X, stakeholders can apply AI and data analytics techniques to derive valuable insights from Earth observation data. Gaia-X's federated infrastructure provides access to computing resources, enabling stakeholders to process and analyze data locally while adhering to data sovereignty principles.

Data Sovereignty and Trust: Earth observation data often includes sensitive information, such as high-resolution imagery or geospatial data. DS, along with Gaia-X's data sovereignty principles, ensure that stakeholders retain control over their data and can define access rights and usage policies. This helps to address privacy concerns and builds trust among data providers and consumers.

Innovation and Value Creation: DS and Gaia-X offer an ecosystem that encourages innovation and value creation. By facilitating collaboration, data sharing, and interoperability, stakeholders in Earth observation can develop novel applications, services, and business models that leverage the combined power of Earth observation data with other data sources. This leads to new opportunities in sectors such as environmental monitoring, agriculture, urban planning, transportation, and natural resource management, promoting sustainable development and informed decision-making.

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References

[1] Witold Kinsner, Dario Schor, Reza Fazel-Darbandi, Brendan Cade, Kane Anderson, Cody Friesen, Scott McKay, Diane Kotelko, and Philip Ferguson, "The T-Sat1 nanosatellite design and implementation through a team of teams," Intern J Cognitive Informatics and Natural Intelligence, vol. 7, no. 1, pp. 32-57, Jan-Mar 2013.

[2] B. Charyyev, E. Arslan and M. H. Gunes, "Latency Comparison of Cloud Datacenters and Edge Servers," 2020 IEEE Global Communications Conference, Taipei, Taiwan, 2020, pp. 1-6.

[3] Y. Qiu et al., "Mobile Edge Computing in Space-Air-Ground Integrated Networks: Architectures, Key Technologies and Challenges," Journal of Sensor and Actuator Networks, vol. 11, no. 4, p. 57, Sep. 2022.

[4] K. Wu Chik and M. Gardill, "Optical communication systems for Micro- and Nano-satellite applications: Current status and future trends," in *IAF*

Space Communications And Navigation Symposium, Dubai, UAE, Oct. 2021.

[5] IEEE Future Directions (2023, July 14). *LEO SatS Initiative Website* [Online]. Available: https://cmte.ieee.org/futuredirections/projects/leo-satellites-systems/

[6] A. Al-Hourani, "An Analytic Approach for Modeling the Coverage Performance of Dense Satellite Networks," in IEEE Wireless Communications Letters, vol. 10, no. 4, pp. 897-901, April 2021.

[7] B. A. Homssi et al., "Deep Learning Forecasting and Statistical Modeling for Q/V-Band LEO Satellite Channels," in IEEE Transactions on Machine Learning in Communications and Networking, vol. 1, pp. 78-89, 2023.

[8] B. A. Homssi, A. Al-Hourani, Z. Krusevac and W. S. T. Rowe, "Machine Learning Framework for Sensing and Modeling Interference in IoT Frequency Bands," in IEEE Internet of Things Journal, vol. 8, no. 6, pp. 4461-4471, March 15, 2021.

[9] K. Dakic, B. Al Homssi, M. Lech and A. Al-Hourani, "HybNet: A Hybrid Deep Learning-Matched Filter Approach for IoT Signal Detection," in IEEE Transactions on Machine Learning in Communications and Networking, vol. 1, pp. 18-30, 2023.

[10] D. Huang, A. Al-Hourani, K. Sithamparanathan, W. S. T. Rowe, L. Bulot and A. Thompson, "Deep Learning Methods for Device Authentication Using RF Fingerprinting," 2021 15th International Conference on Signal Processing and Communication Systems (ICSPCS), Sydney, Australia, 2021, pp. 1-7.

[11] B. A. Homssi et al., 'Artificial Intelligence Techniques for Next-Generation Mega Satellite Networks', arXiv [cs.NI]. 2023.

[12] Qualcomm (2023, July 14), *Snapdragon 855 Mobile Platform* [Online]. Available: https://www.qualcomm.com/products/snapdragon-855-mobile-platform.

[13] Hewlett Packard Enterprise (2023, July 14), *HPE Spaceborne Computer* [Online]. Available: https://www.hpe.com/us/en/compute/hpc/supercomputing/spaceborne.html

[14] E. Dunkel, J. Swope, A. Candela, L. West, S. Chien, Z. Towfic, L. Buckley, J. Romero-Cañas, J. Espinosa-Aranda, E. Hervas-Martin, M. Fernandez, "Benchmarking Deep Learning Models and Running Memory Checkers on Edge Processors Onboard the ISS", IEEE LEO SatS 2023 Workshop.

[15] E. Dunkel, J. Swope, A. Candela, L. West, S. Chien, Z. Towfic, L. Buckley, J. Romero-Cañas, J. Espinosa-Aranda, E. Hervas-Martin, M. Fernandez, "Benchmarking Deep Learning Models on Myriad and Snapdragon Processors Onboard the ISS," Journal of Aerospace Information Systems (JAIS), (in press).

[16] M. Denbina, Z. Towfic, J. Thill, M. Bue, N. Kasraee, A. Peacock, Y. Lou, "Flood Mapping Using UAVSAR and Convolutional Neural Networks," IEEE Intl Geoscience and Remote Sensing Symposium, pp. 3247-3250, 2020.

[17] O. Ronneberger, P. Fischer, T. Brox, "U-net: Convolutional Networks for Biomedical Image Segmentation," Intl. Conf. on Medical Image Computing and Computer-assisted Intervention, pp. 234-241, 2015.

[18] K. Wagstaff, S. Lu, E. Dunkel, K. Grimes, B. Zhao, J. Cai, S.B. Cole, G. Doran, R. Francis, J. Lee, L. Mandrake, "Mars Image Content Classification: Three Years of NASA Deployment and Recent Advances," The Thirty-fifth AAAI Conf on Artificial Intelligence, pp. 15204-15213, 2021.

[19] Deegan Atha, R. Michael Swan, Annie Didier, Zaki Hasnain, Masahiro Ono. "Multi-mission Terrain Classifier for Safe Rover Navigation and Automated Science," IEEE Aerospace Conf, 2022.

[20] Alberto Candela Garza. Bayesian Models for Science-Driven Robotic Exploration. PhD thesis, Carnegie Mellon University, Pittsburgh, PA, September 2021.

[21] Keras.io (2023, July 14). *Keras Applications* [Online]. Available: https://keras.io/api/applications/

[22] S. Yun, A. Wong, "Do all MobileNets Quantize Poorly? Gaining Insights into the Effects of Quantization on Depthwise Separable Convolutional Networks Through the Eyes of Multi-scale Distributional Dynamics", CVPR 2021.

[23] W. Whitaker, "Sabertooth: Integrated Avionics or Small Spacecraft Missions", IEEE Space Computing Conference (SCC), Pasadena, CA, USA, 2019.

[24] Wikipedia (2023, July 14), *Rad750* [Online]. Available: https://en.wikipedia.org/wiki/RAD750

[25] J. Swope, F. Mirza, E. Dunkel, Z. Towfic, S. Chien, D. Russell, J. Sauvageau, D. Sheldon, M. Fernandez, C. Knox, "Benchmarking Space Mission Applications On the Snapdragon Processor On-board the ISS", IEEE LEO SatS 2023 Workshop.

[26] D. Thompson, B. Bornstein, S. Chien, S. Schaffer, D. Tran, B. Bue, R. Castano, D. Gleeson, A. Noell, "Autonomous Spectral Discovery and Mapping Onboard the EO-1 Spacecraft," IEEE Transactions on Geoscience and Remote Sensing, 2012.

[27] T. Doggett, R. Greeley, A. Davies, S. Chien, B. Cichy, R. Castano, K. Williams, V. Baker, J. Dohm, F. Ip, "Autonomous On-Board Detection of Cryospheric Change," Remote Sensing of Environment, Vol. 101 (4) 2005, pp. 447-462.

[28] A. Davies, S. Chien, V. Baker, T. Doggett, J. Dohm, R. Greeley, F. Ip, R. Castano, B. Cichy, R. Lee, G. Rabideau, D. Tran, R. Sherwood, "Monitoring Active Volcanism with Autonomous Sciencecraft Experiment (ASE)," Remote Sensing of Environment, Vol. 101 (4), 2006, pp. 427-446.

[29] A. Candela, J. Swope, S. Chien, "Dynamic Targeting to Improve Earth Science Missions", 2023 Earth Science Technology Forum, June 20-22, Pasadena, CA.

[30] M. Troesch, F. Mirza, K. Hughes, A. Rothstein-Dowden, R. Bocchino, A. Donner, M. Feather, B. Smith, L. Fesq, B. Barker, B. Campuzano, "MEXEC: An Onobard Integrated Planning and Execution Approach for Spacecraft Commanding," Workshop on integrated Execution (IntEx) / Goal Reasoning (GR), International Conference on Automated Planning and Scheduling (ICAPS IntEx/GP 2020), 2020.

[31] David Evans, Georges Labrèche, Tom Mladenov, Dominik Marszk, "OPS-SAT LEOP and Commissioning: Running a Nanosatellite Project in a Space Agency", 36th Annual AIAA/USU Conference on Small Satellite (2022).

[32] European Space Agency (2023, July 14), *OPS-SAT Experimenter Portal* [Online]. Available: https://opssat1.esoc.esa.int/projects/publications

[33] Georges Labrèche, David Evans, Dominik Marszk, Tom Mladenov, Vasundhara Shiradhonkar and Vladimir Zelenevskiy "Image Acquisition with the SmartCam App On-Board the OPS-SAT Spacecraft", 2022 AIAA SCITECH Forum, 3–7 January 2022, San Diego, CA.

[34] G. Labrèche and C. G. Alvarez, "SaaSyML: Software as a Service for Machine Learning On-board the OPS-SAT Spacecraft," 2023 IEEE Aerospace Conference, Big Sky, MT, USA, 2023, pp. 1-9.

[35] European Space Agency (2023, July 14), The Discovery Campaign on OPS-SAT experiments [Online]. Available: https://www.esa.int/Enabling_Support/Preparing_for_the_Future/Discovery_and_Preparation/The_Discovery_Campaign_on_OPS-SAT_experiments

[36] Boris Otto, Michael ten Hompel, Stefan Wrobel, *Designing Data Spaces - The Ecosystem Approach to Competitive Advantage*. Cham: Springer, 2022.

[37] Gaia-X (2023, July 14), *Policy Rules and Labels* [Online]. Available: https://docs.gaia-x.eu/policy-rules-committee/policy-rules-labelling/latest/

[38] Gaia-X (2023, July 14), *Architecture* [Online]: Available: https://docs.gaia-x.eu/technical-committee/architecture-document/latest/

[39] Gaia-X (2023, July 14), *Trust-Framework* [Online]. Available: https://docs.gaia-x.eu/policy-rules-committee/trust-framework/latest/

[40] Otto, B., Jarke, M. Designing a multi-sided data platform: findings from the International Data Spaces case. Electron Markets 29, 561–580 (2019).

[41] Jarke, M., Otto, B. & Ram, S. Data Sovereignty and Data Space Ecosystems. Bus Inf Syst Eng 61, 549–550 (2019).

[42] Alsamhi, Saeed & Curry, Edward & Hawbani, Ammar & Kumar, Santosh & ul Hassan, Umair & Rajput, Navin. (2023). DataSpace in the Sky: A Novel Decentralized Framework to Secure Drones Data Sharing in B5G for Industry 4.0 toward Industry 5.0. 10.20944/preprints202305.0529.v1.