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Advancing Earth observation: a survey on AI-powered image processing in satellites

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ABSTRACT

Advancements in technology and a reduction in its cost have led to substantial growth in the quality and quantity of imagery captured by Earth observation (EO) satellites. This has presented a challenge to the efficacy of the traditional workflow of transmitting this imagery to Earth for processing. An approach to address this issue is to use pre-trained artificial intelligence models to process images onboard the satellite, but this is difficult given the constraints within a satellite's environment. This paper provides an up-to-date and thorough review of research related to image processing on-board Earth observation satellites. The significant constraints are detailed along with the latest strategies to mitigate them.

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Introduction

There has been a considerable increase in the number of satellites launched into space in recent years. The tracking website UNOOSA[1] lists over 13,725 satellites (as of 10 September 2025) in various Earth orbits. While the majority are associated with communications, a considerable number of them are Earth observation (EO) satellites, generating thousands of terabytes of data every day. Relaying this volume of data to Earth is not feasible through traditional radio frequency (RF) communication channels, so other solutions have been investigated, including processing the data directly onboard the satellite at the point where it is produced. This approach reflects the principles of edge computing, wherein computational tasks are performed in proximity to the data source. The paradigm was initially developed to address the challenges posed by the rapid proliferation of interconnected devices, commonly referred to as the Internet of Things (IoT). Machine learning ML) has been a key enabler of the success of edge computing. Furano et al. (2020) examined the key motivations for deploying machine learning onboard satellites for image processing. This includes:

- Sensor data volumes are growing faster than downlink capacities.
- Restricted power in smaller satellites to download large images.
- Issues with ground station availability.

The associated challenges are also highlighted, including:

- Older hardware with insufficient resources.
- Lack of on-board storage or working memory.
- Limited availability of datasets required for model training and evaluation.

The benefits identified were:

- Improved responsiveness resulting from the reduced volume of data requiring downlink.

[1]United Nations Register of Objects Launched into Outer Space.

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- Improved results (including accuracy).
- Bandwidth savings, so less pressure on the communication channels.
- Greater flexibility by enabling image selection or filtering based on the application.

The concept of an intelligent Earth observation (EO) satellite system-integrating onboard sensing, data processing, and communication capabilities-was first introduced by Zhou (2003). Since then, various efforts have sought to realise this vision. Miralles et al. (2021) provided a broad review of machine learning (ML) applications in EO, covering both ground and onboard operations, including mission planning, telecommunications, and image processing. The updated version by Miralles et al. (2023) contributes minimal new insights with respect to onboard image processing. While comprehensive, these reviews lack depth in that specific area. Zhang et al. (2022) examined advances in intelligent remote sensing (RS) satellites over the preceding decade, addressing platforms, payloads, and onboard processing, and highlighting the societal and legal implications of broader data distribution. Gardill et al. (2023) focused on space edge computing, benchmarking deep learning models on commercial processors aboard the ISS and emphasising communication link performance. More recently, Thangavel et al. (2024) reviewed AI in satellite operations, particularly within distributed satellite systems DSS illustrating how AI enables autonomy in spaceflight systems. However, this work pays limited attention to onboard image processing.

The scope of this paper is confined to the processing of satellite imagery on individual platforms and does not address distributed processing across satellite constellations. Additionally, the discussion is limited to model inference and does not consider the potential for onboard model retraining.

To the best of our knowledge, no existing reviews focus specifically on the deployment of machine learning (ML) for onboard image processing on EO satellites. Given the rapid evolution of this field, a focused and up-to-date review is essential to guide efforts in addressing its unique challenges. This survey aims to answer the following questions:

(1) What are the most challenging constraints to deploying pre-trained ML algorithms onboard an EO satellite to facilitate on-board image processing?
(2) What techniques are most effective in overcoming these constraints?

The paper is organised as follows. Section Satellites background provides background information on satellites, including their classification, typical costs, onboard hardware and sensors, the types of data they generate and the methods used for data handling. This section also reviews widely used publicly available remote sensing datasets and describes the process by which satellite imagery is transmitted to Earth. Additionally, it presents a detailed discussion on calculating the power required to transmit a single image to a ground station. Section Future research outlines the significant constraints to deploying AI on-board satellites in detail. Section Conclusion describes various ways to mitigate these constraints. Figure 1 depicts the organisation of this paper in block diagram format.

Satellites background

In 1957, the Soviet Union launched the first artificial satellite (called Sputnik). This was the culmination of much research dating back three centuries, when Isaac Newton's efforts attempted to explain the motion of natural satellites, such as the moon, that orbit around planets (Newton, 1833). This initiative sparked an industry that has led to the launch of over 13,000 satellites from 105 different countries.

Satellite classification

Satellites are typically categorised according to their mission objectives.

- Communication – transmitting telecommunication signals, such as those used for TV, phone, and Internet, from one location on Earth to another. These satellites are typically positioned at an altitude of 35,785 km above the Earth, corresponding to a geostationary or geosynchronous orbit (GEO), because they orbit at the same rotational speed as the Earth, staying over the same point on the Earth. However,

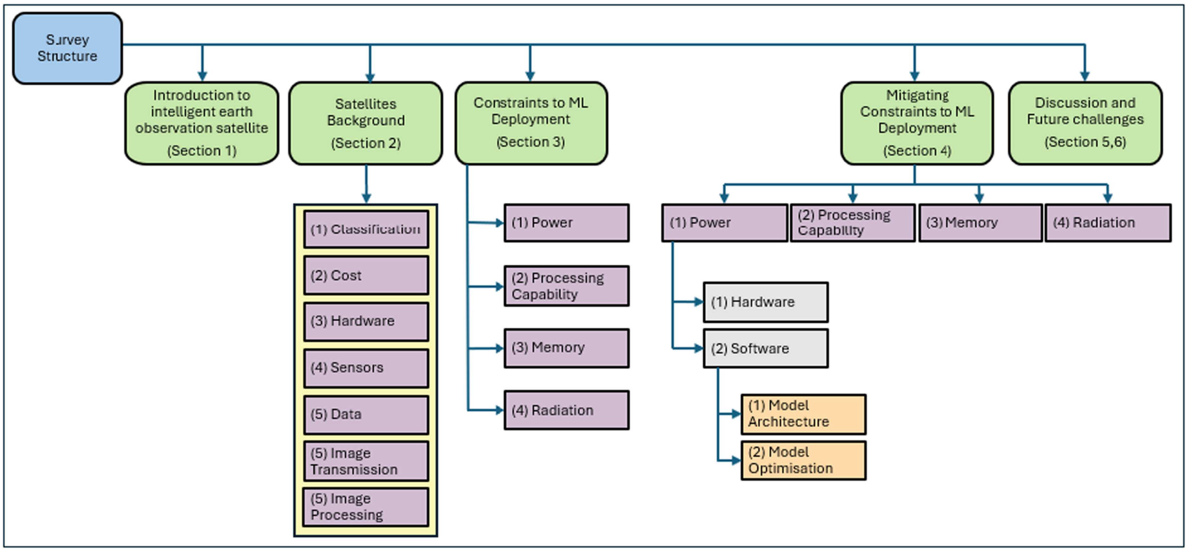

Figure 1. Structure of the survey paper.

this situation is rapidly changing, so satellites at lower altitudes of 600–800 km will dominate the future telecommunications market.

- Earth observation – As the name suggests, this class of satellite is primarily used to take images of the Earth and is used for various applications, such as land/sea monitoring and meteorology. They generally operate at low Earth orbit (LEO) altitudes (160–2,000 km), taking approximately 90 min (altitude-dependent) to orbit the Earth. These satellites include NASA's Landsat satellites, which are used for monitoring the Earth's surface; Sentinel satellites from the European Space Agency's (ESA) Copernicus program for environmental monitoring and disaster management; and Planet Labs' Dove satellites, which provide daily high-resolution imagery.
- Navigation/global positioning – provides position, tracking, and navigation capabilities to devices on Earth that contain an electronic receiver, which uses time signals transmitted along a line-of-sight from a combination of several satellites. They orbit at approximately 20,000 km (MEO – medium Earth orbit), taking approximately 12 h to orbit the Earth.

Satellite cost

Historically, satellites were custom-built for specific tasks and cost hundreds of millions of dollars, so they were accessible only to governments or very large companies. As new technologies, cheaper materials, and fuel types have emerged, along with the miniaturisation and standardisation of electronic parts, satellites have become smaller and considerably more affordable. This trend is predicted to continue. Several commercial companies (e.g. SpaceX in 2012) have entered the market and now offer a "Rideshare" model for small satellite companies to hitch a ride to space. A small satellite can now be built and deployed in orbit for as little as half a million dollars. This has democratised the domain and made it accessible to a much broader population, and given rise to opportunities for both the commercial and research sectors.

Satellite hardware

A satellite is designed primarily to stay functional in space and communicate the data acquired from its sensors (payload) to the ground station. Figure 2 illustrates the classical layout of a satellite, with data handling based on a central on-board computer (OBC) and minimal data processing.

The CubeSat specifications (Heidt et al., 2000) were developed to promote the design of small satellites (smallsat). The form factor of 10 cm cubes, weighing no more than 2 kg, has become the de facto standard for smallsat design. Satellites are defined by the number of cubes (e.g. 6U is six cubes stacked in a two-cube side-by-side form).

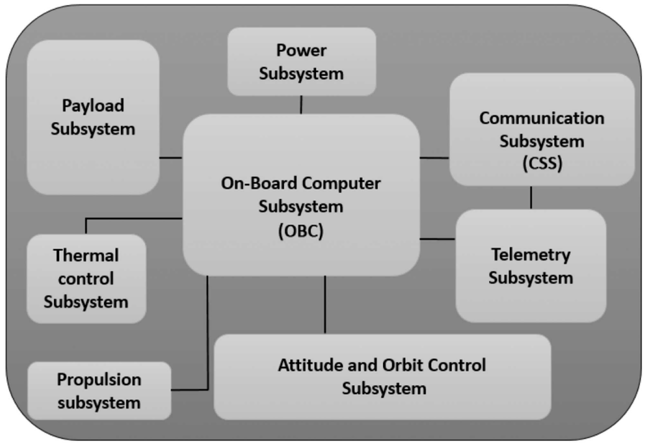

Figure 2. LEO satellite block diagram (El-Bayoumi et al., 2015).

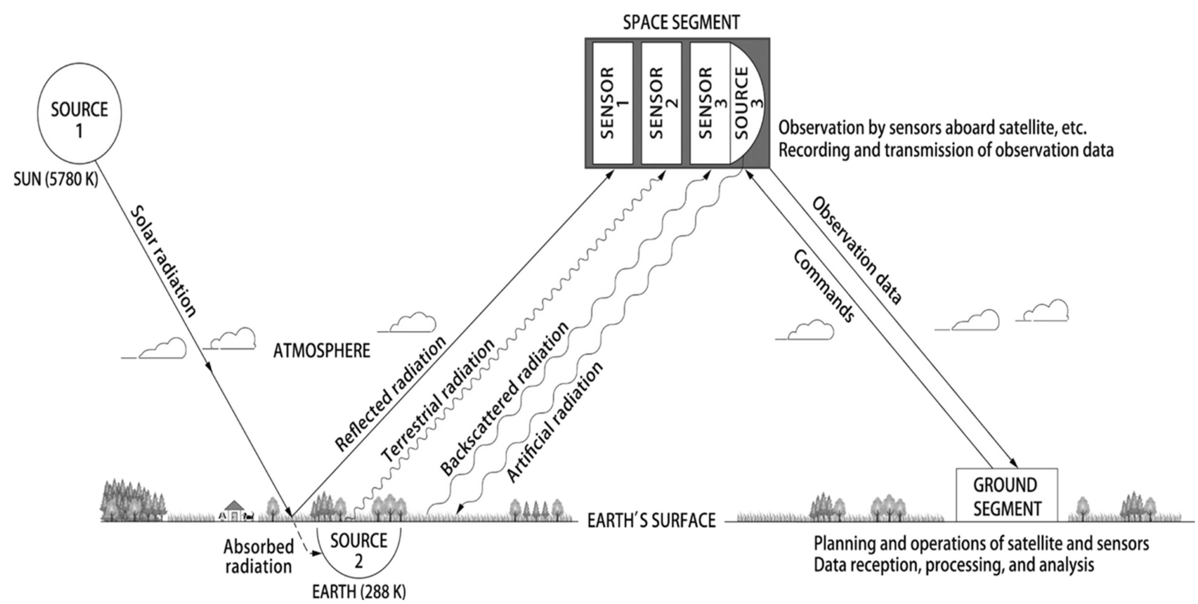

Figure 3. Remote sensing (Kaku, 2019).

Satellite sensors

There are two broad categories of Earth observation sensors based on the radiation source, as shown in Figure 3 (Kaku, 2019).

- Passive – gathers radiation reflected or emitted from a target with external sources, e.g. the Sun, Earth (sources 1 and 2 from Figure 3). These sensors are generally categorised as optical sensors operating at wavelengths typical for visible light (430–720 nm) or for infrared light (750–950 nm). While they can obtain high-resolution images of small areas, they can function only during the day (i.e. need sunlight) and are affected by clouds and weather. Hyperspectral sensors collect information as a set of "images". Each image represents a narrow wavelength range of the electromagnetic spectrum. These "images" are combined to form a 3D hyperspectral data cube and can be used to detect certain minerals or objects if their spectral properties are known.
- Active – An internal source that emits energy (radiation) (source 3 from Figure 3) directed at a target is used, and a sensor gathers the reflected radiation. The difference in time between the emission and gathering is then used to identify the properties of the target. These systems are more generally referred

to as radar-based systems (e.g. synthetic aperture radar (SAR)), operating at longer wavelengths (e.g. microwaves), and can operate at any time, and are unaffected by weather conditions. This is advantageous if constant coverage is required (e.g. for monitoring change at reduced spatial resolution), but the image size can be very large (up to several GB), making it difficult to manage.

Satellite data

In 2017, an article by Intel coined the term "Space Data: The Final Analytics Frontier" to bring people's attention to the potential value of the data being obtained from satellites orbiting the Earth thousands of miles above us. There has been a significant boom in the industry over the last 15 years, driven by the increase in both the quality and quantity of imagery available. Portals such as the Copernicus Ecosystem[2], Earth Explorer[3], Earth Data[4] and Maxar Open Data[5] provide free access to vast amounts of raw remote sensing data and applications to filter the data to meet the user's requirements. Many researchers and organisations have labelled portions of these data and made them publicly accessible for others to use. Table 1 provides an overview of some of the widely used publicly available remote sensing datasets that could be used for training ML models.

Satellite image transmission

Traditionally, data is compressed and accumulated on the satellite and sent to an Earth-based antenna once it passes over ground stations, which are located around the world. The steps are as follows

- **Preparation for downlink** – Image data are broken down into variable-length packets and then encapsulated into fixed-length transfer frames.
- **Satellite transmitter** – The onboard transmitter converts digital frames into a radio frequency (RF) signal. In the past, this would have been in the L-band (1–2 GHz) or S-band (2–4 GHz), but in recent times, the X-band [8–12 GHz] or Ka-band [26–40 GHz] have been used for higher data transmission rates. The signal is amplified by a power amplifier (PA) and directed through the satellite's antenna. Antennas may be omnidirectional (small satellites, low data rates) or high-gain directional (larger satellites, high-resolution imaging).
- **Propagation through space** – The signal travels from the satellite (typically 500–1,200 km altitude) to the ground. It experiences free-space path loss (signal spreading), atmospheric attenuation (rain, water vapour, ionosphere), and pointing errors. The typical contact time per pass is 5–15 min, depending on the orbit and ground station location.
- **Ground station reception** – A ground station equipped with a tracking antenna (2–13 m dishes are common) points its dish towards the satellite. The received signal is downconverted and demodulated into baseband data.
- **Image reconstruction** – Error correction decoding restores the original data packets. The ground system reassembles packets into complete images. Additional image processing (e.g. georeferencing, radiometric calibration) prepares the data for users.

The calculation of the transmission power required for a satellite to send a single image to a ground station is performed as follows (Roddy, 2006):

1. **Data rate:** First, figure out how large the image is (image size S (bits)), then figure out how fast you want to send it (transfer time t (s)):

$$R_b = \frac{S}{t}\,[\text{bits/s}]. \tag{1}$$

[2]https://dataspace.copernicus.eu/
[3]https://earthexplorer.usgs.gov/
[4]https://search.earthdata.nasa.gov/
[5]https://www.maxar.com/open-data

Table 1. Remote sensing datasets.

Name	Description	Size/Scale	Resolution
		Scene classification datasets	
UC merced land use dataset (Yang & Newsam, 2010)	Extracted from USGS National Map Urban Area Imagery collection for various urban areas	2,100 aerial images, 21 land-use classes (100 images per class)	0.3 m, 256 x 256 pixels(px)
AID (Aerial image dataset) (Xia et al., 2017)	Extracted from USGS National Map Urban Area Imagery collection for various urban areas	10,000 images, 30 classes (airport, forest, residential, etc.)	0.5–8 m, 600 x 600px
NWPU-RESISC45 (Cheng et al., 2017)	Large-scale, significant variations in spatial resolution, viewpoint, background, etc., high within-class diversity and between-class similarity	31,500 images, 45 scene classes	0.2–30 m, 256 x 256px
EuroSAT (Helber et al., 2019)	Based on Sentinel-2 multispectral images for land use and land cover classification	27,000 images, 10 classes (agriculture, residential, river, etc.).	10 m, 64 x 64px
		Object detection datasets	
DOTA (Ding et al., 2021)	Object detection in aerial (satellite/airborne) images	11,268 images, 1.7 M object instances, 18 categories	0.1–4.5 m, up to 4k x 4k px
DIOR (Li et al., 2020)	Large-scale on images & categories & variations	23,463 images, 192k instances, 20 classes	0.5–30 m
xView (Lam et al., 2018)	One of the most extensive publicly available datasets, very dense small objects from WorldView-3 satellites	1 M instances, 60 classes; covering 1400 km^2 of the Earth's surface	0.3 m
		Semantic segmentation datasets	
BigEarthNet (Sumbul et al., 2019)	Multi-label & Multimodel(MM) land-cover images from Sentinel-1 & 2(S1/S2) satellites	590,326 S2 (and S1/S2 pairs in -MM) image patches	10–60 m
LoveDA (Wang et al., 2021)	Land-cover semantic segmentation & domain adaptation (urban/rural).	5987 images, 166,768 annotated objects from 3 different cities	0.3 m
SEN12MS (Schmitt et al., 2019)	SAR-optical data fusion; classification/ segmentation using MODIS LULC labels aligned to S1/S2.	180,662 S1/S2-MODIS triplets	10 m
SpaceNet Challenge Datasets[a]	Buildings & road networks. Multi Areas Of Interest (AOI) challenges	67,000 km^2 of high res. satellite imagery, 11M building footprints & 20,000km of road labels	0.3–0.5 m
		Global/large-scale datasets	
So2Sat LCZ42 (Zhu et al., 2019)	Large, labelled dataset for the classification of Local Climate Zones (LCZs) on a global scale from Sentinel-1/2 images	500 k images from 42 cities worldwide	10 m, 32 x 32px
Million-AID (Long et al., 2021)	Large-scale image scene classification dataset for deep learning	1 million aerial images, 51 scene categories	0.5–153 m
RSI-CB (Li et al., 2017)	Worldwide benchmark dataset for RS image scene classification based on massive, scalable, and diverse crowdsource data	2 subsets – RSI-CB256 24,000/RSI-CB128 36,000 images both with 6 classes	0.22–3 m, 256 x 256px/128 x 128px

[a] https://spacenet.ai/datasets/

2. **Free-space path loss (FSPL):** The radio signal spreads out as it travels from the satellite to Earth (like ripples in water). The farther the satellite, the weaker the signal when it reaches Earth. This "weakening" is called free space path loss and depends mostly on the satellite-to-ground distance d (km) and the carrier frequency f (GHz) of the downlink[6].

$$\mathrm{FSPL}(\mathrm{dB}) = 20\log_{10}(d) + 20\log_{10}(f) + 92.45. \tag{2}$$

3. **Noise power:** The ground station receiver is never perfectly quiet – there is background noise (thermal noise, interference, etc.) – so we need to take this into account. The Boltzmann constant $k = 1.38 \times 10^{-23}$J/K, system temperature T_{sys} (K), and receiver bandwidth B (Hz):

$$N = kT_{\mathrm{sys}}B. \tag{3}$$

$$N_{\mathrm{dBW}} = 10\log_{10}(N). \tag{4}$$

The receiver noise figure NF (dB):

$$N_{\mathrm{total,dBW}} = N_{\mathrm{dBW}} + NF. \tag{5}$$

[6] https://www.pasternack.com/t-calculator-fspl.aspx

4. **Required received power:** To receive data without too many errors, the signal must be stronger than the noise by a certain margin (called SNR – signal-to-noise ratio). Faster data rates require a higher SNR, which means more transmission power. If the required E_b/N_0 is known (the ratio of bit energy to noise density needed for reliable decoding for chosen modulation/coding):

$$\mathrm{SNR(dB)} = E_b/N_0\,\mathrm{(dB)} - 10\log_{10}\left(\frac{B}{R_b}\right). \tag{6}$$

If $B \approx R_b$, then $\mathrm{SNR(dB)} \approx E_b/N_0\,\mathrm{(dB)}$.
The required receive power is

$$P_{r,\mathrm{req}} = N_{\mathrm{total,dBW}} + \mathrm{SNR(dB)}. \tag{7}$$

5. **Transmit power:** Antenna gains measure an antenna's ability to focus radio frequency (RF) energy in a particular direction, compared to an ideal isotropic antenna that radiates equally in all directions and are determined by the antenna's size and efficiency (e.g. 0.3 m dish at 8 GHz 26 dBi). Let G_t = satellite antenna gain (dBi), G_r = ground antenna gain (dBi).

$$P_{t,\mathrm{dBW}} = P_{r,\mathrm{req}} - G_t - G_r + \mathrm{FSPL}. \tag{8}$$

Convert to watts:

$$EarthP_t = 10^{\frac{P_{t,dBW}}{10}}. \tag{9}$$

6. **Final result:**

$$P_t\ [watts] \tag{10}$$

Our proposed method for on-board processing results in a reduction in the volume of data that needs to be transmitted from the satellite to the Earth. Hence, we are interested in determining how this correlates with the transmission power required. Therefore, if we rewrite Equation (8) to show transmission power P_t in terms of the data (image) size S, we get the following Equation (11):

$$P_t = 10^{\frac{1}{10}}\left(10\log_{10}\left(kT_{sys}\frac{S}{t}\right) + NF + E_b/N_0 - G_t - G_r + FSPL\right) \tag{11}$$

This can be simplified to

$$Pt \propto \frac{S}{t} \tag{12}$$

That is, the required transmit power grows linearly with the data size (if the transfer time is fixed).

There has been ongoing research (Wertz et al., 2016) into improving the downlink bandwidth, such as switching to Ka-Band (Shi et al., 2017), but these improvements have increased by a factor of 10 compared to the 200 times increase in the data size. SAR image sensors are now capable of acquiring 2–5 TB of raw, high-resolution imagery per day, which presents numerous opportunities but also poses significant challenges. According to Furano et al. (2020), the ability of sensors to produce data increases by a factor of 100 every generation, while our ability to download data increases by only a factor of three, four, or five per generation. This fact, combined with the predicted increase in the number of satellites, will result in an exponential and possibly unsustainable increase in demand for the current communication infrastructure.

Satellite image processing

Satellite image processing refers to the operation of extracting useful information from imagery acquired from a satellite. The processing steps are broken down as follows (Sowmya et al., 2017):

- Pre-processing – the operations required prior to the main data analysis to correct the image for any sensor irregularities and remove unwanted sensor distortion or noise. The categories of pre-processing include geometric correction, atmospheric correction and radiometric correction.
- Image enhancement – improving image quality to a more understandable level for feature extraction or image interpretation. The categories of enhancement include radiometric, spatial, spectral and geometric.
- Image transformation – generation of new images from current sources to highlight particular features or properties of interest. An example is combining two images of the same area within different spectral bands or taken at different times.
- Image analysis – the final step is using the outputs of the previous steps to isolate what we are looking for. Table 2 shows the common satellite image analysis tasks. The use of deep learning (Krizhevsky et al., 2012) has revolutionised the area of image analysis with convolutional neural networks (CNNs) now regarded as the most dominant approach in regard to image analysis (He et al., 2015).

Constraints to deployment of machine learning to satellites

Deploying machine learning (ML) models on Earth observation (EO) satellites is challenging owing to several constraints, including limited power, processing capabilities, memory, and radiation exposure. These are detailed in this section.

Power

Power is the biggest constraint in the space context. The only source of power available to a satellite during its lifetime is the power it generates from its solar panels, which are then stored in batteries on board. The design of the satellite power system has to balance power consumption with power generation (Lee et al., 2013).

During the satellite design process, a power budget is established to ensure that the energy consumption of all the subsystems remains within the limits of what the solar panels can generate. A relevant example is provided by Dahbi et al. (2017), which examines a 1U CubeSat in the low Earth orbit, which completes 15

Table 2. Satellite image analysis.

Task	Description	Example applications
Land cover/land use classification	Assign labels to regions (forest, water, urban, crops).	Mapping deforestation, crop type mapping, and urban expansion.
Object detection	Locate and classify objects (ships, vehicles, buildings).	Ship detection, aircraft monitoring, vehicle tracking.
Semantic segmentation	Pixel-level classification of imagery.	Road extraction, flood extent mapping, land cover segmentation.
Instance segmentation	Pixel-level separation of individual objects.	Building footprint extraction, and tree crown delineation.
Change detection	Compare images over time to detect changes.	Disaster assessment (flood, earthquake), urban growth, deforestation.
Hyperspectral analysis	Use high-dimensional spectral data for classification/detection.	Mineral mapping, crop health monitoring, soil analysis.
SAR image analysis	Microwave radar-based, robust to weather/ day-night.	Ship detection, oil spill detection, terrain classification.
Super-resolution/denoising	Enhance resolution or reduce noise.	Increasing image clarity for small objects, enhancing old/ low-res satellite data.
3D terrain & object reconstruction	Extract height/elevation from LiDAR or stereo imagery.	Digital elevation models (DEMs), vegetation structure, and building height estimation.

orbits per day. Each orbit lasts approximately 94.6 min, with 59 min in sunlight, resulting in an energy generation of 1568 mWh per orbit, or 23,520 mWh per day. Table 3 presents energy consumption during daylight periods, with peak usage observed when both the payload is active and data transmission takes place. The system supports 15 distinct operational scenarios, reflecting variations in sensing, communication, and power generation activities. To ensure energy balance, designers limit the frequency of operations or reduce the number of transmission events. In the case study, the payload is activated once per day during one orbit, communications occur during four orbits, and the remaining orbits are dedicated to energy harvesting. Table 4 provides a summary of the total daily energy consumption, identifying the electrical power system, beacon, onboard computer, and communication modules (COM-TX and COM-RX) as the primary energy consumers. The total daily energy usage is 19,599 mWh, which remains well below the available energy generation of 23,520 mWh per day.

Some examples of satellites currently in orbit are Landsat8[7] launched in 2013, which generates 4.3KW per orbit, whereas EMISat[8] launched in 2019, which generated only 0.8 W. Running an ML model on board will add to the power consumption demand in an environment where power is already very constrained and tightly managed, so this will have to be fully understood to ensure that the power generation can meet the increased demand.

Processing capability

Processing capability is the ability of a computing system to perform tasks efficiently, including calculations, data processing, algorithms, and software execution. A review of standard space processing technologies and applications was performed by Lentaris et al. (2018). Routine tasks such as attitude control, command decoding and system management require minimal power and can run on simple 8-bit MCUs. In contrast, demanding tasks such as data compression, formatting, or encryption require more advanced processors, typically microprocessors or digital signal processors (DSPs).

ML models require millions of computations, demanding processors with substantial computational power, far beyond what is needed for traditional satellite tasks such as attitude control or data encryption. Meeting these demands typically involves using high-performance hardware such as large GPUs, multi-core CPUs, or their combinations, which consume significant resources and occupy considerable onboard space.

Table 3. Power cons. scenario in sunlight with transmission and payload active.

Subsystem	Power (mW)	Duration (hrs)	Energy (mWh)
Elect power system	160	0.99	157.63
On board computer	130	0.99	128.07
COM-RX (receive)	180	0.79	143.01
COM-TX (send)	2640	0.125	330.00
Payload (sensors)	1500	0.17	250.00
Antenna	20	0.99	19.7
Solar panel	10	0.99	8.85
Beacon	2040	0.07	173.39
Total			1211.65

Table 4. Subsystem power and energy consumption.

Subsystem	Power (mW)	Duration (hrs)	Energy (mWh)
Elect power system	258	24	6198
On board computer	130	24	3075
COM-RX (receive)	180	21.5	3884
COM-TX (send)	2640	0.5	1320
Payload (sensors)	1500	0.2	250
Antenna	20	24	473
Solar panel	10	24	237
Beacon	2640	1.7	4163
Total			19599

Memory

The types of memory used on EO satellites are volatile, non-volatile and mass memory. Each serves a different purpose.

Volatile memory

Volatile memory serves the following purposes:

- Program execution: store the satellite's operating system, onboard software and running processes. This includes the instructions and data needed to execute commands, perform computations, and control satellite subsystems.
- Data buffering: serves as a temporary buffer for storing incoming data from onboard sensors or communication systems before they are processed, analysed, or transmitted.
- Temporary storage: store intermediate results and variables generated during onboard data processing tasks, such as image correction, compression, or feature extraction.
- System state: holds the current state of the satellite's subsystems, including sensor configurations, telemetry data, and system diagnostics.

Common types of volatile memory used in EO satellites include dynamic random access memory (DRAM), which provides fast read and write access but requires continuous power to retain data, and static random access memory (SRAM), which is faster and more power-efficient than DRAM and is often used for critical subsystems where fast access times are essential. The size of volatile memory depends on factors such as the complexity of the satellite's systems and the processing requirements of onboard algorithms, but typically ranges from several megabytes to gigabytes. Adding ML data processing will demand a significant amount of volatile memory during inference, and this is where the most significant constraint will be.

Non-volatile memory

Non-volatile memory serves the following purposes:

- Permanent storage: store essential software, firmware, operating system files and configuration data required for the satellite's operation.
- Data logging: log telemetry data, sensor measurements, satellite health diagnostics, and other mission-critical information over extended periods. These data can be later retrieved and analysed for mission planning, troubleshooting, and performance evaluation.

Common types of non-volatile memory include flash memory (which offers fast read and write access, low power consumption, and resistance to shock and vibration) and electrically adaptable programmable read-only memory (EEPROM) (used for storing small amounts of configuration data, calibration parameters, and persistent settings). The introduction of ML image processing should have a limited impact on the consumption of non-volatile memory.

Mass memory

Memory mass units (MMUs) act as buffers for storing large volumes of satellite sensor data, enabling continuous collection when ground stations are unavailable or bandwidth is limited. They store images, spectral measurements, telemetry, and sensor readings, which are typically organised into files or packets. The MMU size depends on the sensor type, resolution, swath, and revisit time, ranging from gigabytes to terabytes. When implemented as Hard Disk Drives HDD or Solid State Drives SSD sometimes within the On-Board Computer (OBC), MMUs must also accommodate any deployed machine learning models.

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[7] https://www.eoportal.org/satellite-missions/landsat-8-ldcm
[8] https://www.eoportal.org/satellite-missions/emisat

Radiation

Space is one of the most extreme environments imaginable. During launch, the contents of a spacecraft are subjected to intense and violent shaking along with extremely loud sound waves. Once it reaches space, it will have to survive extreme temperatures, ranging from very high to very low. However, the most significant risk to the functioning of any electronic device is the radiation that exists in space. Most EO satellites operate at low Earth orbit (LEO) (160–2000 km). At this altitude, they are exposed to the following:

- Solar particle events (SPEs): bursts of energetic protons and electrons from solar flares and coronal mass ejections. A well-known example was the "Halloween Storms" in 2003 (Baker et al., 2004), which caused temporary malfunctions and safe-mode activations in more than half of the Earth's EO satellites, reducing Earth observation data collection for weeks.
- Trapped radiation belts (Van Allen Belts): high-energy protons and electrons trapped around the Earth's magnetosphere. This is particularly damaging in the South Atlantic Anomaly (SAA). In this area, Earth's inner Van Allen radiation belt comes closest to Earth's surface, dipping down to an altitude of approximately 200 km.

Compared to deep-space missions, LEO radiation is moderate but still severe enough to cause frequent upsets. The damaging impact of space radiation on the electronics within space systems has been outlined by Maurer et al. (2008). Because EO satellites rely heavily on onboard processing (for image correction, compression, and real-time data handling), radiation damage directly affects mission performance in the following ways:

- Data integrity – low-energy ions can cause bit flips (the unwanted or intended change of a bit's value from 0 to 1 or 1 to 0 in a computer's memory) and corrupt imaging data, resulting in degraded or unusable images
- System reliability – single-event upsets (a change of state caused by one single ionising particle striking a sensitive node in a live micro-electronic device) in CPUs or GPUs can cause processing hangs during critical image acquisition windows.
- Mission lifetime – cumulative total ionising dose (TID) slowly degrades processors, reducing performance over years.

A recent survey by Lange et al. (2024) examines the robustness of on-board ML models to radiation, highlighting a significant gap in understanding how radiation affects on-board ML models used in spacecraft and a real need for further research, as well as open-source resources that could facilitate realistic experiments for on-board ML.

Mitigating the constraints to deployment of machine learning to satellites

Several strategies have been proposed to address the constraints discussed in Section Future research. In the following section, these approaches are reviewed with reference to each specific constraint.

Power

Running ML onboard consumes significant power, but it offers the major advantage of reducing the amount of data that must be transmitted. As noted in Section Satellite image transmission, transmission power is directly linked to data volume. Therefore, maximising transmission savings and minimising processing power use are crucial to justifying ML deployment on board. Power consumption can be reduced through both hardware and software strategies.

Hardware

The rapid advancement of computer hardware has enabled the emergence of new paradigms such as cloud, fog and edge computing (Gill et al., 2024). With the increasing prevalence of embedded devices, however, challenges related to low-power computing have become more pronounced. These challenges have been explored at different hardware levels, including architecture, algorithms, and memory technologies, with (Sze et al., 2017) highlighting techniques aimed at improving efficiency. Power consumption in such systems is typically divided into active (during processing) and static (idle) modes. Methods such as dynamic voltage and frequency scaling (DVFS), adaptive voltage scaling (AVS), and dynamic power switching (DPS) are frequently employed to reduce active power. At the same time, leakage management is used to minimise static consumption. Further efficiency improvements have been attributed to optimised multiply-accumulate (MAC) operations, temporal architectures, and the development of dedicated AI accelerators. Reuther et al. (2022) reported that these accelerators can achieve performance gains with power consumption between 100 and 1,000 lower than that of general-purpose processors.

In the context of space applications, Ortiz et al. (2023) examined onboard satellite AI processing using low-power chipsets, such as Intel's Myriad family and NVIDIA's Jetson Nano. The Myriad X, which incorporates a vision processing unit (VPU) architecture, is particularly effective for vision and inference tasks. In contrast, the Jetson Nano, which combines a GPU and CPU, supports a broader spectrum of AI and graphics workloads. More recent developments include the Orin Nano, which offers 8GB of RAM, consumes 5–15 W, and delivers up to 40 TOPS. This can be upgraded to "Super" mode, which gives up to 67 TOPS, compared to the Myriad X, which provides 1 GB of RAM, approximately 1 TOPS, and consumes 1–2 W. While the Nano uses more power, it is capable of running larger models, such as YOLOv5, ResNet, and language models for edge applications, and is regarded as an important platform in low-power AI deployment. Its compact form factor (70×45 mm) and lightweight design (174 g) make it particularly suitable for integration into CubeSats and other small satellite platforms.

Software

On the software side, there are several approaches to reduce power consumption, including model architecture and optimisation.

Model architecture. The ML model architecture, defined by its specific arrangement and parameters of layers, directly affects hardware resource requirements. Since the development of LeNet-5 in 1995, a pioneering 7-layer CNN, numerous architectures have emerged. While early designs focused on maximising accuracy, recent efforts also prioritise optimisation for deployment in resource-constrained environments. Table 5 presents some of the significant developments in CNN models.

Table 6 shows some of the model sizes, parameters, flops, accuracy and approximate latency on the PyTorch framework and trained on the ImageNet dataset, sorted by flops. The latencies (where available) are primarily measured on mobile or embedded devices. The number of flops is the best indicator of how much power is required to carry out inference, so reducing this number is the highest priority in the satellite context. The bottom half of the table shows what would be considered lightweight models. The accuracy of these models is comparable to that of heavier models with a fraction of the flops, making them more suitable for deployment in a resource-limited device such as a satellite. MobileNetV4 has a good balance of FLOPs (306 M) and accuracy (87%) with a very low indicative latency, making it an excellent candidate for deployment on a satellite. ShuffleNet has the lowest number of FLOPs (149 M), making it a good option when resources are minimal, although its accuracy is under 70%. Mittal (2024) provides a comprehensive review of many lightweight models.

Before using these models on remote sensing data, they must be trained on relevant case data, which generally involves acquiring labelled data from a dataset such as those shown in Table 1. Adegun et al. (2023) evaluated the performance of 4 models (ResNet, DenseNet, VGG and InceptionV3) by training and testing on three publicly available datasets (EuroSAT, UCMerced-LandUse and NWPU-RESISC45). Table 7 shows the accuracy achieved. DenseNet-121 and ResNet-101, which are both deep CNNs, consistently achieved very high accuracy across all datasets. Interestingly, InceptionV3 and VGG-16 performed moderately poorly, indicating that they require a larger training dataset to improve their performance.

Similarly, Ren (2024) compared the classification performances of AlexNet, VGGNet, GoogleNet and MobileNet by training and testing using the satellite image dataset – RSI-CB256 (Li et al., 2017). Table 8

Table 5. CNN models.

Model	Description
AlexNet (Krizhevsky et al., 2012)	Marked a breakthrough in deep learning by winning the ImageNet classification challenge with over 10% margin. It featured five convolutional layers and three fully connected layers, introducing key innovations such as ReLU activation, dropout to reduce overfitting, data augmentation, and parallel GPU processing.
VGGNets (Simonyan & Zisserman, 2014)	A family of deep CNNs uses 3×3 small convolution filters and up to 19 layers with ReLU activation, achieving superior performance to that of AlexNet.
DenseNet (Iandola et al., 2014)	An open source system that computes dense, multiscale features from the convolutional layers of a CNN-based object classifier.
GoogleNet (or Inception-v1) (Szegedy et al., 2014)	Introduced the idea of an inception layer, running multiple convolutions in parallel. The number of layers was increased up to 22, but produced a large improvement in accuracy, pushing VGG into 2nd place for the 2014 ImageNet challenge.
ResNet (He et al., 2015)	Solved the vanishing gradient problem (Hochreiter, 1998) associated with deep layer network training, introducing the idea of an "identity shortcut connection" that effectively skips layers. It spawned several significant concepts, such as parametric rectified linear units (PReLU) (He et al., 2015), which produced the first model to surpass the reported human-level performance (5.1%) on the ImageNet challenge.
Inception-v4 (Szegedy et al., 2016)	After several different versions of inception with various architecture improvements, v4 was released as a simplified and uniform architecture. Shortly after Inception was merged with ResNet to produce Inception ResNet v1 (Szegedy et al., 2016), incorporating residual modules to increase the network's accuracy and convergence.
Squeezenet (Iandola et al., 2016)	One of the earliest models aimed at resource-constrained devices employs compact design strategies and achieves similar accuracy to that of AlexNet with 50 fewer parameters.
MobileNets (Howard et al., 2017)	A series of lightweight models by Google and TensorFlow's first mobile computer vision models using depthwise separable convolutions and fewer layers and parameters compared to previous models.
SENet (Hu et al., 2018)	Introduced an irregular module called squeeze-and-excitation, which improved accuracy but incurred a substantial computational cost, with 100 million parameters and over 10 billion operations. Since then, research has shifted towards designing lightweight, efficient networks suitable for resource-constrained platforms, including IoT, mobile, and embedded devices.
Mnasnet (Tan et al., 2019)	Generated from an automated neural architecture search (NAS) where the model latency is set as the main objective, along with accuracy, with the focus on deployment to mobile and edge devices.
ShuffleNet v1 (Zhang et al., 2018)	Continued the trend focusing on resource-limited platforms, combining pointwise group convolution (ie 1×1 kernel that iterates through every point) and channel shuffle within just 11 layers with accuracy similar to MobileNet with a 13 speedup compared to AlexNet.
PeleeNet (Wang et al., 2018)	A variation of DenseNet designed for speed and efficiency (no depthwise separable convolutions) using regular convolutions instead of the less []efficienteficient depthwise convolutions.
EfficientNet (Tan & Le, 2019)	A family of 7 models introduced by Google AI in 2019 using compound scaling to scale depth, width, and resolution.
Mobilenet V4 (Qin et al., 2024)	The latest generation of the MobileNet family contains multiple model architectures discovered by NAS, introducing the Universal Inverted Bottleneck (UIB) search block, a unified and flexible structure that merges the Inverted Bottleneck (IB), ConvNext, Feed Forward Network (FFN), and a novel Extra Depthwise (ExtraDW) variant.

Table 6. Comparison of model size, parameters, flops, accuracy and latency[a] sorted by flops.

Model	Size (MB)	Param (Mil.)	Flops (Mil.)	Top-1 Acc (%)	Latency (ms)
SENet-154	440	115.1	20700	81.3	–
Inception v4	172	42.0	13300	80.2	486
ResNet-101	70	44.5	7900	77.4	526
VGG-11	507	132.9	7600	69.0	–
DenseNet-121	31	8.0	2900	74.9	195
GoogleNet	27	6.8	1500	69.8	–
Lightweight models					
SqueezeNet	4.8	1.24	830	57.5	36
AlexNet	233	60.0	715	57.1	–
PeleeNet	5.4	2.8	508	72.6	80
EfficientNet-B0	21	5.3	390	77.1	11
MNASNet 1.0	17	3.1	310	75.2	78
MobileNetV4-small	17	4.3	306	87.0	4
MobileNet v3	21	5.4	225	75.2	75
ShuffleNet v2	8.8	2.3	149	69.4	60

[a] Latency is indicative only and can vary based on hardware, batch size and software optimisation.

Table 7. Comparison of model accuracy performance in remote sensing classification.

Model	EuroSAT dataset	UCMerced-LandUse (%)	NWPU-RESISC45
DenseNet-121	98	98	98
ResNet-101	98	98	98
InceptionV3	75	74	68
EfficientNet	65	–	–
VGG16	79	74	70

Table 8. Comparison of model accuracy performance in remote sensing classification 2.

	AlexNet	VggNet	GoogleNet	MobileNet
Accuracy (%)	93.3	95.4	97.9	99.8

Table 9. Comparison of ML optimisation methods.

Method	Compression ratio	Accuracy loss	Hardware compatibility	Advantages	Disadvantages
Layer decomposition	2–5	Slight-moderate	Good (dense ops still used)	Keeps dense structure (hardware-friendly)	Compression limited compared to pruning/ quantisation
Knowledge Distillation	2–10 Model size reduction (depends on student design)	Low if well-trained	Excellent (student model runs on any hardware)	Produces small, fast models, flexible	Training student requires additional effort; depends on quality of teacher
Pruning (Unstructured)	2–10 (depending on sparsity)	Low if fine-tuned	Poor on most hardware (irregular memory access)	Very high compression, simple to apply	Sparse formats often unsupported, little real speedup without specialised hardware
Pruning (Structured)	2–5	Slight-moderate (depends on aggressiveness)	Good (maps well to existing GPU/CPU/ TPU kernels)	Real inference speedup, reduced memory footprint	May require careful retraining, can reduce representational capacity
Quantisation (8-bit)	4 memory reduction	Minimal (<1% on many models)	Excellent (CPU/GPU/ TPU/Edge NPUs)	Fast, widely supported, low accuracy loss	Sensitive in some tasks (e.g. speech, generative models)
Quantisation (4-bit/Binary)	8–32	Moderate-high (varies by model)	Limited (some accelerators support, CPUs/ GPUs less so)	Extreme compression and speed	Sharp accuracy drop if not carefully fine-tuned

shows the accuracies achieved, which are all above 95%, with the lightweight model MobileNet being the best performer.

Model optimisation. Techniques have been developed to adapt machine learning models to enable them to be deployed on hardware subject to resource constraints. Collectively, these methods are called acceleration or optimisation techniques. The goal of the optimisation is to reduce the computational complexity during training/inference and hence allow the model to function on less resourced platforms. The high redundancy within CNN models was investigated by Vé and Stias (2019), suggesting significant potential for model simplification. Many efforts have been made to take advantage of this redundancy, which can be broadly classified as follows:

- Layer decomposition – an approach to reduce the network computational complexity by reducing the size of individual CNN layers.
- Knowledge distillation – a training strategy of distilling and transferring knowledge from a large (teacher) model (or an ensemble/group of models) to a smaller (student) model to improve accuracy and speed.
- Pruning – removing parameters. There are two types:
  - Unstructured – Removes individual weights (connections) in the model based on some criterion (e.g. magnitude pruning: set the smallest weights to zero).
  - Structured – removes entire groups of weights such as channels, filters, or even whole layers.
- Quantisation – reducing the bitwidth of values by encoding full-precision parameters (i.e. weights and activations) with lower-precision. This would typically be 8-bit, but can be as low as 2-bit (binary).

Table 9 compares each of these optimisation techniques by compression ratio, impact on accuracy, hardware compatibility as well as outlining their advantages/disadvantages.

The power consumption behaviour of various ML algorithms deployed to resource-limited 'edge' devices, such as satellites, was investigated by Duggan et al. (2023). Their study discovered that quantisation can reduce inference power consumption by up to 87% without significantly impacting accuracy.

Processing capability

Advances in processor chips have improved the computing capability without impacting the size or power requirements, and opening up satellites onboard processing opportunities. In 2018, George and Wilson (2018) investigated the challenges and opportunities for onboard computers within small satellites. Two possible approaches have been proposed to meet this challenge:

- Reconfigurable computing – this is an alternative architecture to the expensive custom-built hardware, such as application-specific integrated circuits (ASICs). He proposed the use of field-programmable gate arrays (FPGAs) and listed some of the advantages of this approach, including energy efficiency, the ability to load new software while the satellite is in orbit and parallelisation support.
- Hybrid computing – a combination of several computing technologies to gain the advantages of each of them, such as combining a radiation hardened device with a higher grade commercial device to achieve both high reliability and performance. An example is a system-on-chip (SoC) device commonly used on mobile systems.

The same study reviews processor options for SmallSat computing, ranging from microcontrollers to high-performance microprocessors, highlighting their respective strengths and limitations. A comparative analysis (Figure 4) normalises performance by power consumption across processor types, showing that system-on-chips (SoCs, purple) achieve the greatest efficiency, with field programmable gate arrays (FPGAs, green) performing similarly and much better than microcontrollers (light blue), Rad-hard (red) and microprocessors (black).

Hybrid processing architectures have driven advances in spaceborne computing. SpaceCubeX, introduced as a CPU/FPGA/DSP testbed (Schmidt et al., 2017), evolved into NASA's SpaceCube processor card (Geist et al., 2019), enhancing on-orbit processing capability. In parallel, commercial low-power systems such as NVIDIA's Jetson SoCs, launched in 2014, have been widely adopted for accelerating machine learning, offering high performance in a compact form factor suitable for small satellites.

Early work demonstrated the feasibility of deploying computer vision algorithms on resource-constrained SmallSat platforms. Buonaiuto et al. (2017) provided a proof of concept on the NVIDIA Jetson TX1, which was later extended to CNNs on the Jetson TX2 (Arechiga et al., 2018). Manning et al. (2018) achieved over 90% accuracy with several CNN architectures on a Xilinx Zynq-7020 SoC, with execution times of 89–1383 ms and memory use of 8–41 MB, underscoring the suitability of such platforms for onboard inference.

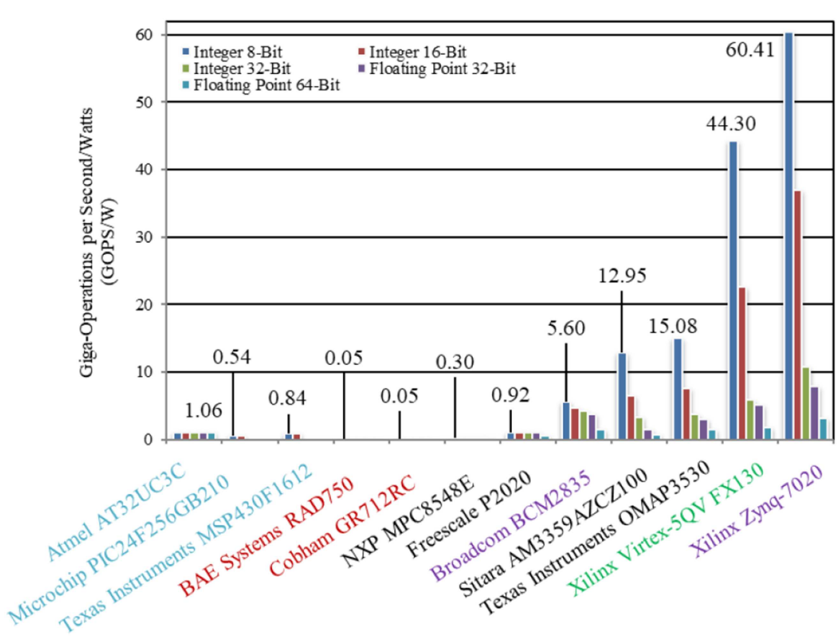

Figure 4. Onboard processors performance (George & Wilson, 2018).

The first real-world deployment of deep learning onboard a SmallSat was CloudScout, developed by [20] for the ESA-supported ϕ-sat-1 mission. Integrated into the HyperScout-2 payload, CloudScout filters images before transmission using the eyes of things (EoT) board (Deniz et al., 2017), which is powered by Intel's Movidius Myriad 2 VPU. When trained on more than 21,000 Sentinel-2 hyperspectral cubes, the system achieved 92% accuracy with only 1.8 W of power consumption and a 2.1 MB footprint, highlighting the efficiency of Myriad 2 compared to GPU (100–200W) and CPU (≈50 W) alternatives. A subsequent study by Giuffrida et al. (2021) reported positive mission outcomes.

Rapuano et al. (2021) compared CloudScout with a custom FPGA-based accelerator. While the FPGA reduced inference latency (from 346 to 142 ms), it consumed more power (3.4 vs. 1.8 W) and required longer, more costly development. The FPGA's superior radiation tolerance and mission-specific adaptability, however, make it more suitable for long-duration or deep-space missions, whereas the Myriad 2 remains attractive for short-term, low-power operations despite lacking full space qualification.

More recently, NVIDIA's Jetson Orin series has expanded onboard AI capability. The AGX Orin 32GB was released in 2022, followed by the Orin NX and Orin Nano in 2023. The Orin Nano has 8GB RAM, is equipped with 1024 GPU cores and 16 tensor cores, delivering up to 40 TOPS (upgradable to 67 TOPS with "Super" mode). Barnell et al. (2022) demonstrated its real-time vehicle detection from drone imagery, while Rad et al. (2023) confirmed the suitability of both the Nano and AGX Orin for computationally intensive space applications. Duggan et al. (2023) further profiled Orin Nano's power consumption during CNN-based image classification, reinforcing its relevance for energy-aware deployment in space contexts.

Memory

Integrating ML into Earth observation satellites increases demands on both mass memory (for storing models) and volatile memory (for inference execution). Memory requirements depend on model complexity, parameter count, and framework serialisation, with sizes ranging from kilobytes (e.g. SqueezeNet) to hundreds of megabytes (e.g. VGG). Optimisation techniques (4.1.2.2), such as pruning, quantisation, knowledge distillation, and layer decomposition, reduce both the memory footprint and computational load, enabling deployment on resource-constrained platforms.

Onboard data pre-processing further mitigates memory and transmission demands by filtering irrelevant data. Examples include CloudScout for cloud detection (Giuffrida et al., 2020), CubeSatNet in the BIRDS-3 project (Maskey & Cho, 2020), and other cloud-detection frameworks such as Zhang et al. (2018). Such processing is particularly valuable in regions with frequent cloud cover. Partial onboard processing and transmitting intermediate CNN outputs could substantially reduce data volume, but the literature on transmitting intermediate results remains limited, representing an area for possible further research.

Radiation

As described previously in section Radiation, radiation in low Earth orbit (LEO) – from the South Atlantic Anomaly, trapped belts, solar events, and cosmic rays – can cause bit flips, processor crashes, or long-term degradation to electronic equipment onboard a satellite. Maurer et al. (2008) provided a further detailed description on both the cumulative effects and single-event effects that this radiation has on solid-state microelectronics. The report also provides an overview of the main approaches to mitigate these effects. Mitigation strategies aim to ensure data integrity, system reliability, and mission longevity and can be broadly divided into:

- Shielding & placement – using protective materials such as aluminum, tantalum, or polyethylene around critical computer modules or housing flight computers in central, well-shielded parts of the spacecraft to minimise radiation exposure. Fan et al. (1996) outlined the general principles for designing effective shields for satellite microelectronics while Daneshvar et al. (2021) described the design process for daneshvar2021multilayer. This approach can be very effective, but it also adds weight to the satellite, which adds both launching and ongoing costs to the satellite.

- Radiation-hardened hardware – specially designed processors (e.g. RAD750, LEON3/4FT) to resist single-event effects (SEE) and tolerate higher total ionising dose, along with error-correcting memory cells that are less susceptible to bit flips. This is probably the most common strategy used to mitigate the effects of radiation. Mystkowska et al. (2025) provided a good review of recent advancements in hardware architectures for space on-the-edge applications, including an overview of radiation-hardening techniques delineating them by radiation hardening by process (RHBP) and radiation hardening by design (RHBD). It also includes a list of radiation-hardened chips that are currently available on the market. The authors noted that radiation hardening substantially increases the cost compared to off-the-shelf commercial components, adds to power consumption and adds a time delay, often resulting in approved hardware being at least one generation behind the latest hardware being used on Earth.
- Redundancy & fault tolerance – this approach uses backup computers automatically to take over in case of failure. It also includes recovery routines within the OS and onboard software, such as built-in watchdog timers to reset the system if it hangs and checkpointing/self-repair to manage any disturbances. Zhang et al. (2024) demonstrate a good example of this with a fault tolerance scheme based on on-board resource backup
- Hybrid architectures – this approach combines previous strategies with a radiation hardened computer for critical tasks (e.g. satellite control) and commercial off-the-shelf (COTS) processors for high-performance image processing, protected with shielding and error mitigation software. This strategy reduces costs while enabling higher onboard processing capabilities.
- Operational mitigation – this involves switching EO satellites to a safe, low-power mode during strong solar storms and also planning the orbit to avoid long dwell times in high-radiation regions such as the South Atlantic Anomaly. This is a low-cost strategy to minimise exposure to radiation and its impacts and could potentially allow the use of more recent hardware onboard a satellite.

Discussion

The increasing volume of data generated by Earth observation satellites is pushing the limits of traditional satellite workflows, creating a need for innovative approaches such as onboard artificial intelligence processing. The implementation of ML models in this context presents several challenges, particularly regarding power availability, processing capability, and memory constraints. This review highlights that these challenges can be mitigated through careful system-level design, including the selection of energy-efficient components and ML models, as well as the development of comprehensive power budgets that account for all satellite subsystems.

The emergence of low-power processors and hardware accelerators, such as the Nvidia Jetson Orin Nano, demonstrates that even small platforms such as CubeSats can feasibly execute lightweight deep learning models. Several in-orbit deployments have validated that these systems can operate reliably under the constraints imposed by small satellite form factors. Memory limitations remain a critical consideration, particularly when deploying more complex ML models. Strategies such as selecting compact architectures, as exemplified by SqueezeNet, or applying optimisation techniques including quantisation, pruning and knowledge distillation, can substantially reduce memory footprints while maintaining acceptable performance. These approaches not only enable the practical use of ML on resource-limited satellites but also contribute to reducing the volume of data that must be transmitted to Earth. Such reductions have cascading benefits, including decreased power consumption for communication and lower overall demand on on-board storage, both of which are essential for efficient satellite operation.

While the number of real-world applications of on-board ML remains relatively limited, the potential advantages are significant. Pre-processing or filtering data before downlinking can drastically reduce storage and transmission requirements, particularly in regions with frequent cloud or environmental interference. Additionally, radiation effects continue to pose challenges for satellite computing, requiring a multi-layered mitigation approach. The combination of radiation-hardened components, error correction and redundancy, shielding, hybrid architectures, and adaptive operational strategies ensures fault-tolerant, reliable performance in harsh space environments. These measures collectively extend mission lifetimes and improve the quality and continuity of Earth observation data, reinforcing the feasibility and value of integrating ML into future satellite missions.

However, there is no one-size-fits-all approach in regard to the potential deployment of ML models to a satellite, and it is very much case-dependent. The satellite designer must strive to find a balance between the resources required by the chosen ML model for onboard processing and the limitations of the satellite. It is possible that the satellite cannot generate enough power to support the ML processing or has insufficient space to fit a suitable processor and the required memory. It is equally possible that the satellite mission will expose the onboard electronics to radiation levels that cannot be mitigated further and preclude the use of an appropriate processor.

Future research

A key benefit of deploying image processing onboard satellites is the potential energy savings from transmitting smaller data volumes to Earth. In some cases, the energy saved through reduced transmission may offset or even exceed the energy required for onboard processing. Further research is needed to quantify these trade-offs and optimise processing strategies. As outlined in Section Satellite image transmission, the energy required to transmit an image to Earth depends on satellite parameters such as the data rate, antenna frequency, transmission power, image size and compression rate. Future work should investigate strategies to balance the additional power required for onboard processing with the energy savings from reduced data transmission.

Another promising direction is partial image processing, where computation is distributed between the satellite and ground stations. Quantifying the associated resource savings and performance impacts of such distributed inference remains an open question. Similarly, selecting the most appropriate model architecture for space deployment requires a more holistic approach, considering real-world trade-offs beyond individual constraints. The development of a unified evaluation framework to guide architecture selection and optimisation strategies systematically could provide significant benefits.

Satellite constellations represent another area for future investigations. While traditionally focused on communication and navigation, constellations may offer a means to overcome resource limitations through decentralised processing. Comparative studies between monolithic and constellation-based architectures could provide valuable insights into their respective advantages and trade-offs. Likewise, the implementation of onboard retraining or model fine-tuning remains largely unexplored. Current approaches rely on retraining models on Earth and uploading updates via reprogrammable platforms, such as FPGAs. Exploring alternative approaches could increase flexibility, improve performance, and enable satellite repurposing.

Finally, the availability of large-scale, open-access satellite imagery through platforms such as the Copernicus Data Space Ecosystem and USGS Earth Explorer presents opportunities for model development. Future initiatives could focus on centrally cataloguing and labelling these datasets across multiple domains, supporting the creation of lightweight, targeted models optimised for onboard deployment. Addressing these research directions will be critical for fully realising the potential of onboard machine learning in Earth observation satellites.

Conclusion

The past decade has seen a dramatic increase in the number of Earth observation (EO) satellites, driven by advances in miniaturisation, computing, and reductions in launch costs. This expansion has created unprecedented opportunities to exploit satellite data across a wide range of applications, from disaster response and environmental monitoring to maritime surveillance and land-use analysis. However, realising the full potential of EO missions increasingly depends on addressing the resource limitations inherent to small satellites, particularly in the context of deploying machine learning (ML) algorithms for onboard processing.

This review highlights how constraints in power, memory, and processing capability shape the feasibility of onboard ML inference. While emerging hardware platforms and AI accelerators offer promising solutions, the trade-offs between computational load, memory footprint, and energy consumption remain critical considerations. Techniques such as pruning, quantisation, knowledge distillation, and efficient model architectures are central to enabling lightweight, high-performance ML on resource-constrained platforms. Moreover, onboard pre-processing and intelligent data selection can significantly reduce transmission costs, improving mission efficiency and extending operational lifetimes.

However, challenges remain. The balance between the energy required for onboard computation and the savings achieved through reduced data transmission is not fully understood and warrants deeper investigation. Similarly, the question of how best to select and optimise model architectures for specific satellite use cases requires more systematic approaches, supported by unified evaluation frameworks. Beyond single-satellite missions, distributed processing in satellite constellations and the potential for onboard retraining or fine-tuning represent important frontiers for future research.

Ultimately, overcoming these challenges will not only expand the range of feasible onboard applications but also unlock the underutilised potential of EO data. By enabling real-time, autonomous decision-making in space, ML-equipped satellites could transform the role of EO in delivering timely, actionable insights for science, policy, and society. Continued collaboration between the space systems and machine learning communities – alongside coordinated efforts to catalogue and share open-access datasets – will be essential for driving this progress.

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Data availability statement

Data sharing is not applicable to this article as no new data were created or analysed in this study.

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