SSC23-WIV-09

The ESA Φsat-2 mission: an A.I enhanced multispectral CubeSat for Earth Observation

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ABSTRACT

As part of an initiative to promote the development and implementation of innovative technologies on-board Earth Observation (EO) missions, the European Space Agency (ESA) kicked off the first Φsat related activities in 2018 with the aim of enhancing the already ongoing FSSCAT project with Artificial Intelligence (AI).

The selected Φsat-2 concept will provide a combination of on-board processing capabilities (including AI) and a medium to high resolution multispectral instrument from Visible to Near Infra-Red (VIS/NIR) able to acquire 8 bands (7 + Panchromatic) provided by SIMERA SENSE Europe (BE). These resources will be made available to a series of dedicated applications that will run on-board the spacecraft. The mission prime is Open Cosmos (UK), supported by CGI (IT) to coordinate the payload operations for at least 12 months after LEOP and commissioning phase. During the nominal phase the various AI applications will be fine-tuned after the on-ground training and then routinely run.

A series of AI applications that could be potentially embarked are under development. The first one is called SAT2MAP and is expected to autonomously detect streets from acquired images. It is developed by CGI (IT).

The second AI application is an enhancement of the Φsat-1 cloud detection experiment, able to prioritize data to be downloaded to ground, based on standard cloud coverage and new concentration measurements. It is developed by KP Labs (PL) and it is based on a U-Ne. This application will mainly act as an on-board service for the other applications, relieving them of the task of assessing the presence of the clouds.

The Autonomous Vessel Awareness application aims to detect and classify various vessel types in the maritime domain. This would enable a reduced amount of data to be downloaded (only image patches including the vessel) improving the response time for final users (e.g maritime authorities). In this case the AI technique used is a combination of Single Image Super resolution (SRCNN) and Yolo-based Convoluted Neural Network (CNN).

The Deep Compression application generically reduces the amount of data to be downloaded to ground with limited information loss. The image is compressed on-board and then reconstructed on ground by means of a decoder. It can achieve a compression rate of about 7 per band. It is based on the use of a Convolutional Auto Encoder (CAE).

Two more AI applications will be selected by ESA through a dedicated challenge open to institutions, Agencies and industries that will be run in the first half of 2023. The Φsat-2 mission successfully passed the CDR phase at the end of 2022 aiming for a launch in 2024.

INTRODUCTION

As part of an initiative to promote the development and implementation of innovative technologies on-board Earth Observation (EO) missions, the European Space Agency (ESA) kicked off the first Φsat related activities in 2018 [1] with the aim of enhancing the already ongoing FSSCAT [2] mission with Artificial Intelligence (AI). The underlying idea was to combine the fast development cycles and reduced cost of new space with new Earth Observation concepts to boost innovation. Φsat-1 experiment successfully flown in 2020[3] demonstrating the benefits of edge computing through AI and paving the way for its successor: Φsat-2.

With Φsat-2 ESA wanted to capitalize on the results of the initial experiment and to design a dedicated mission to fully explore the benefits and capabilities of having extended onboard processing. Many different concepts were considered during the evaluation of the proposals resulting from the initial call issued in 2019. The selected one is based on the use of a single 6U CubeSat equipped with a multispectral camera and a dedicated payload processing unit able to handle multiple onboard applications. The following mission objectives were established at the beginning of the project:

1. Demonstrate the enabling capabilities of running onboard Artificial Intelligence applications.
2. Demonstrate relevance for applicative scenarios and operational missions.
3. Demonstrate the ability of running multiple applications on board (either segregated or combined in a sequential way) and to update and upload them in different moment throughout the entire mission lifetime.

Four baseline applications were already identified at the proposal stage, for autonomous cloud detection, deep compression, vessel detection and street detection in case of emergency situations like flooding. Two additional applications are expected to be selected through a dedicated challenge, called OrbitalAI, that has been organized in parallel to the mission development and which was open to any person, start-up or large enterprise willing to test and validate their own innovative ideas in space.

The project has been initially divided into two separate phases:

- Phase 1, focused on the definition and initial development of the baselined applications and the overall end to end onboard data handling approach (ended in 2021).
- Phase 2, in which the mission is being implemented and exploited, this phase is expected to end after at least 12 months of nominal operations.

The Φsat-2 mission consortium is led by Open Cosmos (UK) as Prime Contractor, CGI (IT) as coordinator of the various application providers and in charge of the development of NanosatMO Framework, Simera Sense Europe (BE) and Ubotica Technologies (IL) providing the payload main components (Multispectral Camera and AI accelerator) and KPLabs, CEiiA and GEO-K providing the remaining baselined applications. The role of the main AI application providers, in the context of the Φsat-2 mission was extremely important since they also acted as reference end users for the final data products. The data produced by the mission will be freely available being distributed under an open and free data policy.

ΦSAT-2 MISSION

The Φsat-2 mission architecture is provided in Figure 1 where the various segments are identified. Because of the very specific demonstration nature of the mission, the final users correspond to the application developers.

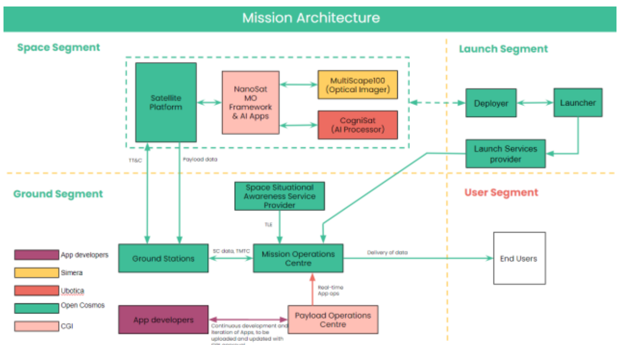

Figure 1: Mission Architecture

SPACE SEGMENT

The Φsat-2 spacecraft is composed of the spacecraft platform and the payload chain, which are described in the following subsections. According to the baseline launch service and to ensure the required Sun illumination conditions, the parameters of the reference orbit used for the Φsat-2 design are reported in the following table.

Table 1 Orbital Parameters

Launch Date	2024
Baseline Orbit Altitude	500 km
LTDN	10:30 PM
Inclination	SSO

Platform

The Φsat-2 platform is based on the standard Open Cosmos Opensat in its 6U variant (Figure 2). The platform is equipped with a state of the art On Board Computer (OBC) that constitutes the heart of the On Board Data Handling subsystem. It includes a multicore processing unit, an high speed data switch, the mass memory, the reconfiguration unit in charge of the system level FDIR and the GNSS receiver. Power is handled by an Electrical Power Subsystem (EPS) that includes 2 deployable solar arrays in an asymmetrical configuration (single deployable stowed on -Y face and double deployable on +Y face, Figure 3) and six body mounted panels for a total of 89 solar cells. The solar cells strings are then connected through six independent MPPTs that provides current to the protected power distribution rails at 3.3V and 5V and to charge the battery whose capacity is around 140 Wh.

The platform will be controlled from ground through a high-speed S-Band transceiver (5MBd) that will also act as a backup in case of unavailability of the High Speed Data Transmitter (HSDT). The payload data is downloaded via an X-Band HSDT, capable of up to 500 Mbit/s. The ground station network is provided by KSAT through their KSAT lite service and thanks to the co-location of both the S-Band and X-Band antennas an acknowledged protocol (Tsunami [4]) can be utilized to request corrupted or missed packages, improving the overall effectiveness of the link. Both units are connected to the main OBC through a Gigabit Ethernet link.

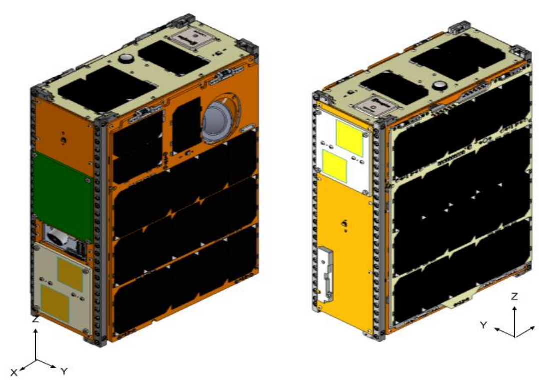

Figure 2: Φsat-2 spacecraft in stowed configuration

To achieve the expected mission performances and to meet the image quality requirements a high-performance Attitude Determination Control System (AOCS) has been selected. The package includes a processing unit, a series of magnetometers and Sun and Earth horizon sensors, a Star Tracker and a 3-Axis MEMS rate sensor. The Star Tracker has been purposely tilted to minimize the chances of having the Earth in its Field of View during nominal operations. On the actuators side, four Reaction Wheels (RWs) are elastically mounted to the platform in a pyramidal configuration to maximize controllability and minimize the effect of the jitter on the payload. Magnetorquers are finally used for detumbling, sun-spin mode and desaturation of the RWs.

The final mass of the system, including the payload, in this configuration will be around 10 Kg.

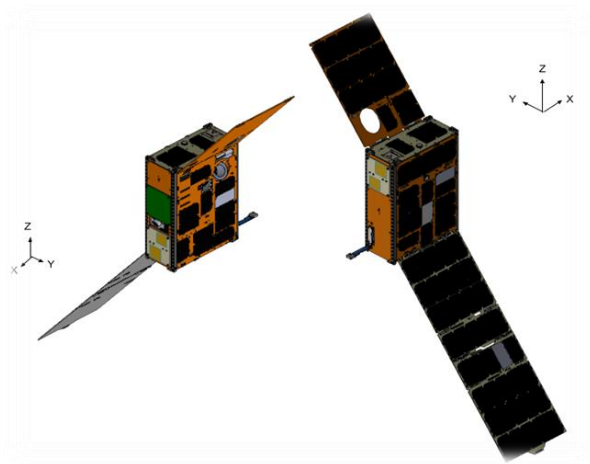

Figure 3: Φsat-2 spacecraft deployed

Payload

The Φsat-2 payload is an ensemble of three different hardware units, with distinct functions and connected through the platform main OBC as shown in the figure below.

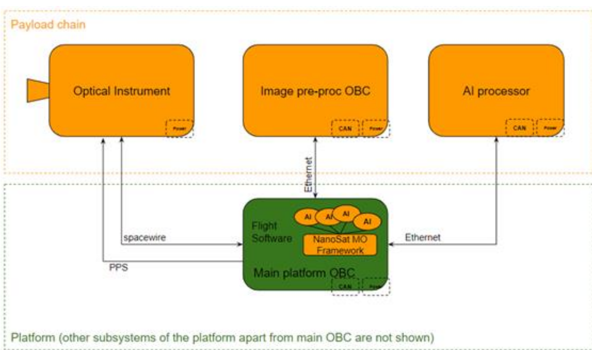

Figure 4: On Board Data Handling Architecture

The SIMERA Sense Multiscape100 CIS, is a pushbroom compact 1.5U multispectral camera selected in the very early stages to support the Φsat-2 mission. Its main characteristics are report in Table 2.

Table 2: SIMERA MultiScape100 CIS

Characteristic	Specification
Focal Length	580 mm
Aperture	95 mm
Full field of View (across track)	2.22 deg
Detector	CMOS, 4096 pixels AT
Pixel Size	5.5 μm
Pixel Depth	12, 10, 8 bit selectable
Spectral Range	450 to 900 nm
Spectral Bands	7 + Panchromatic
Digital TDI Stages	Up to 16 per Band

The camera is characterized by a GSD of 4.75 m and a swath of 19.4 km at 500 km altitude (5.1 m and 21 km respectively with an altitude of 540 km). Onboard Digital Time Delay Integration (dTDI) operations are carried out automatically and the number of usable stages depends on the spacecraft stability (8 to 16 for the Φsat-2 mission). The unit uses a Spacewire link for both TT&C and high speed data download operating up to 100 Mbit/s. For the Φsat-2 mission SIMERA has provided a series of updates/upgrades that will improve the overall performance of the device in multiple areas:

- An enhanced thermal solution that allows for a better decoupling between the payload and the rest of the spacecraft; this solution validated through a dedicated thermal vacuum test campaign, consists in the change of the optical characteristics of some the external surfaces (Figure 5),
- A new Multispectral filter that provides an additional Panchromatic band (500-750 nm),
- A firmware update that allows to perform a simplified relative calibration on board.

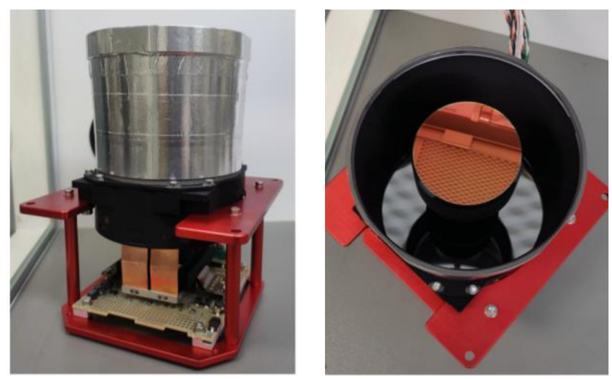

Figure 5: New reflective coatings on the Multiscape100 external surfaces

The End-to-End performances of the system have been extensively simulated during the design phase to create a series of representative datasets for the training of the various AI applications. At 500 Km of orbital altitude the modulation transfer function (MTF) for separate spectral bands is expected to be between 3.9% and 7.2% at Nyquist Frequency while the SNR to be between 54 and 129. A higher SNR level, equal to 256 is predicted for the panchromatic band.

The Multiscape100 CIS is connected directly to the platform main OBC that act also as the system mass memory. Once an image is captured is then moved to main OBC as shown in Figure 4.

Once the images are stored on the main OBC are ready to be sent to the image pre-processor. From a physical standpoint this unit is a copy of the main OBC, with the same processing power and memory size (both volatile and non-volatile) with the sole exception of the GNSS receiver which is not present.

Table 3: Multiscape100 CIS Spectral Bands

Band (order)	Centre Wavelength (nm)	FWHM Bandwidth (nm)	Cut on (nm)	Cut-Off (nm)
#4: PAN	625	250	500.0	750.0
#1: MS 1	490	65	457.5	522.5
#2: MS 2	560	35	542.5	577.5
#3: MS 3	665	30	650.0	680.0
#5: MS 4	705	15	697.5	712.5
#6: MS 5	740	15	732.5	747.5
#7: MS 6	783	20	773.0	793.0
#5: MS 7	842	115	784.5	899.5

The third unit, completing the payload system is represented by the AI processor. The Ubotica CogniSAT-XE1TM CubeSat Board serves both as a powerful edge computer and AI compute accelerator. It is built around the Intel Movidius Myriad 2 Computer Vision (CV) and Artificial Intelligence (AI) COTS VPU whose 12 vector cores provide high-performance parallel and hardware accelerated compute within a low power envelope and in PC/104 form factor compatible with the CubeSat standard. In the Φsat-2 implementation CogniSat is integrated in the payload processing chain through a Gigabit ethernet link enabling data rates sufficient to handle many CV and AI applications at near-streaming throughput.

Common Neural Network (NN) frameworks (e.g., TensorFlow, PyTorch, Caffe) can be used for NN model development and training, with the model subsequently imported into Intel's OpenVINO toolkit for targeting to the Myriad device. CogniSat leverages the broad range of pre-qualified models and layers available within OpenVINO.

Custom Computer Vision pipelines can easily be deployed and executed on CogniSat using the CVAI Toolkit software toolkit. Deployment to the hardware platform involves the transfer of only a single configuration file, and runtime updates enable the updating of pipelines without requiring application re-compile or system reboot.

Payload Data Pre-Processing

Since the beginning of the project, it has been clearly identified the need to provide the Φsat-2 end users with usable/actionable information without further processing on ground. This requires the correct pre-condition of the data before the AI inference process stage that includes, among others, the radiometric and geometric calibration and different band co-registration that rotates and shifts each acquired band to generate the data-cube. In Table 4, the available (onboard) data products are listed.

Table 4: Φsat-2 onboard data products

Name	description
Level 1A	Top of Atmosphere Radiance in sensor geometry, no geo-referenced, no band-to-band alignment
Level 1B	Top of Atmosphere Radiance in sensor geometry, fine geo-referenced, fine band-to-band alignment (<10 m RMSE).
Level 1C	Top of Atmosphere Reflectance in sensor geometry, fine geo-referenced, fine band-to-band alignment (<10 m RMSE). This product level is not orthorectified.

Processing is done in steps, through the use of a series of algorithms, that are applied according to the specific data product and the number of bands required. These algorithms have been tested on the Φsat-2 FlatSat and in Table 5 the associated execution time per frame (19.4x19.4 km^2) is presented.

Table 5: Algorithms execution time

Algorithm	Execution Time [s]
Data Preparation	0.8306
Relative Calibration	0.5859
Cosmetic Filling	0.0189
Denoising	11.0114
Absolute Calibration	0.2993
Bands Co-Registration (per band)	9.617
Radiances to TOA Reflectancies (per band)	10.0912
Geolocation	8.9405
Data formatting/saving (per band)	7.6781

Every AI application has different requirements in terms of pre-processing like the number of bands or the necessity for the fine geolocation of the input. In Table 6 the typical pre-processing time for the different applications is provided.

Table 6: L1B processing time per AI Application

Application	Execution Time [s]
Cloud Detection (standalone application)	79.4930
Cloud Detection (Service)	79.0614
Street Mapping	78.8457
Vessel Detection	67.5177
Deep Compression	78.8457
All bands	297.2039

NanosatMO Framework

The NanoSat MO Framework (NMF)[5] is a software framework for CubeSats based on CCSDS Mission Operations services. It facilitates not only the monitoring and control of the nanosatellite software applications, but also the interaction with the nanosatellite platform. This is achieved by using the latest CCSDS standards for monitoring and control, and by exposing services for common peripherals that are available in nanosatellite platforms, such as, GPS, Camera, ADCS, and others. Furthermore, it can manage the software on-board by exposing a set of services for software management. In simple terms, the NanoSat MO Framework introduces the concept of apps in space that can be installed, and then simply started and stopped from ground. An NMF App can be easily developed, distributed, and deployed on a spacecraft.

The main objective of the NanoSat MO Framework is to facilitate the development of software for small satellites and to simplify its orchestration. For example, new software can be easily deployed in a satellite just by starting and stopping Apps. Beyond the standard adaptation of the framework to support the additional hardware components (e.g. extending camera service, AI service), for the Φsat-2 mission the NMF has been enhanced to support a more robust execution and extending the monitoring and control of the various application states during their execution.

To be compatible with the initial mission requirements an additional functionality related to the chaining of multiple applications has been developed and implemented. Users will be able to use two or more applications in series to further improve the output quality.

Training dataset preparation

A basic simulator has been developed to offer AI app developer an easy-to-use tool that could simulate the various products generated onboard, without any limitations in terms of geographic or temporal coverage, while also providing relatively trustworthy outputs.

Despite having conducted comprehensive studies on the intrinsic performance of the various COTS elements of the Φsat-2 payload, including integration into FlatSat and Engineering Model configurations, it is not possible to fully simulate its actual performance once it is in orbit. The use of end-to-end simulators would have been the most accurate solution to account for the payload optic system and processing chain. However, this type of simulators is generally limited in their capabilities to simulate realistic environment as input. In addition, to enable simulation of any Area Of Interest (AOI) without being constrained by cost or commercial licenses, the simulator is required to use openly available missions with comparable spatial and spectral properties as input.

For instance, the spectral and spatial characteristics of Sentinel-2 (S-2) represent a very good starting point for Φsat-2 even considering the notable differences in spatial resolution (Φsat-2 with a GSD equal to 4.75m, 10-20m for S-2).

The necessary auxiliary data comprises the Spectral Response Function (SRF) of S-2 and Φsat-2 missions, Earth-Sun distance and Sun Irradiance spectrum as well as the parameters required in the modeling of the Signal-to-Noise Ratio (SNR), the sensor-specific Point Spread Function (PSF) and knowledge of the acquisition geometry.

1. Spectral adjustment: A comparative analysis reveals a substantial correspondence of the central wavelengths and bandwidths of (seven of the) S-2 bands and Φsat-2 bands. Φsat-2 panchromatic band (with central wavelength at 625 nm and bandwidth 250 nm) is simulated *via* a linear combination of S-2 multispectral bands (from B2 to B6) [4]

2. Spatial resampling: a bicubic interpolation method is foreseen to reduce interpolation artifacts. As well known, in bicubic interpolation, the intensity value assigned to the point under analysis is obtained using the knowledge of its sixteen nearest neighbors in terms of function values and derivatives

3. Band-misalignment: The band-to-band mis-alignment of remote sensing images acquired by multi-spectral pushbroom spectrometers refers to the co-registration error between different bands caused by differences in the imaging time or angle between detector elements. For Level 1A products, for each subsequently acquired band, the misalignment direction is considered fully random while the magnitude is computed by adding a Gaussian random offset to a constant shift evaluated with respect to the previous acquired band. For L1A products the mis-alignment error accumulates from band to band. For Level 1B products, a band co-registration algorithm will run on board to reduce the misalignment error. As a result, for L1B products, no shift accumulates across bands and the simulated error is just a random shift noise w.r.t. a reference band.

4. Signal-To-Noise Ratio (SNR): the noise to be added to the signal is modeled as a normally distributed random variable with zero mean and a standard deviation equal to the expected noise level. The total noise level will be the square root of the quadrature sum of the noise levels. For each band of Φsat-2 sensor, the equivalent noise is evaluated making use of the SNR for each sensor band as well as the reference radiance used to generate the specific SNR reported.

5. Modulation transfer function: In the case of Φsat-2, the average system MTF (along and across track) at 8 dTDI fluctuates around 5% depending on the band under consideration. Because of the (much) higher spatial resolution of the S-2 source sensor with respect to the Φsat-2 target, the blurring affecting S-2 data has not been corrected. The corresponding Point Spread Function (PSF), computed as Inverse Fourier Transform of the MTF, provides the 7-by-7 kernel to be used for convolving the input image.

6. Radiance to reflectance conversion: the reflectance can be easily obtained from the corresponding radiance value from the pixel radiance value, the Earth-Sun distance, the Sun irradiance captured by the target sensor and the Sun-Zenith angle. This information are extracted from S-2 metadata. For the PAN band, since the radiance values have been computed as a linear combination of overlapping S-2 multispectral bands, we take the sun irradiance values at multispectral bands and then perform a weighted average by considering with weights given by the (normalized) areas under the spectral response function curves for each band limited by the panchromatic SRF.

BASELINED AI APPLICATIONS

Cloud Detection

Onboard cloud detection was one of the main goals of the Φsat-1 experiment and for this second, follow on mission, it has been decided to expand the original concept going into two different directions:

1. First to develop a cloud detection app service to be used by other AI applications to offload them from the task of cloud assessment. Given the limited resources onboard, only cloud free (or images with a cloud coverage within the limits specified by the different users) will be moved to the successive processing stages; the service won't manipulate the data (e.g removing cloud scenes) and will also provide ancillary data that the final user can use as input for further processing down the line,

2. Second a proper cloud detection demonstration application, based on the service described in the previous point to be used in the initial stages of the mission for validation and fine-tuning purposes.

The optimized U-Net architecture for cloud detection is exploited [6]. To accelerate the inference process offered by this deep learning model, this has been thoroughly benchmarked, and the second convolutional layer was removed, with minor impacts on the detection accuracy (the FPS was increased from 1.62 fps to 5.57 fps here). The models were benchmarked on the Intel Movidius Myriad-2 connected by the USB port to a PC computer (the inference time was measured for a 19.4 x 19.4 km scene, and it amounted to approximately 12 seconds). The segmentation quality of the models was verified over the unseen test data (obtained using a GPU and Myriad), and it was quantified using classic metrics, including the Dice coefficient, accuracy, precision, recall, specificity and the Jaccard's index (elaborated for the Sentinel-2 and simulated Φsat-2 multispectral imagery). The results showed that the optimized U-Net model offers high-quality multi-class cloud segmentation (clouds, semi-transparent clouds, cloud shadows and background, Figure 6) reaching 0.81 categorical accuracy (for the original KappaZeta test set [7]) and fast operation.

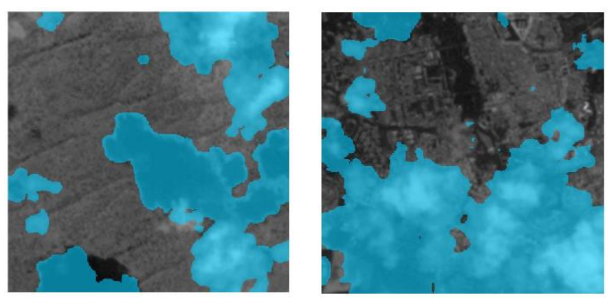

Figure 6: Examples of cloud masks from the processing of the training dataset

Vessel Detection

The Autonomous Vessel Awareness experiment (AVA) aims to demonstrate the capability to autonomously develop awareness about vessels in the maritime domain using AI. AVA will run onboard Φsat-2 and will make use of machine learning techniques (in particular deep learning) to autonomously detect and classify vessels in optical imagery captured by the Φsat-2 camera (e.g., based on the following elements: absence of clouds, presence of ocean water, presence of ships in the image). It will then determine if a given scene (or areas) is interesting and requires further monitoring. Based on this, the sensor could further acquire data and transmit the data to the ground for further analysis. This will enable faster responses, and potentially higher value detections. AVA will enable:

- A reduction in the volume of downlinked images;
- A reduction in image processing and analysis time by human operators;
- A reduction in operational costs of satellite missions;

AVA results will be of interest to specific EO user communities such as maritime authorities and regulators in countries with coastal areas and Exclusive Economic Zones (EEZ), as well as their potential use in the detection of illegal fisheries and monitoring of fisheries in general.

The implementation of the model consists of two parts: image enhancement and vessel detection. For image enhancement, a deep learning model (Single Image Super-Resolution Model) is used. This model uses the concept of Convolutional Neural Network (CNN), intending to increase the original image quality, and consequently the performance of the whole AVA app (considering physical satellite limitations and onboard devices). Regarding vessel detection in sea and oceans satellite images, YOLO can be used both to detect and classify the vessels according to the image high score regions when compared with predefined vessel classes. YOLOv3-tiny is a real-time detection algorithm developed for devices with a lack of data processing capacity. The model structure is simpler than YOLO, and the detection is very fast. YOLOv3-tiny is a lightweight target detection algorithm applied to embedded platforms.

During the test stage, a single neural network is applied to the whole image. Hence, the model looks for a full image and separates it into smaller tiles. The bounding boxes (tiles) and probabilities are predicted for each location of the image. The bounding boxes are weighted by the predictions, since it allows the model to look at the whole image during tests, leading to informed predictions for the global context in the image.

YOLO scores each region based on the similarities with predefined classes (from AIS clustering developed classification). To train the model, a dataset of vessel images was created by converging the information of AIS and satellite imagery. Some of the performance metrics of YOLOv3-tiny trained with the vessel dataset are presented in Table 7.

Table 7: Performance values of YOLOv3-tiny trained with vessel dataset for a Intersection over Union (IoU) value of 30%

Metric	Value
Precision (IoU threshold 30%)	0.74
Recall (IoU threshold 30%)	0.87
F1-score (IoU threshold 30%)	0.80

Street Mapping (SAT2MAP)

Sat2Map is an AI software application developed by CGI, extracting street map data from satellite images. The idea behind the application was to be able to supply updated actionable information to the ground teams in emergency scenarios (e.g. a flooding event). In this specific case the end user on the ground would use the information provided by the application to support evacuations or the routing of rescuers.

The software implements Generative Adversarial Networks (GANs), a specialized neural network architecture capable of modelling the underlying data distribution in a given dataset such as to be able to create another data set following the same distribution. In case of Sat2Map, GANs are used to learn the data distribution of images to create images following the same distribution and create new images. In other words, GANs empower Sat2Map to learn how street maps derived from satellite imagery shall look like and apply this knowledge to unknown satellite imagery. In general, GANs use two different networks, a Generator and a Discriminator network competing against each other. With the Sat2Map setting, the Generator creates new “fake” images mimicking the source images, i.e. learns to create images showing same data distribution as the input imagery. The Discriminator in turn learns to distinguish between fake and real imagery. The result of the Discriminator’s decision is subsequently fed back to the Generator, enabling the latter to adapt and improve the next set of fake images. Once the Discriminator is not able to distinguish real from fake imagery, the training concludes and the final model for generating target imagery is found. Conditional GANs are a slight variation of GANs that can further direct the results of a GAN into a desired direction. Within Sat2Map, the target direction is the generation of road maps based on satellite images.

Sat2Map uses three different implementations of such conditional GANs: CycleGAN, Pix2Pix and Jerin Paul. CycleGAN is a technique that involves the automatic training of image-to-image translation models without paired examples, whereas Pix2Pix uses paired training data. Lastly, Sat2Map uses an algorithm developed by CGI for model training. This algorithm is based on ideas presented by Jerin Paul. The models are trained using a collection of images from the source (i.e., satellite images) and target (i.e, street maps). These techniques are powerful, achieving visually impressive results on a range of diverse application domains. Finally, the Jerin Paul model has been chosen for the Sat2Map App for its final implementation.

The model has been trained exploiting synthetic representative dataset generated by processing different mission including PlanetScope and S-2. The dataset was prepared aiming at enabling the model to learn distinguishing between streets, flooded streets, and cloudy areas (Figure 7).

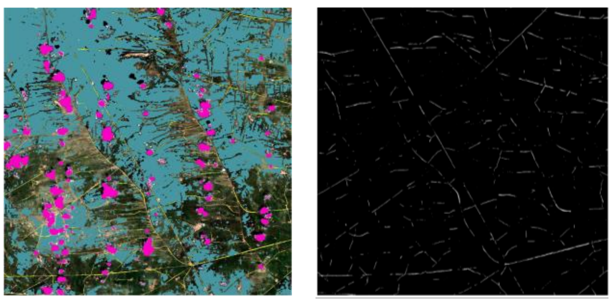

Figure 7: Example of Street Mapping output

The model has been trained over a specific area in the Assam region (Northern India) for which relevant images including flooded streets were available and tested again over a different area with similar characteristics in Pakistan.

A series of metrics have been identified to evaluate the performance of the application from an end user perspective that will be furtherly refined during the nominal phase of the mission. To support the on-ground users of the processed maps, a quick georeferencing procedure has also been designed to improve the quality of the provided information.

Deep Compression

The Deep Compression application performs image compression exploiting a Convolutional AutoEncoder (CAE) i.e., a Convolutional Neural Network (CNN) with an AutoEncoder (AE) structure. The model was developed to demonstrate how onboard AI post processing can reduce the amount of data to be sent to the ground with a limited information loss. The compression of the image is performed on-board: the model accepts as input single band images acquired by the multispectral camera which are compressed through the encoder part of the CAE. Reconstruction is performed on the ground by means of the dedicated decoder.

AEs are Neural Networks (NNs) with a symmetrical structure consisting of an encoding and a decoding part, with one or more hidden layers, and an internal bottleneck layer that forces a compressed knowledge representation of the original input. Essentially, AEs transform input data to a lower dimensional representation and ensure the reconstruction of the input based on these characteristics. AEs are commonly used for feature learning and data compression [8]. The CAE model on which the Deep Compression application is based is summarized in Figure 8. The encoder comprises blocks of convolutional layers (CONV block) and the innermost bottleneck layer which returns the compressed representation of the input images and determines the Compression Ratio (CR). CR is defined as the ratio between the size of the input image in terms of pixels and the number of units in the bottleneck layer. Symmetrically, the decoder part includes transposed convolutional blocks (DE-CONV block) and return back the output with the same dimension as the input. In the encoder, convolutional layers progressively extract deeper feature maps through an increasing number of filters. Then, the output of the last convolutional layer is flattened to return the compressed representation of the image through the bottleneck layer. In the decoder the reverse process is performed, returning the reconstructed image as final output.

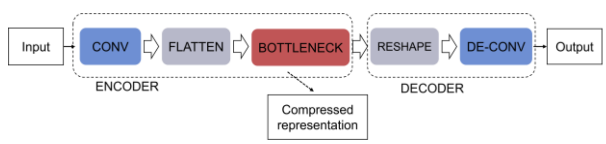

Figure 8: Deep Compression Application CAE Network

The final definition of the model was determined considering the requirements imposed by the mission, especially in terms of memory footprint and computing power usage. The dataset used for training and validating the application is based on SIMERA Sense MultiScape100 CIS simulated acquisitions. After the training phase, the encoder and decoder parts are used separately.

The quality of the reconstructed image was evaluated using standard metrics, i.e., Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure

(SSIM) widely used for lossy compression evaluation. PSNR depends on Mean Squared Error (MSE), and higher PSNR values indicate higher image quality. SSIM is related to the perception of image quality by the human eye and ranges between 0 and 1 [9]. Additionally, an applicative metric was implemented that aims at assessing the practical use of the reconstructed images. The images compressed and reconstructed through the CAE were indeed used in a real application scenario, that is semantic segmentation. More in detail, the decompressed images were used to predict building masks along with the original acquisitions. The obtained masks were then compared to assess the differences between the two cases, confirming that the decompressed images can be used with the same results as the originals.

Table 8 reports the values for CR, SSIM, and PSNR computed as an average over all the patches of the test set.

Table 8: Deep Compression Application metrics

Metric	Value
CR	8
SSIM	0.977
PSNR	38.58

Figure 9 shows on the top a test image (a) with the respective reconstruction (b). A more detailed view of the areas bounded by the boxes is shown on the bottom. The SSIM value is also reported.

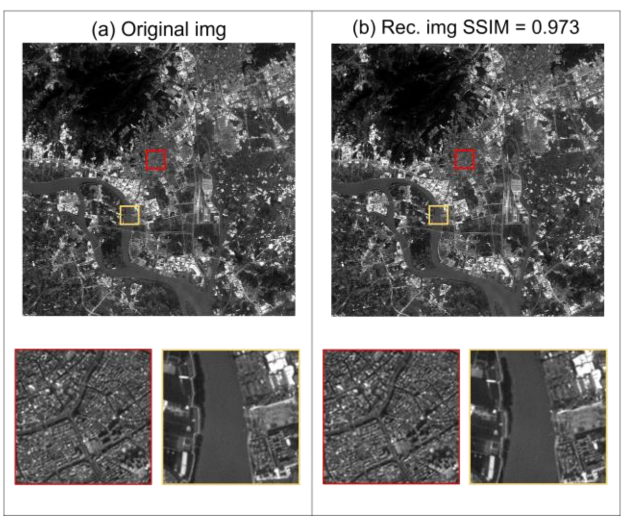

Figure 9: Deep Compression Application results

CONCLUSIONS

In this paper the current status and all the work done since the selection of winning proposal in 2020 has been presented. The mission required the design and implementation of a dedicated 6U cubesat platform capable to support the power and pointing requirements of the selected multispectral camera and processing units. To allow the proper execution of the six different applications that will be run onboard (four of which already pre-selected) the ability to generate the equivalent of Level 1B data has been implemented though a series of software algorithm orchestrated in a dedicated hardware unit.

The pre-selected applications have been extensively developed since the beginning of the activity and they have been already tested in a representative Φsat-2 FlatSat. The spacecraft is currently being assembled and it is planned to be launched in 2024.

References

1. M. Pastena et al., “Overview of ESA’s Earth Observation upcoming small satellites missions” Proceedings of the 34th Annual AIAA/USU Conference on Small Satellites, Logan, UT, 2020.
2. A. Camps et al., "FSSCat Mission Description and First Scientific Results of the FMPL-2 Onboard 3CAT-5/A" 2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS, Brussels, Belgium, 2021, pp. 1291-1294, doi: 10.1109/IGARSS47720.2021.9554589.
3. G. Giuffrida et al, “The Φ-Sat-1 Mission: The First On-Board Deep Neural Network Demonstrator for Satellite Earth Observation” *2020, IEEE Transactions on Geoscience and Remote Sensing*. 60. 1-1. 10.1109/TGRS.2021.3125567.
4. M. Meiss, “Tsunami: A High-Speed Rate-Controlled Protocol for File Transfer”, 2004.
5. C. Coelho et al, “NanoSat MO Framework: Enabling AI Apps for Earth Observation”, Proceedings of the 35th Annual Small Satellite Conference, Logan, UT, 2021
6. B. Grabowski, M. Ziaja, M. Kawulok and J. Nalepa, "Towards Robust Cloud Detection in Satellite Images Using U-Nets," 2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS, Brussels, Belgium, 2021, pp. 4099-4102, doi: 10.1109/IGARSS47720.2021.9554170.

7. Domnich, M.; Sünter, I.; Trofimov, H.; Wold, O.; Harun, F.; Kostiukhin, A.; Järveoja, M.; Veske, M.; Tamm, T.; Voormansik, K.; Olesk, A.; Boccia, V.; Longepe, N.; Cadau, E.G. KappaMask: AI-Based Cloudmask Processor for Sentinel-2. Remote Sens. 2021, 13, 4100. https://doi.org/10.3390/rs13204100

8. G. Guerrisi, F. Del Frate and G. Schiavon, "Satellite On-Board Change Detection via Auto-Associative Neural Networks," Remote Sensing, vol. 14, no. 12, p. 2735, 2022.

9. U. Sara, M. Akter and M. Shorif Uddin, "Image Quality Assessment through FSIM, SSIM, MSE and PSNR—A Comparative Study," Journal of Computer and Communications, no. 7, pp. 8-18, 2019.