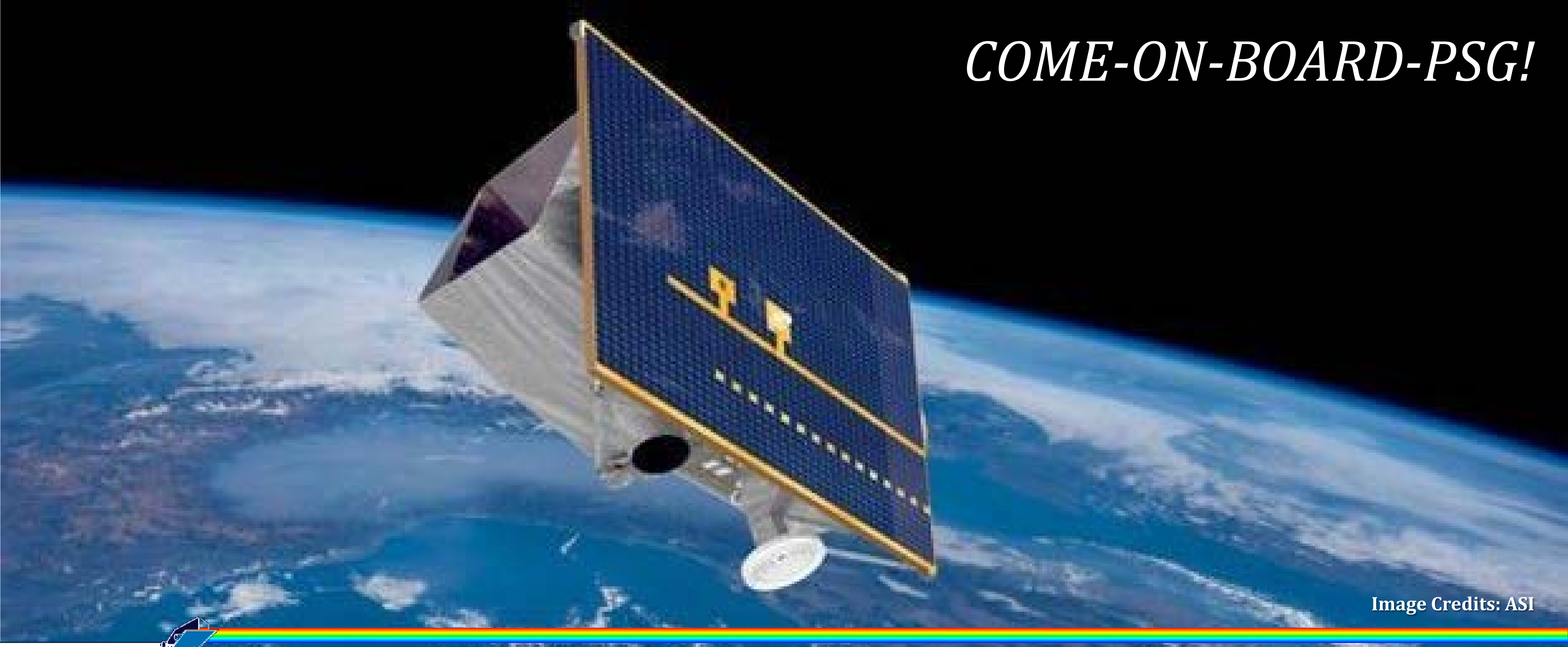

ASI Workshop: *"Tecnologie satellitari e analisi multi-rischio"*

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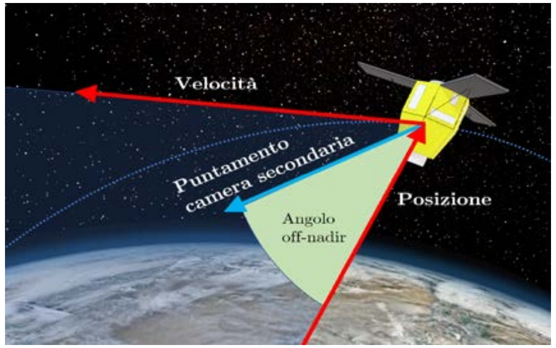
COME-ON-BOARD-PSG! Project

ComeOnBoardPSG! *“Computazione autonoma con machine learning on-board per ottimizzazione acquisizionene analisi real-time dei dati iperspettrali su PRISMA Secoda Generazione”*

ComeOnBoardPSG! is a project developed at the School of Aerospace Engineering of the University of Rome “La Sapienza”.

The proposal of this project responds to the ASI call for abstracts **"Design and development of modules for on-board computing based on machine learning enabling new remote sensing missions with hyperspectral payloads.”** and it is co-funded by the Italian Space Agency (ASI).

COME-ON-BOARD-PSG! Project



1) Optimization of acquisitions through real-time evaluation of cloud cover

(a) High impact solution with an additional forward-looking RGB camera onboard PSG

The onboard ML algorithm will provide the cloud cover (%) using the **forward-looking camera's RGB acquisitions**. This information can be used in two distinct ways:

- **Selective Acquisition**: real-time attitude adjustments are not possible, the onboard system processes the preplanned acquisition schedule and identifies targets that will likely be obscured by high cloud cover.
- **Adaptive Attitude Planning**: If the Guidance Navigation and Control (GNC) system has the capability, the satellite's attitude can be adjusted in real-time to optimize image acquisition.

(b) Low impact solution without an additional forward-looking RGB camera

Cloud cover can not be predicted before HS data acquisition. A low-impact, non-intrusive module assesses the cloud cover in each **PSG hyperspectral image** in real-time.

2) Generation of real-time alerts concerning natural disasters, specifically referring to wildfires

Integrating a computing board within the PSG that features an onboard neural network (NN) specifically trained to perform **real-time analysis of PRISMA HS images** for **detecting high temperature events**, such as wildfire and volcanic eruptions.

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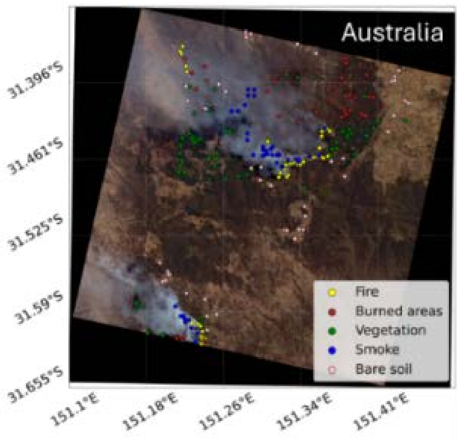
Dataset for Wildfire Detection

Dataset for Wildfire Detection

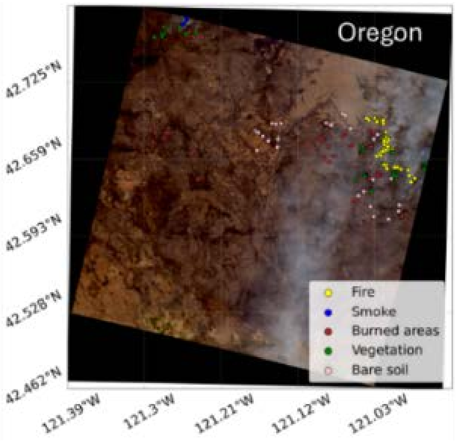
Hyperspectral Wildfire Detection: Neural Network Training and Performance Analysis

- Starting from the **Landsat-8 training dataset**, the images were resized to 128×128 pixels, resulting in a total of 161 image patches. This resizing process effectively increased the dataset's diversity.
- The dataset was then divided into:
  - **Training set (70%)** further split into: **90% for actual training** and **10% for validation**
  - **Testing set (30%)**

- **Transfer learning** tested on **14 patches of 128x128 pixels from PRISMA hyperspectral** images acquired over wildfires in Australia and Oregon.
- Wildfire scenario into seven classes: *Fire*, *Smoke*, *Burned Area*, *Vegetation*, *Bare Soil*, *Water, and Cloud*



Australia 27 December 2019



Oregon 5 August 2021

Considering only pixels classified as active fire for the performed binary classification *"fire"* or *"not fire"*.

Algorithms Implementation and Training

Algorithms Implementation and Training

Hyperspectral Wildfire Detection

- **U-Net neural architecture** is considered for the **wildfire detection task on the hyperspectral images** captured by PSG's primary payload.
- **Input** size of the network has been selected according to the **chosen PRISMA hyperspectral bands** to enable efficient onboard wildfire detection.
- Specifically, the input will be adapted to exploit the following **hyperspectral bands**:
  - **Blue** (450–510 nm)
  - **Green** (530–590 nm)
  - **SWIR1** (1570–1650 nm)
  - **SWIR2** (2110–2293 nm)

Algorithms Implementation and Training

U-Net Architecture Overview

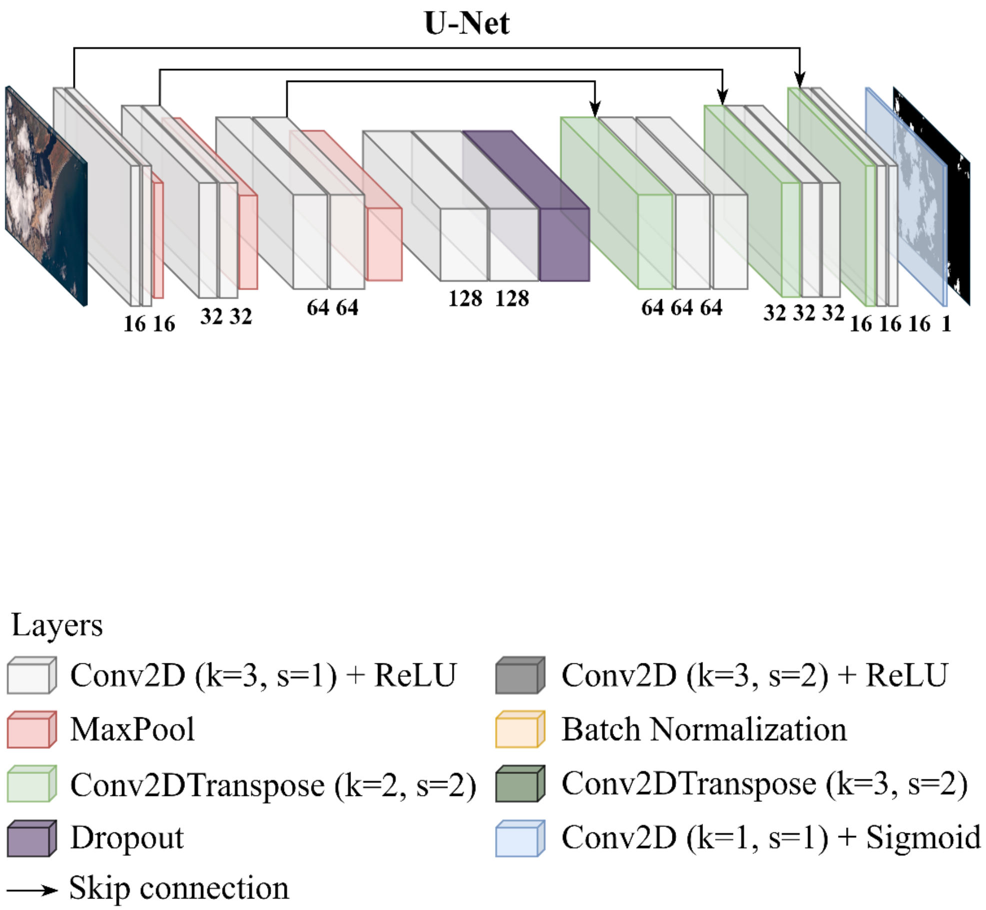
- **Encoder Structure:** three blocks, each containing:
  - ➢ **Two Conv2D layers** (ReLU activation, same padding).
  - ➢ **One max pooling layer**.
  - ➢ Feature maps: **[n, n, 2n, 2n, 4n, 4n]** (where *n* is the number of filters).
- **Bottleneck Layer:**
  - ➢ Two **Conv2D layers** (8n filters, ReLU activation).
  - ➢ **Dropout layer** to reduce overfitting.
- **Decoder Structure:** mirrors the encoder with:
  - ➢ **Transposed convolution** (Conv2DTranspose).
  - ➢ **Skip connections** for feature reuse.
  - ➢ **Two Conv2D layers** to restore spatial resolution.
- **L2 regularization** applied to all layers.
- **Final segmentation mask**: 1×1 Conv2D with **sigmoid activation**.

Layers	Filters
Conv2D	16
Conv2D	16
MaxPool2D	
Conv2D	32
Conv2D	32
MaxPool2D	
Conv2D	64
Conv2D	64
MaxPool2D	
Conv2D	128
Conv2D	128
Dropout (best)	
Conv2DTrasp	64
Concatenate	128
Conv2D	64
Conv2D	64
Conv2DTrasp	32
Concatenate	64
Conv2D	32
Conv2D	32
Conv2DTrasp	16
Concatenate	32
Conv2D	16
Conv2D	16
Conv2D	1
Parameters: 482.033	

Algorithms Implementation and Training

Hyperparameters Tuning

- *Bayesian Optimization (BO)* for hyperparameter tuning.
- BO targeted the following hyperparameters:
  - **Learning rate (η)**: $[10^{-5}, 10^{-3}]$
  - **L2 regularization strength (λ)**: $[10^{-6}, 10^{-3}]$
  - **Dropout rate (p)**: [0.1, 0.5]
  - **Batch size (b)**: [8, 32]
- The optimization process ran for 15 iterations, each consisting of 30 training epochs, aiming to maximize a custom objective function that balanced segmentation accuracy while minimizing false positives (FPs) and false negatives (FNs).
- Once the **optimal hyperparameters** were identified, final training was conducted for up to 200 epochs, with *early stopping* applied based on a patience of 30 epochs.



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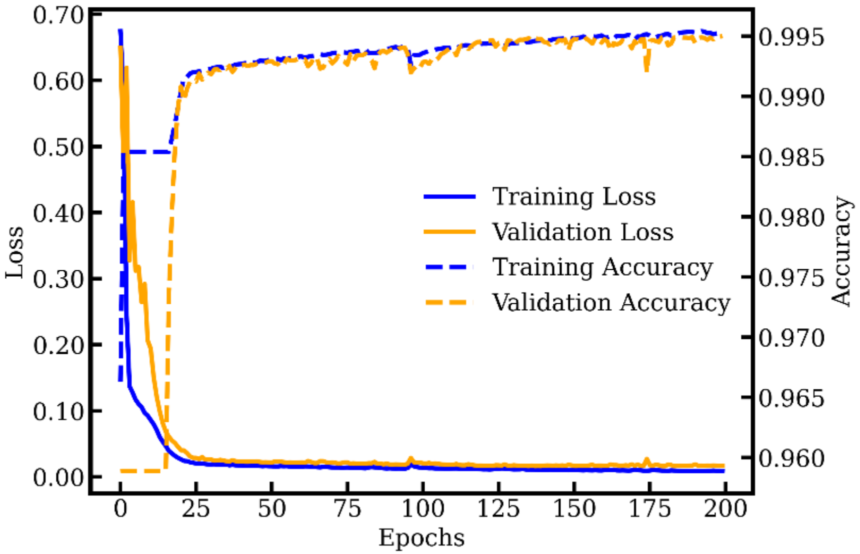
Training and Testing Results

Training and Testing Results

- **Training** and **validation loss** and **accuracy trends** for the U-Net model.



	U-Net model
Training loss	0.008558
Validation loss	0.016170
Training accuracy	0.997422
Validation accuracy	0.995020

- **Final performance metrics** of the U-Net model on the **test dataset:**

	Predicted fire	Predicted not fire
Actual fire	97.38%	2.62%
Actual not fire	4.06%	95.94%

Metric	Value (%)
Accuracy	97.27
F1 Score	84.48
Recall	95.93

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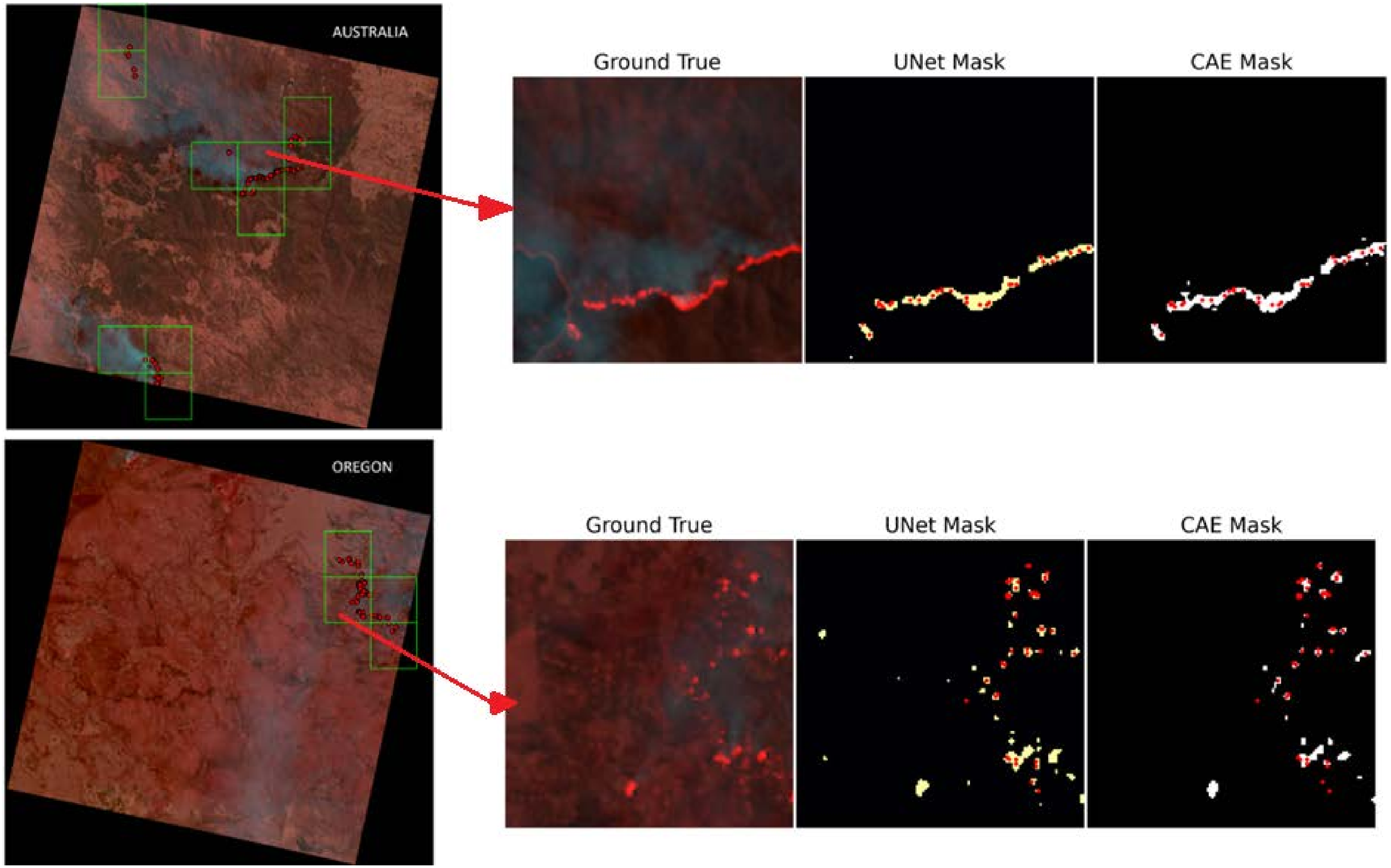
Training and Testing Results

Results of Transfer Learning on PRISMA test dataset

- **Quantitative and qualitative results** of the inference on the **PRISMA test set**, composed of patches extracted from **PRISMA hyperspectral images** of **Australia and Oregon**.

	Unet (%)
Accuracy	93.83
F1 Score	96.82
Recall	93.83



COTS Solutions for Edge Computing

COTS Solutions for Edge Computing

- Selection based on in-house hardware accelerators*:

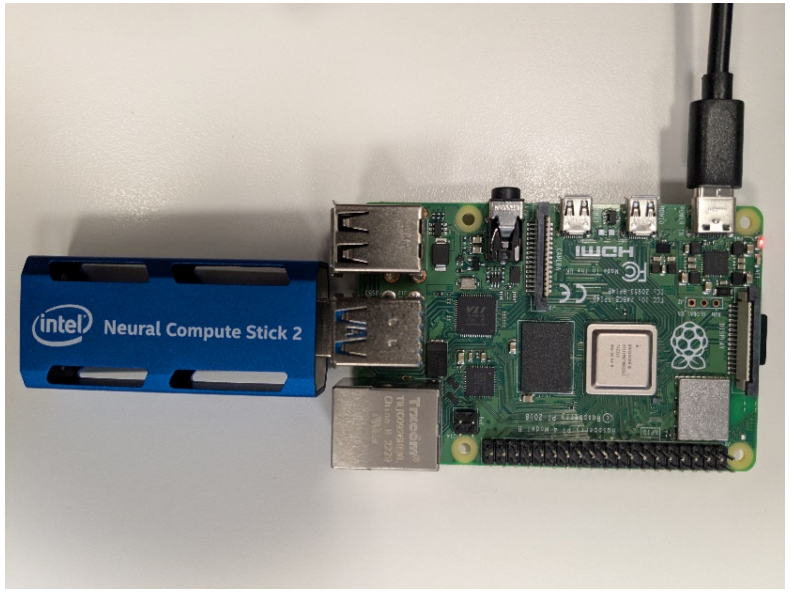
Hardware accelerator	Selected model	Rationale	Advantages	Future upgrades
Visual Processing Unit (VPU)	Intel® Movidius Myriad Neural Compute Stick (NCS2)	Selected as an in-house solution with a history of successful deployment in previous works [1]. Predecessor (NCS) used in space onboard the Φ-Sat-1 mission [2].	• Low power consumption. • Compact and efficient for AI inference	No upgrade planned for VPU.

*Other boards, such as Raspberry Pi 3B and Raspberry Pi 4B, are considered for use in tandem with the NCS 2.

- The final setup features the **Intel Neural Compute Stick 2 (NCS2)** connected to a **USB 3.0 port** of the **Raspberry Pi 4B**.

[1] D. Spiller, K. Thangavel, S. T. Sasidharan, S. Amici, L. Ansalone, and R. Sabatini, "Wildfire segmentation analysis from edge computing for on-board real-time alerts using hyperspectral imagery," in *2022 IEEE International Conference on Metrology for Extended Reality, Artificial Intelligence and Neural Engineering (MetroXRAINE)*, Rome, Italy: IEEE, Oct. 2022, pp. 725–730.
[2] G. Giuffrida *et al.*, "The Φ-Sat-1 Mission: The First On-Board Deep Neural Network Demonstrator for Satellite Earth Observation," *IEEE Trans. Geosci. Remote Sens.*, vol. 60, pp. 1–14, 2022.

VPU Solution

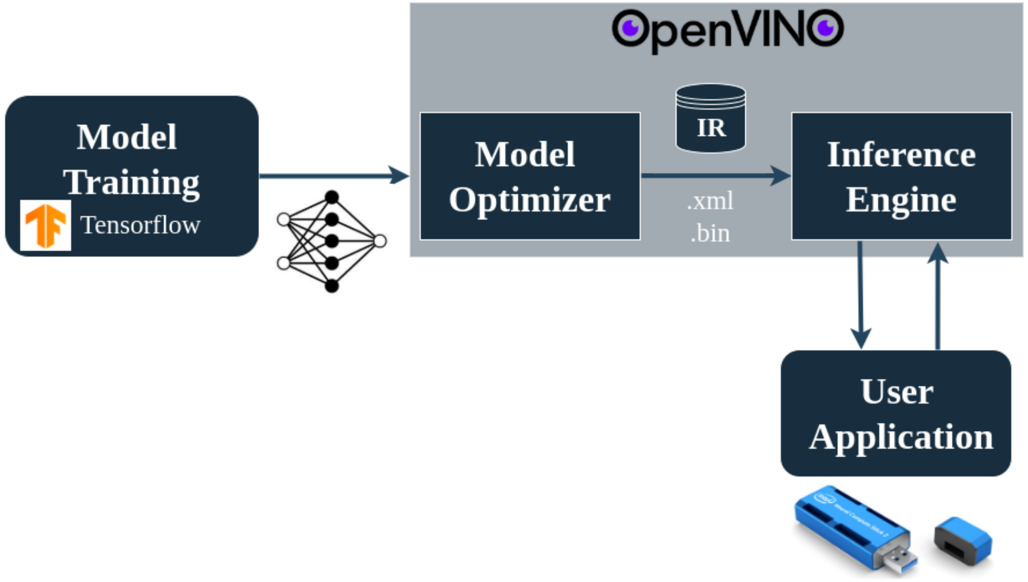


Final setup selected, consisting of a Raspberry Pi 4B with a Intel® Movidius Myriad Neural Compute Stick 2 (NCS2) connected to one of its USB 3.0 ports.

VPU Deployment for Real-Time Wildfire Detection

- The workflow for deploying the deep learning model using **OpenVINO (OpenVINO (Open Visual Inference and Neural Network Optimization) on the NCS2** consists of the following key steps:

  1. **Model Training**: the **U-Net** model is trained using TensorFlow Keras and saved in the saved_model format to ensure compatibility with OpenVINO.
  2. **Model Conversion:** Since the models were custom and not pre-optimized, we used *OpenVINO's Model Optimizer* to convert the model into Intermediate Representation (IR) format in floating Point 16 (FP16) precision. This process generates .xml and .bin files.
  3. **Inference:** after successful conversion, we used the *OpenVINO Inference Engine* execute the neural network on the user application.



Note: To ensure proper inference execution, the **test dataset** was preprocessed and converted to **FP16 precision** before being input into the inference engine.

COTS Solutions for Edge Computing

- **Efficiency** of the proposed **VPU and U-Net model pair**.

- **Performance considerations** about the proposed **U-Net/VPU pair:**

Metric	Intel® NCS2 VPU
Final accuracy	93.83%
Inference time	299 ms
Power consumption	1.32W
(Idle) Power consumption	0.48 W

Lesson Learned and Future Works

Lesson Learned and Future Works

- **Challenges encountered:**
  - ➢ **Outdated documentation** on OpenVINO-NCS2 integration, with many resources obsolete or unavailable.
  - ➢ **Intel suspended support** for NCS2 starting with **OpenVINO 2022.3.2 LTS**, limiting troubleshooting options.
  - ➢ **Difficult integration process** due to lack of up-to-date documentation and support, making system deployment more complex.

- **Future** hardware accelerators deployment:

Hardware accelerator	Selected model	Rationale	Advantages	Future upgrades
Field Programmable Gate Array (FPGA)	AMD/Xilinx Zynq UltraScale+ MPSoC with DPUCZDX8G IP core specifically the B1600 architecture.	Previously successfully explored in research group's prior work [3].	• Low power consumption. • High inference efficiency.	No upgrades considered up to now due to price constraints.
Graphic Processing Unit (GPU)	NVIDIA Jetson TX2 Developer Kit	Selected due to prior successful use in similar applications.	• Strong parallel processing capabilities.	Possible upgrade to **NVIDIA Orin Nano 4GB.**

[3] A. Cratere *et al.*, "Efficient FPGA-Accelerated Convolutional Neural Networks for Cloud Detection on CubeSats," *IEEE J. Miniaturization Air Space Syst.*, pp. 1–1, 2025.

THANKS FOR YOUR ATTENTION!