Background

1. State-of-the-art CNNs for Cloud Image Segmentation

CNNs are a class of neural networks that apply small, learnable filters – known as convolutional kernels – across an image to extract spatial features. A CNN typically consists of multiple convolutional layers stacked sequentionally. Each layer applies a set of filters that capture different visual patterns, such as edges or textures. As the network goes deeper, the spatial resolution of the image decreases, while the depth (i.e., number of channels) increases. This is a result of applying multiple filters and optionally using pooling layers, which downsample feature maps to reduce computational complexity and introduce spatial invariance.

In image segmentation tasks such as cloud detection, preserving spatial resolution is critical. Therefore, architectures often include an upsampling mechanism to reconstruct high-resolution output from compressed feature representations. This is achieved through transposed convolution (also known as deconvolution). While standard convolution reduces spatial resolution by aggregating local pixel values, transposed convolution performs the reverse: it distributes each value in the smaller feature map across a larger output, effectively increasing spatial dimensions and reversing the compression.

One of the most influential architectures for image segmenation is the U-Net. Originally introduced by Ronneberger et al [\*\*\*] for biomedical image segmentation, U-Net has become a standard in many domains, including remote sensing and cloud detection. A U-Net consists of an encoder-decoder structure. The encoder compresses the input image spatially while increasing its feature dimensionality. The decoder then reconstructs the spatial dimensions, progressively reducing the number of channels. The U-Net architecture shown in the diagram 1 was used by Mohajerani et al. [\*\*\*] for their cloud detection algorithm.

A key innovation in U-Net is the use of skip connections, which dierectly link feature maps from the encoder to corresponding layers in the decoder with the same spatial size. These connections preserve fine-grained spatial details and significantly enhance segmentation quality. Moreover, they mitigate the vanishing gradient problem, facilitating the training of deeper networks and improving convergence.

1. Google Coral Dev Board Mini and Edge TPU

Running machine learning inference on embedded systems is referred to as edge inference. The Coral dev Board Mini, developed by Google, is a compact single-board computer designed for such edge AI applications. It features quad-core MediaTek 8167s System-on-a-Chip (SoC) on the Armv8-A architecture, along with a dedicated Edge TPU – a hardware accelerator optimized for executing TensorFlow Lite models using 8-bit integer operations.

The Edge TPU delivers up to 4 trillion operations per second (TOPS) of performance while consuming only around 2 watts of power, making it ideal for use in resource-constrained environments such as satellites, where energy efficiency and reliability are crucial.

To deploy a model on Edge TPU, it must be:

* Converted into the TensorFlow Lite (.tflite) format,
* And fully quantized to 8-bit integers.

These requirements directly affect model architecture, training strategy, and tooling. For instance, certain operations unsopported by Edge TPU must be avoided, and quantization aware training or post-training quantization must be considered early in the development process.

The following image from Coral documentation summarizes the model conversion and deployment workflow.

1. 38-Cloud Landsat 8 dataset

Landsat 8 is an Earth observation satellite launched on February 11, 2013, providing high-resolution multispectral imagery, including visible, near infrared (NIR), and thermal infrared bands. For cloud segmentation tasks, the red, green, blue (RGB) and NIR channels are particularly valueable due to their ability to capture both visual and athmospheric information.

This thesis utilizes a dataset consisting of 38 annotated satellite images from the Landsat 8 mission, commonly referred to as the 38-Cloud dataset. [\*\*\*]. The dataset has been introduced and adapted in the following scientific publications [\*\*\*]. Each image contains four spectral channels (RGB and NIR), along with a manually annotated dround truth mask that labels cloud pixels at the pixel level.

The dataset is divided into a training set containing 18 scenes and a test set with the remaining 20 scenes.

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*In this thesis, a dataset consisting of 38 cloud-annotated images from the Landsat 8 mission is used. The dataset was presented and adjusted in the following scientific papers. Each image includes 4 channels – RGB and NIR – as well as the corresponding manually extracted pixel-level ground truth. The dataset is split into training part containing 18 sceneids and testing part containing respectively 20 sceneids.*

Motivation

Electronic components in satellites and spacecraft are exposed to intense radiation, high-energy particles, and extreme temperature fluctuations. To ensure reliability under these harsh conditions, manufacturers traditionally use certified space-grade components. However, design, production, and certification of such components are costly and time-consuming.

The AITHER project aims to investigate whether COTS (Commercial Off-The-Shelf) components can be effectively used in mano- and microsatellites (10-100 kg). Specifically, the project explores the feasibility of using COTS-based onboard architecture to perform reliable and computationally demanding tasks, such as matrix operations, directly in space.

As part of this initiative, the 10kg nanosatellite OOV-CUBE was launched into orbit on July 9th 2024. Among its hosted payloads is the Coral Dev Board Mini – a single-board computer developed by Google with an embedded Edge TPU designed for fast, low-power machine learning inference in constrained environments.

Alongside radiation shielding and thermal managements strategies, a technology demonstrator is being developed to assess the tolerance of these components to space radiation (e.g. protons, gamma rays). A central objective of the project is to determine not only how broadly COTS components can be applied in space systems, but also whether complex image processing tasks can be carried out onboard. This would reduce the need for data downlink and significantly improve the efficiency of Earth observation and communication missions.

Thesis goal

AITHER project launched a 10kg nanosatellite OOV-CUBE on 9th of July 2024. Besides other hosted payloads not relevant for this thesis it is carrying Coral Dev Board Mini developed by Google – a single-board computer with an embedded Edge TPU module primarily made to provide fast machine learning inferencing in a small form factor. Radiation shielding and thermal diffusion were already taken into consideration by design of the satellite. The software for AI inference has now to be developed and uploaded to the board in orbit. As a software a CNN for cloud segmentation was chosen. Even though efficient CNN architectures are already existing and were studied in scientific papers, the embedded implementation of a complex deep learning algorithm has its own caveats. Due to restricted resources provided by an embedded system such as limitations in flash and RAM-memory, CPU and TPU capacity and speed, there are certain decisions to be made and the tricks applied in order to implement the CNN model in Coral Dev Board mini flawlessly. This is the main goal of this thesis

While the satellite’s structure was designed with radiation shielding and thermal management in mind, the software for onboard inference still needs to be developed and uplinked in the orbit. This thesis focuses on the implementation of a convolutional neural network (CNN) for cloud segmentation from satellite imagery. Although lightweight CNN architectures already exist and have been described in recent scientific literature, porting such a model to an embedded platform introduces unique challenges. These include limitations in memory, computation power of both central processing unit (CPU) and tensor processing unit (TPU) as well as model format compatibility.

The goal of this thesis is to design, train and deploy a CNN model for cloud segmentation on the Coral Dev Board Mini. The core task is to adapt the model for efficient inference on the Edge TPU, overcoming hardware constraints while maintaining acceptable segmentation performance. This work serves as a demonstration of the potential to carry out deep learning inference onboard a satellite using COTS hardware.

**Chapter 1: Introduction**

Electronic components used in satellites and spacecraft are exposed to intense radiation, high-energy particles, and extreme temperature fluctuations. To ensure reliability in such harsh conditions, traditional space missions rely on certified space-grade hardware. However, this approach significantly increases development time and cost.

The AITHER project, launched by TU Berlin, aims to explore the feasibility of using commercial off-the-shelf (COTS) components in small satellites, particularly nanosatellites in the 10–100 kg range. As part of this initiative, the 10 kg nanosatellite OOV-CUBE was launched into orbit on July 9th, 2024. Among its hosted payloads is the Coral Dev Board Mini, a single-board computer equipped with an Edge TPU module designed for fast and efficient AI inference in embedded applications.

While the satellite’s hardware was designed with radiation shielding and thermal management in mind, the software for onboard inference still needs to be developed and uploaded. This thesis focuses on the implementation of a convolutional neural network (CNN) for cloud segmentation from satellite imagery. Although lightweight CNN architectures already exist and have been described in recent literature, porting such a model to an embedded platform introduces unique challenges. These include limitations in memory, computation, and model format compatibility.

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The scope of the thesis is limited to software-side implementation and validation. No real-time satellite communication is covered, and radiation tolerance is considered only in context, not experimentally. The input dataset is restricted to the publicly available Landsat 8 satellite imagery.

To achieve this goal, the thesis first reviews the relevant CNN architectures for cloud detection, selects an appropriate model, and trains it using available satellite data. The trained model is then converted and quantized for deployment on the Edge TPU. Finally, inference performance is evaluated directly on the Coral Dev Board Mini.

The structure of the thesis is as follows:  
Chapter 2 provides background on cloud segmentation and embedded deep learning.  
Chapter 3 outlines the implementation steps, from model selection to deployment.  
Chapter 4 presents the evaluation results.  
Chapter 5 concludes the work and discusses possible future directions.