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Advances in Long-term Water Quality Monitoring through Data Fusions

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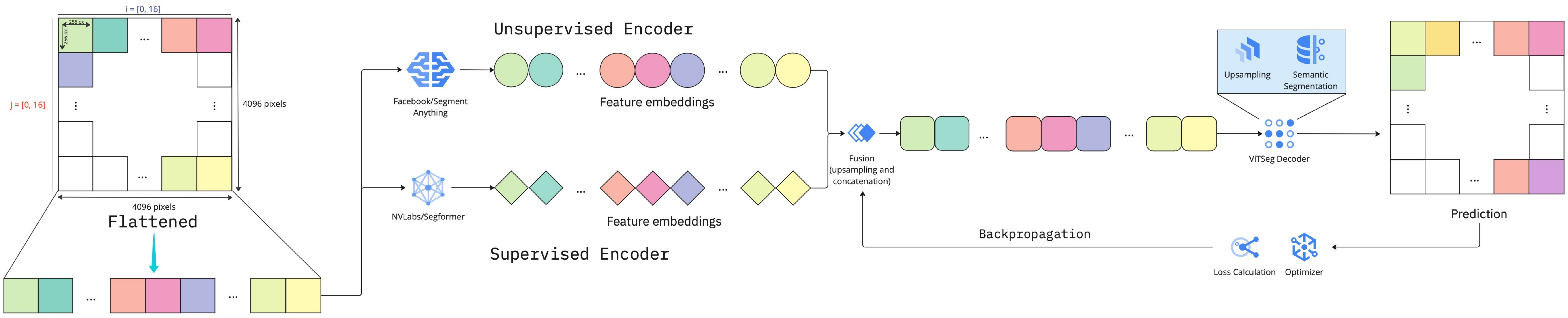
Introduction

Images of inland water bodies from space can provide insights into the spatial and temporal distributions of ecological phenomena that indicate water quality, such as harmful algae blooms, blackwater events and acid sulphate soils (Fan et al., 2021). This first half of the research is tackling the upstream challenge of segmenting water from other ecological artifacts (such as land, animals, vegetations, etc) in satellite images in order to clean the data for downstream tasks. Furthermore, as we train the semantic segmentation model, the (later) detection model will also learn to partially detect features of water as well.

Methods

We utilize the pretrained checkpoints of two state-of-the-art models in semantic segmentation, Facebook's SAM and Nvidia's Segformer, for our dual branch encoder. SAM is an unsupervised, zero-shot model; therefore, it will pick up and learn the relationships between independent features. On the other hand, Segformer is traditional supervised model; thus, it will handle connecting the identified features with the ground truth. Our biggest contribution is the VitSeg decoder, which will upscale the features to the original size while also performing prediction using self-attention network.



Aims

This project aims to:

- develop a semantic segmentation model, using vision transformer backbone, for ultra-high resolution satellite data
- produce state-of-the-art performance (mIoU), while solving current SOTA model's biggest challenge, memory scarcity (Chen W, 2022)
- enable downstream tasks of water quality detection, on pixel level
- integrate deep learning models with practical use cases set by our industry partner, the Bureau of Meteorology

References

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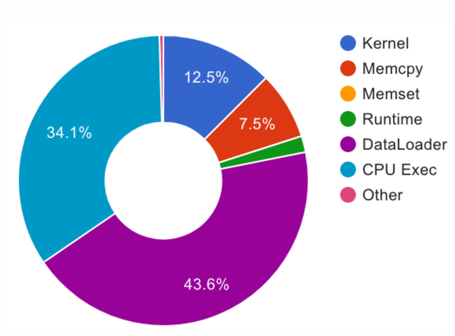
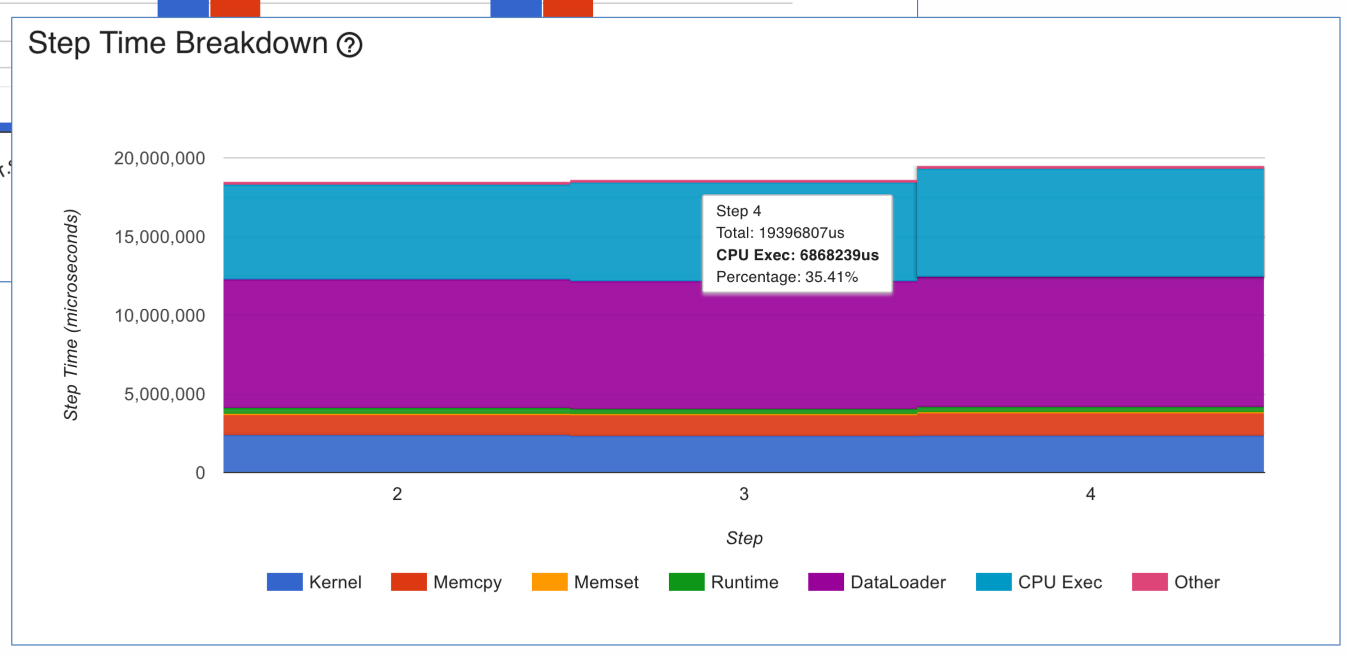
Results

The model yields satisfactory initial results, with mIoU at around 70, in comparison to the current benchmark set by ElegantSeg, which is at 62 mIoU. Given that our first goal was satisfied, we are working on the second one, which is to reduce the memory demand for each training cycle. Our result was achieved by splitting the original 4k image into 16x16 patches of 256x256 crops. Each crop is fed through the encoders and turned into an embedding and then subsequently put through the decoder. This process was proposed as a measure to reduce the memory footprint, because we save the embeddings to disk and reload them back to the model, so the memory did not have to store the entire model. However, this posed a successive problem, which is the bottle neck caused by the data loader. As can be seen in the diagram on the right, the model spends 44% of the time loading the encoded embedding. One solution we are persuiting is reducing the channels of the embeddings, so that they can be loaded faster. This comes with the trade-off of having fewer features for the decoder to work with. A few other solutions are: using mixed precision, reducing model depth, data parallel, etc.





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