UCC AI Quest 2023

Infection Team

Outline

1. Introduction (About the team)
2. Problem Investigation (Describe your understanding of the problem)
3. Challenges
4. Solution (Architecture / AI Model / Validation / Testing)
5. Discussions & Insights (What is good about your solution)
6. Conclusion

Introduction - Our Team

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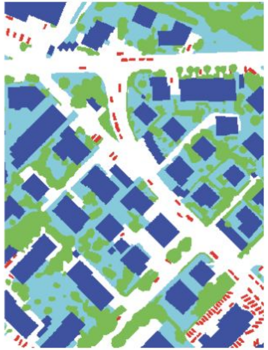
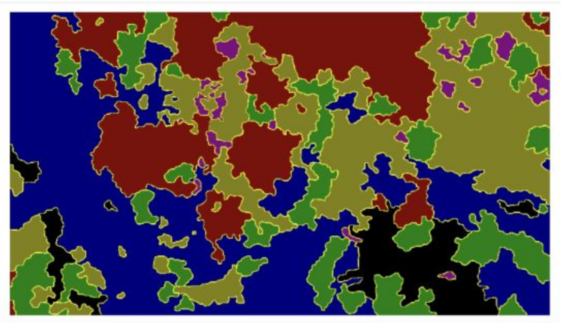
Problem Investigation

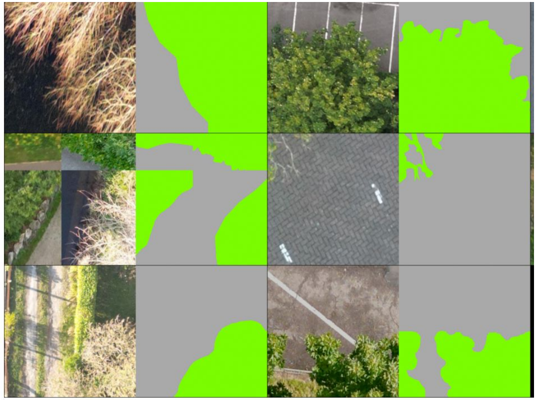
- This is a new problem, limited literature investigation
- Similar to remote sensing image segmentation, Aerial and Optical Images-Based Plant Species Segmentation





Challenges

- The small-scaled of the dataset:
  - **Public**: 4322 images in Train set & 689 images for Valid Set
  - **Warmup + Public**: 4658
  - **Private**: 783



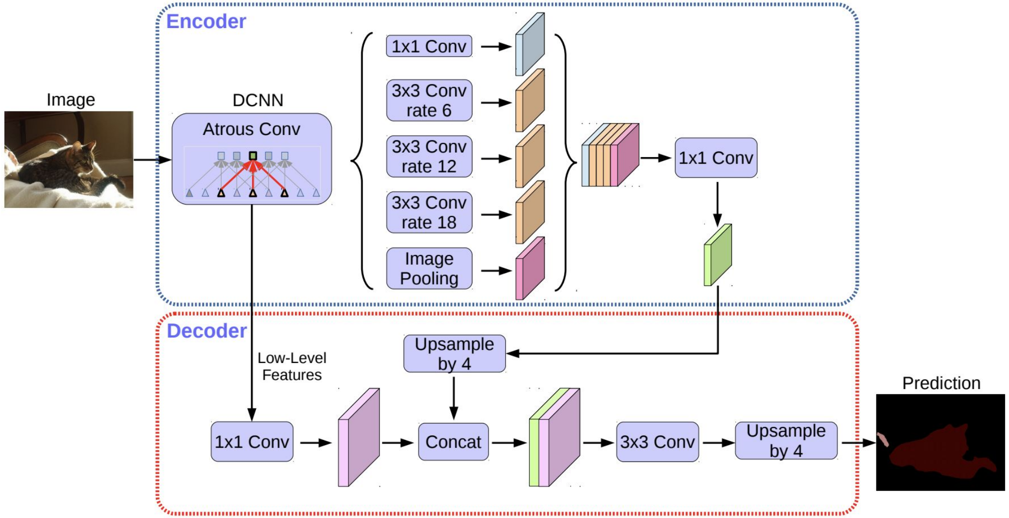
Some input examples

Results on Private Test

Models	High Vegetation IoU	High Vegetation Acc
Ours (DinoV2 & UNet++ & DeepLabv3+)	**86.67**	**93.97**
Ours (DinoV2)	86.5	94.00
Ours (UNet++ & DeepLabv3+)	84.6	92.43
vantuan5644	85.61	92.85
philip1	83.35	89.60

Solution - Models

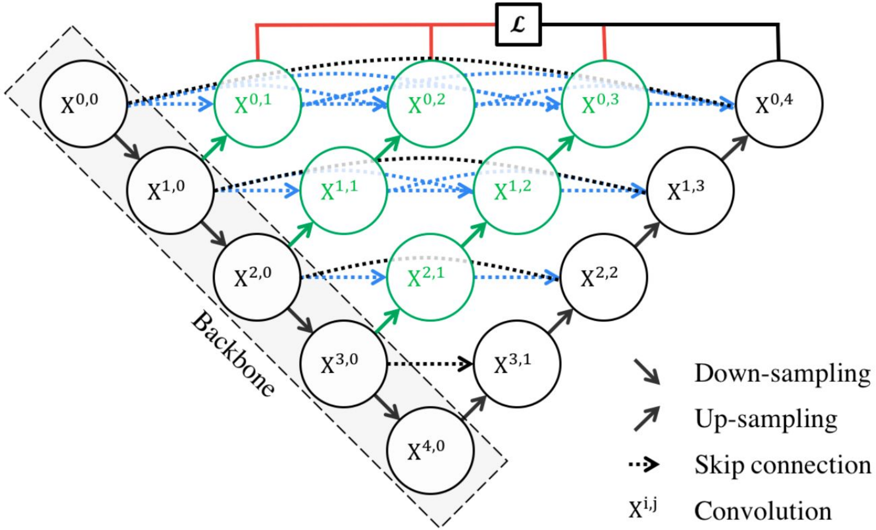
- Two **DeepLabV3+** with EfficientNet-b4 & EfficientNet-b5 backbone



Encoder-Decoder with Atrous Separable Convolution for Semantic Image Segmentation (Chen; 2018)

Solution - Models

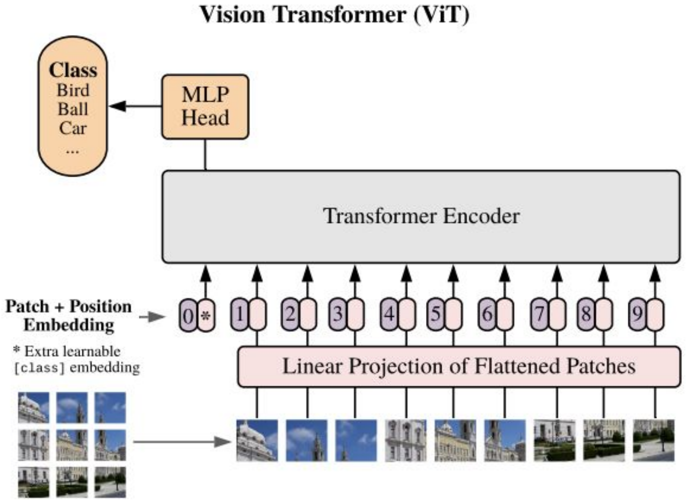
- One **UNet++** model with EfficientNet-b4 backbone



UNet++: A Nested U-Net Architecture for Medical Image Segmentation (Zhou; 2018)

Solution - Models

- Use ViT-b14 of DinoV2 as backbone, **add two Fully Convolutional Network Layers**, then re-train the model



DINOv2: Learning Robust Visual Features without Supervision (Oquab; 2023)

Solution – Loss function & Data Augmentation

- Our Loss function is the summation of **Dice Loss** and **Bootstrapping Cross Entropy Loss** (OHEM)
- For data augmentation, we employed **Mosaic image augmentation** with **spatial & color augmentation** including Random Crop, Horizontal & Vertical flip, Hue Saturation on the train set.

Solution – Training Methods

- **Challenges: Small-scaled dataset → Large-scaled model would be hard to converge during training**
- **Training tricks for fast convergence:**
  1. Freeze the encoder backbone layers, only train/fine-tune the segmentation head/decoder layers.
  2. Unfreeze all the layers of the network, fine-tune the whole model with 10 times smaller learning rate

Solution – Models Ensemble

- We choose top 5 models that have highest metric score on our validation set:
  - two deeplabv3+ (efficientnet B4&B5)
  - one unet++ (efficientnet B4)
  - and one DinoV2 (base);
- We gathered all the probability masks predicted by the models and average them to get the final segmentation mask for the private set

Results on Private Test

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Discussion and Insights

Ideas:

- Talk about what we have tried? What worked and what didn’t?
    - ViT as backbone but didn't improve the results
    - Try to “smoothen” the boundary of the segment in predictions but didn't improve the results
    - YOLOv8 but data conversion is complicated, requires high-quality masks.
- How to improve in the future?
    - Implement hyperparameter tuning more thoroughly
    - Replace two-layer FCNs with more complex segmentation head (for example, Mask2Former head)

Conclusion

Our main contributions:

- Training a **DinoV2-ViTB14** with a **customized two-layer FCN** for semantic segmentation task.
- Combining both region-based and class-based loss functions as objective function, namely **Dice loss and OHEMCE loss**
- Applying **Mosaic augmentation** to generate variety of complex data scenarios to enhance models' training
- Introducing simple yet effective **technique to finetune** small-scaled dataset on such large state-of-the-art model
- Employing **ensemble method** that further boost the precision of predicted masks

Thank you