Remote Sensing Data Augmentation for Building Damage Extraction

GISLab Short-Term Course 2025 Summer

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Outline

- What is Sementic Segmentation?
- How Can We Improve It? (Data Augmentation)
- Real-World Example: Disaster Images
- Project: Can AI-Generated Images Help?

Introduction to Sementic Segmentation

What is Semantic Segmentation?

- Semantic segmentation means labeling each pixel in an image with a class (e.g., building, road, water).
- It helps computers understand exactly where objects are in a picture.

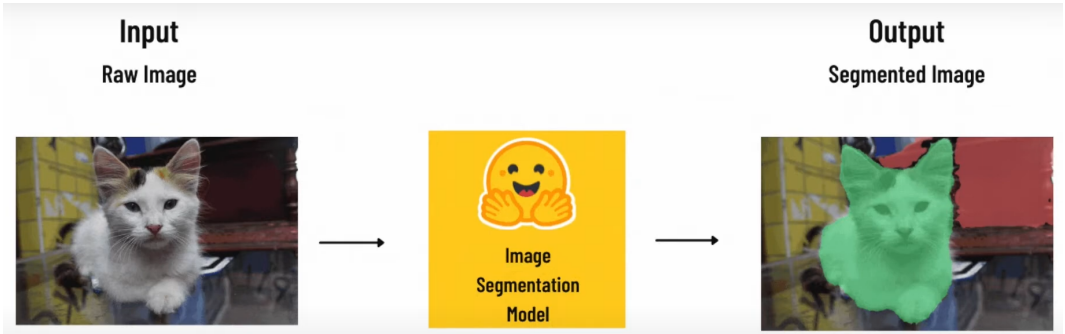

Figure: Illustration of Image Segmentation.

SegEarth-OV: Training-Free Open-Vocabulary Segmentation

Figure: SegEarth-OV framework for open-vocabulary segmentation (Li et al., 2025).

Li, et al. SegEarth-OV: Towards Training-Free Open-Vocabulary Segmentation for Remote Sensing Images, CVPR(Oral), 2025.

How Can We Improve Sementic segmentation? (Data Augmentation)

Why Use Data Augmentation?

- Sometimes we do not have enough images to train a good model.
- Data augmentation means making new images from existing ones.
- It helps the model learn better and avoid mistakes.

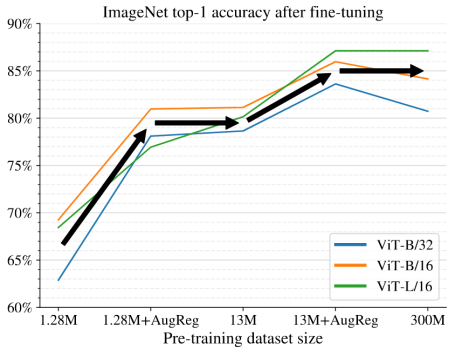

Figure. Adding the right amount of regularization and image augmentation can lead to similar gains as increasing the dataset size by an order of magnitude. (Steiner et al., 2022)

Steiner, et al. How to Train Your ViT? Data, Augmentation, and Regularization in Vision Transformers. TMLR. 2022.

How Do We Augment Data?

Classic Methods:

- Flip, rotate, crop, change colors, etc.

Modern Methods:

- Mix two images together (Mixup) (Zhang et al., 2018).
- Cut and paste parts of images (CutMix) (Yun et al., 2019).

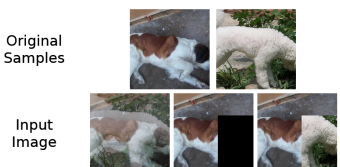

Figure: Illustration of modern augmentation methods. From Left to Right: Mixup (Zhang et al., 2018), Cutout (DeVries and Taylor, 2017), and CutMix (Yun et al., 2019).

Soft Label Example (CutMix):

$$\text{cutmix\_label} = \lambda \cdot \text{label}_A + (1 - \lambda) \cdot \text{label}_B$$

Example: $\lambda = 0.5, \quad \text{label}_A = [1, 0], \quad \text{label}_B = [0, 1]$

$$\text{cutmix\_label} = 0.5 \times [1, 0] + 0.5 \times [0, 1] = [0.5, 0.5]$$

Zhang, et al. Mixup: Beyond Empirical risk minimazation, ICLR, 2018.
Yun, et al. CutMix: Regularization Strategy to Train Strong Classifiers With Localizable Features, ICCV, 2019.
DeVries, et al. Improved Regularization of Convolutional Neural Networks with Cutout, arXiv, 2017.

Using Gen AI to Make New Images

- Generative models can create new, realistic images.
- We can use them to make more training data.
- Example: Give a "before" image and a description, get a new "after" image.

X_{pre}

+ suffer from volcano eruption

C_T

$X_{post} \sim p(X|X_{pre}, C_T)$

Generative Models

X_{post}

Real-World Example: Disaster Images (xBD)

xBD: A Large-Scale Disaster Damage Dataset

xBD (Gupta et al., 2019) is a bi-temporal remote sensing dataset covering 19 distinct disaster events. Pre-disaster imagery (top) and post-disaster imagery (bottom). From left to right: Hurricane Harvey; Joplin tornado; Lower Puna volcanic eruption; Sunda Strait tsunami.

Table. 19 Disaster events in xBD.

Disaster Type	Disaster Event	Event Date
Earthquake	Mexico City earthquake	Sep 19, 2017
Wildfire	Portugal wildfires	Jun 17–24, 2017
Wildfire	Santa Rosa wildfires	Oct 8–31, 2017
Wildfire	Carr wildfire	Jul 23–Aug 30, 2018
Wildfire	Woolsey fire	Nov 9–28, 2018
Wildfire	Piner fire	Nov 25–Dec 2, 2018
Volcano	Lower Puna volcanic eruption	May 23–Aug 14, 2018
Volcano	Guatemala Fuego volcanic eruption	Jun 3, 2018
Storm	Tuscaloosa, AL tornado	Apr 27, 2011
Storm	Joplin, MO tornado	May 22, 2011
Storm	Moore, OK tornado	May 20, 2013
Storm	Hurricane Matthew	Sep 28–Oct 10, 2016
Storm	Hurricane Florence	Sep 10–19, 2018
Flooding	Monsoon in Nepal, India, and Bangladesh	Aug 2017
Flooding	Hurricane Harvey	Aug 17–Sep 7, 2017
Flooding	Hurricane Michael	Oct 7–16, 2018
Flooding	Midwest US floods	Jan 3–May 31, 2019
Tsunami	Indonesia tsunami	Sep 18, 2018
Tsunami	Sunda Strait tsunami	Dec 22, 2018

Gupta, et al. xBD: A Dataset for Assessing Building Damage from Satellite Imagery, arXiv, CVPRW, 2019.

Project: Can AI-Generated Images Help?

Project: What Will You Do?

- Test if adding AI-generated images helps the model learn.
- Try three ways:
  - Only real images
  - Only generated images
  - Both real and generated images
- See which way gives the best results!

Project: Dataset Details & How to Generate Images

- Use 100 real images per disaster type (6 types, 600 images total).
- For each type, generate 100–400 new images using AI.
- Try different mixes: 1:1, 1:2, 1:3, 1:4 (real:generated).
- Use commercial AI models (e.g., GPT-Image-1 (OpenAI, 2025), Gemini 2.5 Pro (Gemini Team, Google, 2025), SeedEdit 3.0 (Wang et al., 2025)) to generate images.
- Input: a "before" image and a short description (e.g., "make it suffer from flooding").
- Output: a new, realistic "after" image.

OpenAI. GPT-Image-1, 2025.
Gemini Team, Google (2025). *Gemini 2.5: Pushing the Frontier with Advanced Reasoning, Multimodality, Long Context, and Next Generation Agentic Capabilities.*
Wang, et al. SeedEdit 3.0: Fast and High-Quality Generative Image Editing. arXiv. 2025.

Which Models to Use & How to Measure Success

- **Try these models:**
  - CLIPSeg (Lüddecke and Ecker, 2022)
  - MaskCLIP (Zhou, Loy, and Dai, 2022)
  - ClearCLIP (Lan et al., 2024)
- **How to measure success:**
  - Use standard metrics for segmentation:
    - **IoU (Intersection over Union):** Measures overlap between predicted and true regions.
    - **F1 Score:** Harmonic mean of precision and recall for segmentation.
    - **Pixel Accuracy:** Percentage of correctly classified pixels.
  - Compare results for each data mix (real, generated, both).
  - Visualize and analyze which combination works best.

Lüddecke, et al. Image Segmentation Using Text and Image Prompts, CVPR, 2022.
Zhou, et al. Extract Free Dense Labels from CLIP, ECCV, 2022.
Lan, et al. ClearCLIP: Decomposing CLIP Representations for Dense Vision-Language Inference, ECCV, 2024.