Integration of Deep Learning (DL) in Geospatial Object-Based Image Analysis (GEOBIA) for Image Segmentation in Remote Sensing Tasks

Project - CSE598: Machine Learning for Remote Sensing

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Problem Statement

Traditional remote sensing image analysis often relies on pixel-based segmentation followed by machine learning classification. This approach has limitations, particularly in handling high-resolution imagery and capturing contextual information, and is therefore being replaced by Object-Based Image Analysis (OBIA), which consists of two steps: segmentation (grouping of pixels into super-pixels to generate “objects”) and classification (classifiying the objects obtained from the previous steps into different required classes). OBIA offers advantages by incorporating spatial and spectral context, reducing noise, and better reflecting real-world structures.

However, OBIA's segmentation stage often involves manual feature selection and parameter tuning, making it subjective and time-consuming. While deep learning (DL) excels at automatic feature extraction, its integration within OBIA workflows remains limited. This is due to challenges in adapting pixel-centric DL segmentation models to object-based frameworks, concerns about computational overhead, and the lack of clear advantages of DL over traditional machine learning techniques in terms of accuracy (Blaschke, 2010)for OBIA classification.

This project aims to bridge this gap by developing a novel framework that effectively integrates DL into OBIA pipelines for remote sensing image analysis. The goal is to automate feature extraction for segmentation, improve classification accuracy, and address the challenges of scale variance in DL models, ultimately enhancing the efficiency and performance of OBIA workflows.

Related Work

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Dataset(s)

Since OBIA is more suited for high-resolution images, I will use high-resolution imagery with resolution <= 10 meters. Furthermore, I am interested in exploring if any special treatment is required for image segmentation and classification for the agricultural domain. I searched on Google for the dataset selection, but the most relevant results were from the EarthNets website and other benchmark datasets covered in the class. For the filtering criteria, I chose the resolution <= 10 m, task as semantic segmentation, and area as agriculture. Here are the final datasets that I found relevant for this project:

Dataset	# Classes	Resolution (meters)	Image type	Volume (GB)	Link
Geo-bench 6 datasets	2, 7, 10	0.1, 1, 10	RGB, Sentinel-2, Hyperspectral	65	GEO-Bench: Toward Foundation Models for Earth Monitoring
Sustainbench Field Delineation	2	10	Sentinel-2	0.0003	Field Delineation - SustainBench
GF2 Dataset for 3DFGC	5	4	RGB-NIR	0.056	GF2 Dataset for 3DFGC
TimeSen2Crop	16	10	Sentinel-2	1.1	TimeSen2Crop: a Million Labeled Samples Dataset of Sentinel 2 Image Time Series for Crop Type Classification
Agriculture-Vision	9	0.1~0.2	RGB-NIR	4.4	Vision for Agriculture - Prize Challenge 2024
WHU-Hi 3 datasets	8, 9, 11	0.04~0.46	Hyperspectral	0.8	WHU-Hi: UAV-borne hyperspectral and high spatial resolution (H 2) benchmark datasets for crop precise classification
Sen4AgriNet	158	10~60	Sentinel-2	10,240	Sen4AgriNet
ZueriCrop	48	10	Sentinel-2	39	https://polybox.ethz.ch/index.php/s/uXfdr2AcXE3QNB6
EuroCrops	43	10	Sentinel-2	8.6	The official repository for the EuroCrops dataset.

In the interest of time, I would start my analysis first with GEO-Bench, which provides six different datasets for semantic segmentation tasks, which would be appropriate to try out models across different types of datasets. Moreover, GEO-Bench provides an easy download link, preprocessing steps, and benchmarks, allowing me to evaluate my method's efficacy compared to the GEO-Bench baselines.

Geobench Dataset	Image Size	# Classes	Train (%)	Val (%)	Test (%)	# Bands	Resolution (m)	Sensor
m-pv4ger-seg	320x320	2	80	10	10	3	0.1	RGB
m-chesapeake-landcover	256x256	7	60	20	20	4	1.0	RGBN
m-cashew-plantation	256x256	7	75	22	3	13	10.0	Sentinel-2
m-SA-crop-type	256x256	10	60	20	20	13	10.0	Sentinel-2
m-nz-cattle	500x500	2	80	10	10	3	0.1	RGB
m-NeonTree	400x400	2	60	20	20	5	0.1	RGB + Hyperspectral + Elevation

Method(s)

I will employ a three-pronged comparative analysis to evaluate the efficacy of integrating deep learning (DL) into object-based image analysis (OBIA) for remote sensing image segmentation:

1. OBIA Baseline

- **Image Segmentation:** will be conducted using both ArcGIS (leveraging my ASU license) and a Python-based OBIA implementation employing the standard computer vision segmentation algorithms such as Simple Linear Iterative Clustering (SLIC).
- **Justification**: This establishes two baselines: (a) results achievable with commercial GIS-OBIA tools, and (b) a replicable open-source implementation for broader comparison.

2. DL-Only Segmentation

- **Models**: Standard DL segmentation models, including UNet and Mask R-CNN, will be trained and evaluated on selected datasets.
- **Optimization**: These models will utilize standard pixel-level loss functions during optimization.

3. Hybrid DL-OBIA Approach

- **Segmentation Feature Extraction**: DL models (potentially modified from those used in step 2) will be employed for feature extraction on the object level rather than the pixel level. These features will then drive the segmentation process within an OBIA framework.
- **Loss Function**: Object-level loss functions will be investigated and implemented to guide DL model training, ensuring alignment with the object-based nature of the task.

Dataset and Tools

- **Datasets**: Six semantic segmentation datasets from Geobench will be utilized, ensuring a diverse benchmark.
- **Preprocessing and Data Handling**: GEO-Bench will provide standardized dataset loading and preprocessing.
- **DL Implementation**: PyTorch and the TorchGeo library will serve as the core frameworks for DL model development and modification using Python.

Additional Considerations

Literature Review: Thorough research on existing literature addressing DL-OBIA integration will be conducted to inform model architecture choices and identify potential novel approaches.
Use of Generative AI: I have prepared the report in my own words after doing research from multiple sources cited. I used ChatGPT and Gemini to refine my writing to increase the readability, understanding, and presentation of the ideas.

Experiments/Evaluation

1. Experimental Design

- **Dataset Selection**: Six GEO-Bench semantic segmentation datasets.
- **Comparative Setup**:
  - Train and evaluate the OBIA baselines (ArcGIS & Python w/ SLIC).
  - Train and evaluate the DL-only models (UNet, MaskRCNN).
  - Develop the DL-OBIA hybrid model, specifying the feature extraction architecture and object-level loss function.
  - Compare all approaches against the GEO-Bench benchmark results

2. Quantitative Evaluation

- **Metrics**:
  - **Core**: DICE score, Intersection over Union (IoU), precision, recall, F1-score.
  - **Object-Level (if applicable)**: Metrics that evaluate whole-object segmentation quality. Research might be needed to find these.
- **Statistical Analysis**: Employ appropriate statistical tests (e.g., t-tests, ANOVA) to determine the significance of performance differences between the OBIA baseline, DL-only, and the proposed DL-OBIA hybrid approach.

3. Qualitative Assessment

- **Visual Inspection**: Carefully examine the segmentation masks produced by each method alongside the ground truth (or high-resolution reference imagery) manually. Identify specific qualitative strengths and weaknesses, such as:
  - Object boundary accuracy
  - Differentiation of visually similar classes
  - Reduction of over- or under-segmentation compared to the baselines.
- **Expert Evaluation (optional)**: If feasible, involve domain experts (remote sensing specialists) and/or people from the Kerner Lab to provide qualitative feedback on the real-world applicability of the results.

4. Comparison to Prior Work

- **Literature Search**: Expand the literature review to identify relevant studies that have used DL-OBIA methods or similar segmentation approaches on remote sensing datasets.
- **Comparative Analysis**: Where possible, compare the results (especially DL-OBIA hybrid) to the performance reported in those studies. Discuss similarities, differences, and any insights gained for furthering the research.

Initial Hypothesis

The integration of DL techniques into the segmentation stage of OBIA has the potential to significantly improve segmentation accuracy and robustness compared to traditional OBIA methods. This project will investigate how DL-driven segmentation within OBIA workflows can be optimized and adapted to perform consistently across diverse remote sensing domains and datasets.

The template for my future results are as follows:

METRIC Dice Score	Previous Method A (OBIA only)	Previous Method B (DL only)	My Proposed Method (OBIA + DL)
Dataset X			
Dataset Y			

METRIC IoU	Previous Method A (OBIA only)	Previous Method B (DL only)	My Proposed Method (OBIA + DL)
Dataset X			
Dataset Y			

References

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