Self-Supervised Learning for Crop Field Boundary Detection in Satellite Imagery

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Accurate delineation of crop field boundaries from satellite imagery is a critical task for agricultural monitoring, especially in smallholder farming systems. However, the availability of high-quality, annotated data for training supervised segmentation models remains a major bottleneck. Recent work [1] has demonstrated the effectiveness of transfer learning and weak supervision to mitigate this issue. In this study, we investigate the potential of self-supervised learning (SSL) as an alternative strategy for learning useful image representations without relying on large labeled datasets.

We focus on binary semantic segmentation for detecting crop field boundaries in high-resolution multispectral images from the PlanetScope satellite, covering the Kharkiv region in Ukraine. Ground truth field boundaries were manually collected for a subset of images. Given the limited size of this dataset, we adopt a U-Net architecture with a ResNet-18 encoder as our baseline model.

Our SSL-based approach explores several recent methods for representation learning, including DenseCL [2] and SimSiam [3]. Pretraining is conducted on unlabeled satellite images, followed by fine-tuning on the limited labeled set. Performance is evaluated using per-pixel F1 score and matching field F1 score, the latter being more sensitive to the geometrical correctness of predicted boundaries.

Additionally, we experiment with foundation models such as Clay [4], which was pretrained on large-scale remote sensing data using SSL. These experiments aim to assess the performance of large SSL-based encoders in downstream segmentation tasks and to evaluate their potential benefits in low-annotation regimes.

Preprocessing steps include image enhancement and extraction of square patches to standardize inputs across spatial contexts.

This study aims to highlight the applicability of SSL methods in remote sensing scenarios with scarce annotations and to provide insight into their advantages over traditional transfer learning approaches.

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1. Wang S., Waldner F., Lobell D. B. Unlocking large-scale crop field delineation in smallholder farming systems with transfer learning and weak supervision. arXiv preprint arXiv:2201.04771, 2022.
2. Wang X., Zhang R., Shen C., Kong T., Li L. Dense Contrastive Learning for Self-Supervised Visual Pre-Training. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2021, 3024–3033. arXiv:2011.09157.
3. Chen X., He K. Exploring Simple Siamese Representation Learning. arXiv preprint arXiv:2011.10566, 2020.
4. Clay Foundation. Clay Foundation Model: An Open Source AI Model for Earth. Available at: `https://clay-foundation.github.io/model/`, 2023.