**Semantic Segmentation of Agricultural Field Patterns Using a Semi-Supervised Deep Learning Approach**

Team AgriVision - Francis Lin, Stanislav Sheludko, Juanwen Lu, Bryce Meyering

**Project Summary and Related Work**

Agricultural production has been revolutionized by advancements in remote sensing to pinpoint problems in the field caused by weeds, nutrient deficiencies, and flooding etc., allowing farmers to manage their crops efficiently using RGB-NIR images taken from drone or satellites (Sishodia et al., 2020). An important direction on agricultural visual recognition is aerial image semantic segmentation to identify the regions of farmland patterns from the images (Chiu et al., 2020; Gu et al., 2023; Li et al., 2024; Syed et al., 2023; Tao et al., 2023). And many agricultural applications are developed based on this concept such as detection of grapevine trunks (Slaviček et al., 2024), crop row detection for automated field equipment (Cao et al., 2022), and differentiation between weeds and crops (Milioto et al., 2017; Steininger et al., 2023).

However, the remote sensing image data needed to train large, deep learning segmentation models can be expensive to acquire and time-consuming to annotate, since the images need to be fully labeled at the pixel level(Tik Chiu et al., 2020, Luo Z et al.,2023). While training schemes like transfer learning and fine tuning work well to quickly spin up smaller prototype models, And newly proposed by other researchers to provide a more robust model with better performance, semi-supervised learning (SSL) is introduced to solve some of these data limitations by generating “pseudo-labels” in a self-training or mutual training way for the unlabeled data and adding the loss term for unlabeled data with the weight controlling the unsupervised part (Lee D H, 2013; Wu H et al., 2017; Amorim W P et al,.2019; van Engelen et al., 2020; Zhou, 2021) . And SSL has successfully been applied in different deep learning segmentation challenges (Casado-García et al., 2022; Jang et al., 2023; Picon et al., 2023).

The present project, with the fully labeled farmland aerial images released in 2020 and the images without any labels released in 2024, seeks to compare the semantic segmentation performance between the vanilla supervised deep learning methods using 2020 dataset only and the semi-supervised learning pseudo-label methods using both 2020 and 2024 dataset. (Chiu et al., 2020).

**Approach**

The 2024 dataset includes 105Gb of new, unlabeled RGB-NIR photos, whereas the original dataset released in 2020 is 20Gb and is fully annotated. For the labeled data, there are a total of 9 classes including double plant, drydown, endrow, nutrient deficiency, planter skip, storm damage, water, waterway and weed cluster. And the generated dataset is split with a 6/2/2 train/validation/test ratio. At the same time, some categories occupy significantly larger areas than others, resulting in extreme class imbalance. And the concept of focal loss is used to put more weight on the less frequent classes during the training.

There are several primary methods this project seeks to implement for the comparison. Firstly, for label prediction on the images from 2024, the dataset of 2020 is trained under supervised deep training models as the baseline models reviewed in the related literature survey and discussed in the paper releasing first dataset in 2020 including U-Net and DeepLab (Tik Chiu et al., 2020, Luo Z et al.,2023). Secondly, the labeled data from 2020 and the unlabeled training dataset from 2024 are used for the semi-supervised learning models generating pseudo labels in self-training method including original pseudo-labeling method (Lee D H, 2013) and in mutual-training method such as Dynamic Mutual Training (Z. Feng et al., 2022) reviewed in the related literature survey (van Engelen et al.,2020)

The models will be evaluated against a holdout test set used for the Agriculture Vision 2024 challenge with mean Intersection-over-Union (mIoU) as the final evaluation metric defined in the original paper providing the dataset (Tik Chiu et al., 2020).

**Datasets**

We will be using two related datasets for this project. First, the 2020 agriculture vision dataset which is fully annotated

<https://www.agriculture-vision.com/agriculture-vision-2020>

<https://github.com/SHI-Labs/Agriculture-Vision>

Second, the 2024 agriculture vision dataset, which contains unlabeled images

<https://www.agriculture-vision.com/agriculture-vision-2024/prize-challenge-2024>

<https://www.dropbox.com/scl/fo/7yzzc8hqtvaki2y1md6h4/h?rlkey=su71dij6xfb964zfwe1d6kros&dl=0>

**Team Members**

1. Francis Lin [flin96@gatech.edu](mailto:flin96@gatech.edu)
2. Stanislav Sheludko [ssheludko3@gatech.edu](mailto:ssheludko3@gatech.edu)
3. Juanwen Lu [jlu435@gatech.edu](mailto:jlu435@gatech.edu)
4. Bryce (Bo) Meyering [bmeyering3@gatech.edu](mailto:bmeyering3@gatech.edu)

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