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servir-aces: A Python Package for Training Machine Learning Models for Remote Sensing Applications

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Summary

servir-aces Agricultural Classification and Estimation Service (ACES) is a Python package for generating training data using highly parallelized apache-beam and Google Earth Engine (GEE) (Gorelick et al., 2017) workflows as well as for training various Machine Learning (ML) and Deep Learning (DL) models for remote sensing Applications (Bhandari & Mayer, 2024; Mayer et al., 2023).

Statement of Need

Despite robust platforms, specialized technical knowledge is required to set up and run various Machine Learning (ML) and Deep Learning (DL) models, making it difficult for many development practitioners, scientists, and domain experts to implement them. The **servir-aces** Python package is designed to address this challenge by significantly lowering the barrier for users to export training data and both train and run DL models using cloud-based technology with their GEE workflows. Several examples are provided via a user friendly notebook to make it easier for scientists to utilize this emerging field of DL.

With petabytes of data available via GEE, and integration of the TensorFlow (TF) platfrom, models trained in TF can be easily loaded into GEE. This package provides functionalities for 1) data processing, 2) data loading from GEE, 3) feature extraction, 4) model training, and 5) model inference. The combination of TF and GEE has enabled several large scale ML and DL remote sensing applications, including Wetland Area Mapping (Bakkestuen et al., 2023), Crop Type Mapping (Bakkestuen et al., 2023), Surface Water Mapping (Mayer et al., 2021), and Urban Mapping (Parekh et al., 2021). However, these applications tend to be developed ad-hoc without using a common package.

Several unified libraries like torchgeo (Stewart et al., 2022) and rastervision (Azavea/Element 84, n.d.) exists, but they are primarily targeted for PyTorch user community. Some efforts for GEE & TensorFlow users, such as geemap (Wu, 2020), are mostly used for classical ML approaches like Random Forest, while geospatial-ml has not been developed further since its inception. Thus, there is a need for unified libraries to train DL models integrating the GEE & TensorFlow user community.

servir-aces addresses this need by 1) Offering a streamlined application of commonly employed architectures (CNN, DNN, and U-NET); 2) Allowing end-users to rapidly adjust a wide range of model parameters for these common architectures, including activation functions, optimizers, loss functions, early stopping, dropout rate, batch size, etc.; 3) More efficiently and effectively connecting across the Google Cloud ecosystem, linking Google Cloud, improved methods of parallelization via Apache beam, Vertex AI, TensorFlow, and Google Earth Engine; and 4) Enabling broader development and incorporation of several methods through the package's utility functions, such as providing a collated set of evaluation metrics for easier model performance comparisons, a class for generating remote sensing features essential for the scientific community, and utility functionality for Apache Beam and Earth Engine. Although **servir-aces** was originally developed for agricultural-related applications, the library has been further developed to work for any kind of DL image segmentation tasks.

servir-aces Audience

servir-aces is intended for development practitioners, researchers, scientists, software developers, and students who would like to utilize various freely available Earth Observation (EO) data using cloud-based GEE and TF ecosystem to perform large scale ML/DL related remote sensing applications.

We also provide several notebook examples to showcase the usage of the **servir-aces**. Here we show how **servir-aces** can be used for crop-mapping related applications. Ideally, the same process can be repeated for any of image segmentation task.

servir-aces Functionality

The major high-level functionalities of the **servir-aces** packages are:

- Data loading and processing from GEE.
- Generation of training data for various ML and DL models.
- Training and evaluation of ML/DL Models.
- Inferences of the trained ML/DL models.
- Support for remote sensing feature extraction.
- Integration with Apache Beam for data processing and parallelization.

The key functionality of **servir-aces** is organized into several modules:

- data_processor: this module provides functionality for data input/output and preprocessing for the image segmentation project.
- model_builder: this module provides functionality for creating and compiling various Neural Network Models, including DNN, CNN, U-Net.
- model_trainer: this module provides functionality for training, buidling, compiling, and running specified deep learning models.
- metrics: this module provides a host of statstical metrics, standard within the field, for evaluating model performance and provide utility functions for plotting and visualizing model metrics during training.
- ee_utils: this module for providing utility functions to handle GEE API information and authentication requests.
- remote_sensing: this module provides various static methods to compute remote sensing indices for analysis.

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References

Azavea/Element 84, R. C. (n.d.). *Raster Vision: An open source library and framework for deep learning on satellite and aerial imagery (2017-2023)*. https://doi.org/10.5281/zenodo.11123303

Bakkestuen, V., Venter, Z., Ganerød, A. J., & Framstad, E. (2023). Delineation of Wetland Areas in South Norway from Sentinel-2 Imagery and LiDAR Using TensorFlow, U-Net, and Google Earth Engine. *Remote Sensing*, *15*(5), 1203. https://doi.org/10.3390/rs15051203

Bhandari, B., & Mayer, T. (2024). *Comparing Deep Learning Models for Rice Mapping in Bhutan Using High Resolution Satellite Imagery*. https://doi.org/10.48550/arXiv.2406.07482

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, *202*, 18–27. https://doi.org/10.1016/j.rse.2017.06.031

Mayer, T., Bhandari, B., Martínez, F. G., Walker, K., Jiménez, S. A., Kruskopf, M., Maganini, M., Phalke, A., Wangchen, T., Phuntsho, L., & others. (2023). Employing the agricultural classification and estimation service (ACES) for mapping smallholder rice farms in Bhutan. *Frontiers in Environmental Science*, *11*, 1137835. https://doi.org/10.3389/fenvs.2023.1137835

Mayer, T., Poortinga, A., Bhandari, B., Nicolau, A. P., Markert, K., Thwal, N. S., Markert, A., Haag, A., Kilbride, J., Chishtie, F., & others. (2021). Deep learning approach for Sentinel-1 surface water mapping leveraging Google Earth Engine. *ISPRS Open Journal of Photogrammetry and Remote Sensing*, *2*, 100005. https://doi.org/10.1016/j.ophoto.2021.100005

Parekh, J. R., Poortinga, A., Bhandari, B., Mayer, T., Saah, D., & Chishtie, F. (2021). Automatic detection of impervious surfaces from remotely sensed data using deep learning. *Remote Sensing*, *13*(16), 3166. https://doi.org/10.3390/rs13163166

Stewart, A. J., Robinson, C., Corley, I. A., Ortiz, A., Lavista Ferres, J. M., & Banerjee, A. (2022). TorchGeo: Deep Learning With Geospatial Data. *Proceedings of the 30th International Conference on Advances in Geographic Information Systems*, 1–12. https://doi.org/10.1145/3557915.3560953

Wu, Q. (2020). geemap: A Python package for interactive mapping with Google Earth Engine. *Journal of Open Source Software*, *5*(51), 2305. https://doi.org/10.21105/joss.02305