GeoAI Challenge Estimating Soil Parameters from Hyperspectral Images by ITU

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1. Introduction

1.1 Competition Overview

The ESA Φ-lab, in collaboration with KP Labs and partner QZ Solutions, has orchestrated a groundbreaking challenge aimed at revolutionizing the future of farming through the integration of in-orbit processing. The challenge focuses on leveraging cutting-edge technologies such as Earth observation and artificial intelligence to enhance agricultural management practices.

1.2 Problem Statement

As agriculture plays a pivotal role in sustaining our growing population, the need for innovative solutions to optimize farming practices becomes increasingly crucial. One significant challenge faced by farmers is the timely acquisition of accurate soil parameter information. The traditional methods of quantifying soil parameters are not only time-consuming but also often rely on manual labour-intensive processes. The limitations in the scalability and efficiency of in-situ analysis hinder the ability to provide farmers with timely and precise information.

1.3 Importance of the Challenge

The competition addresses this agricultural challenge by proposing a paradigm shift—utilizing state-of-the-art airborne and satellite hyperspectral imaging technology. By doing so, the competition aims to pave the way for a more sustainable and planet-friendly agriculture. The integration of in-orbit processing, exemplified by the upcoming Intuition-1 mission, is set to redefine the landscape of farming practices. This mission introduces a 6U-class satellite equipped with a hyperspectral instrument and onboard computing unit capable of advanced processing of hyperspectral images in orbit—a milestone in satellite technology.

1.4 Significance

The competition holds immense significance in not only addressing the immediate needs of farmers but also contributing to the broader vision of sustainable agriculture. The advancements sought in soil parameter retrieval from hyperspectral data have the potential to transform the way farmers optimize fertilization processes. This, in turn, can lead to the selection of better fertilizer mixes and a reduction in overall fertilizer usage, contributing to cost efficiency and environmentally friendly farming practices.

2. Objective

2.1 Challenge Objective

The primary objective of the competition is to advance the state of the art in soil parameter retrieval from hyperspectral data. This pursuit is particularly significant in the context of the imminent Intuition-1 mission, which will leverage in-orbit processing capabilities to observe Earth using a hyperspectral instrument. By harnessing the power of artificial intelligence, the competition seeks to enhance the accuracy and efficiency of extracting vital soil parameters crucial for informed agricultural decision-making.

2.2 Target Soil Parameters

The competition focuses on the estimation of four key soil parameters:

1. **Potassium (K):** A critical nutrient for plant growth and overall crop health.
2. **Phosphorus Pentoxide (P2O5):** Essential for energy transfer in plants and a key component of fertilizers.
3. **Magnesium (Mg):** Plays a vital role in chlorophyll formation and photosynthesis.
4. **pH:** A measure of soil acidity or alkalinity, influencing nutrient availability to plants.

3. Data

3.1 Hyperspectral Data Details

The competition dataset comprises hyperspectral data with the following characteristics:

- **Number of Bands:** 150 contiguous bands covering the spectral range from 462 nm to 942 nm.
- **Spectral Resolution:** Each band has a spectral resolution of 3.2 nm.

This rich hyperspectral information enables a detailed analysis of the soil composition, providing a comprehensive basis for the estimation of target soil parameters.

3.2 Dataset Size

The dataset is structured into patches with a Ground Sampling Distance (GSD) of 2 meters. The dataset size is as follows:

- **Total Patches:** 2886
- **Training Patches:** 1732
- **Testing Patches:** 1154

4. Solution Overview

4.1 Key Components

The ensemble solution combines the strengths of two individual notebooks, each bringing unique components to the table.

4.1.1 Notebook 1 Components

- **Random Forest and K-Nearest Neighbors (KNN) Models:** Employing a combination of Random Forest and KNN models, Notebook 1 ensures adaptability across various field sizes.
- **Advanced Preprocessing Techniques:** Leveraging advanced techniques such as wavelet transforms, fast Fourier transforms, singular value decomposition, and derivatives, the preprocessing stage extracts high-level features from raw field data.
- **Model Training for Large and Small Fields:** Distinguishing between large and small fields, Random Forest models are trained for larger areas, while KNN models handle smaller fields (<=11x11 pixels).
- **Performance Evaluation Metrics:** Rigorously evaluating models on the validation set using mean squared error (MSE) for individual soil parameters and different field sizes.
- **Submission Generation:** Combining predictions from Random Forest models for large fields and KNN models for small fields to create the final hybrid submission.

4.1.2 Notebook 2 Components

- **PyTorch and PyTorch Lightning:** Leveraging the PyTorch deep learning framework for building and training neural network models, Notebook 2 utilizes PyTorch Lightning to streamline training processes and enhance code readability.
- **Timm Library:** The solution incorporates the timm (PyTorch Image Models) library to efficiently access pre-trained vision models. The chosen ResNet10t architecture serves as the backbone, benefiting from its feature extraction capabilities.

4.1.3 Novel Aspects in Notebook 2

- **Hyperparameter Tuning:** Adopting a systematic approach to hyperparameter tuning, key parameters such as learning rate, weight decay, and image size are fine-tuned to strike a balance between model accuracy and training efficiency.
- **K-Fold Cross-Validation:** Implementing K-Fold cross-validation with 5 folds ensures robust assessment of the model's generalization performance. This technique exposes the model to diverse training and validation sets, enhancing its adaptability to various field conditions.
- **Use of PyTorch Lightning Callbacks:** Employing PyTorch Lightning callbacks, including ModelCheckpoint and EarlyStopping, automates model selection based on validation performance, contributing to the efficiency of the training process.

4.2 Novel Aspects in Ensemble

- **Integrating Diverse Approaches:** The ensemble approach combines the diverse strengths of both notebooks, capitalizing on the unique features and methodologies brought by each solution.
- **Improving Robustness:** The ensemble enhances the overall robustness of the solution by leveraging the strengths of individual notebooks, thereby mitigating the weaknesses inherent in any single approach.

The ensemble strategy brings together the best of both worlds, incorporating the novel aspects and strengths of each notebook to create a cohesive and high-performing solution.

5. Advanced Data Preprocessing In Notebook 1

5.1 Hyperspectral Data Extraction

The hyperspectral data is extracted through a systematic preprocessing pipeline, ensuring that it is appropriately formatted for model training. The following steps are involved:

1. **Data Loading:** The data is loaded using a custom function that reads the hyperspectral data from the provided .npz files.
2. **Parallelized Extraction:** To expedite the extraction process, the loading and extraction of data are parallelized using the Pandarallel library. This improves the efficiency of reading and processing a large volume of hyperspectral patches.
3. **Normalization:** The hyperspectral data is normalized by dividing it by 10,000. This normalization step is crucial for bringing the pixel values within a range that is conducive to model training, preventing numerical instability during optimization.

6. Model Architecture in Notebook 2

6.1 HsiModel: PyTorch Lightning Module

The **HsiModel** class is implemented as a PyTorch Lightning Module, facilitating efficient training and evaluation pipelines. Here are the key components of the model:

- **Backbone Architecture:** The ResNet10t architecture is selected as the backbone for the model. ResNet architectures are renowned for their effectiveness in image classification tasks, and ResNet10t specifically is tailored for remote sensing image classification. The choice of a pre-trained backbone allows the model to benefit from feature extraction capabilities learned from diverse datasets.
- **Activation Function:** The Softplus activation function is applied to the output of the model. Softplus ensures non-linearity and smoothness, allowing the model to capture complex relationships in the hyperspectral data.
- **Loss Function:** Mean Squared Error (MSELoss) is employed as the loss function during training. MSELoss measures the mean squared difference between predicted and target values, aligning with the regression task of estimating soil parameters.
- **Evaluation Metric:** The evaluation metric for the competition is Root Mean Squared Error (RMSE). RMSE provides a measure of the average deviation between predicted and ground

truth values, penalizing larger errors more significantly. Minimizing RMSE during training aligns with the competition's goal of accurate soil parameter estimation.

6.2 Pretrained Weights

The model leverages the timm (PyTorch Image Models) library to access the ResNet10t architecture with pre-trained weights. Pretrained weights enhance the model's ability to extract relevant features from hyperspectral data, especially considering the limited size of the competition dataset.

7. Results Analysis

The performance of the ensemble and individual notebooks on the public leaderboard provides valuable insights into their effectiveness.

7.1 Public Leaderboard Scores

- **Ensemble 1:** Achieving a remarkable score of **0.258790** on the public leaderboard, the ensemble demonstrates the power of combining diverse approaches. This result surpasses the scores of both individual notebooks.

- **Notebook 1:** With a competitive score of **0.2596** on the public leaderboard, Notebook 1 showcases its efficacy in addressing the challenges of soil parameter retrieval.

- **Notebook 2:** Notebook 2, with a public leaderboard score of **0.2641**, contributes significantly to the ensemble's success. While slightly lower than Notebook 1 individually, its unique strengths enhance the overall performance when combined.

7.2 Ensemble Performance Analysis

- **Improvement Over Individual Notebooks:** The ensemble outperforms both individual notebooks, indicating that the combination of diverse methodologies and approaches leads to a more effective solution. This improvement underscores the value of ensemble strategies in addressing complex challenges.

8. Conclusion

8.1 Key Findings and Achievements

The Competition has witnessed significant accomplishments and insights from the individual approaches of Notebook 1 and Notebook 2, each contributing uniquely to the field of soil parameter prediction.

8.1.1 Notebook 1 Insights

- Notebook 1, scoring 0.2596 on the public leaderboard, introduces novel aspects such as advanced preprocessing techniques, Random Forest, and K-Nearest Neighbors models. The focus on distinguishing between large and small fields showcases the adaptability of the approach to various scenarios.

8.1.2 Notebook 2 Insights

- Notebook 2, with a competitive public leaderboard score of 0.2641, highlights the effectiveness of leveraging PyTorch, PyTorch Lightning, and the Timm library. The meticulous hyperparameter tuning and the incorporation of K-Fold cross-validation underscore the importance of a systematic approach in achieving accurate soil parameter estimations.

8.2 Implications for Future Work
The achievements in this competition lay the groundwork for future advancements in soil parameter prediction and related domains.

8.2.1 Diverse Approaches
- The success of both notebooks underscores the value of diverse approaches. Future work can explore the integration of deep learning techniques, advanced preprocessing, and ensemble strategies to further enhance prediction accuracy and robustness.

8.2.2 Model Generalization
- The generalization capabilities observed in the individual approaches pave the way for broader applications. Future efforts could focus on extending these models to different geographic regions and diverse agricultural landscapes.

8.3 Acknowledgments
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