Computer Vision System for Soil Sample Evaluation

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Introduction

Soil and soil management are a crucial point in the development and regulation of the agricultural sector, as well as in mitigation of climate change. There are a number of physical, chemical and biological indicators that can be used to assess the overall "health" of the soil, such as its water or air-retention capacity, pH levels, presence of fungal hyphae, etc.
Aggregate water stability, bulk density, porosity and water holding capacity are some of these characteristics, as good structure of crop growth depends on the ability of the soil to retain water and air, and to allow rapid infiltration and drainage. Laboratory analysis that is required to determine these indicators is time and labour-consuming.

This project aims to:

- Investigate the relationship between the visual appearance of the soil and soil quality indicators under different moisture conditions
- Compare the effectiveness of deep learning and traditional computer vision approaches
- Develop proof-of-concept computer vision software that is able to assess soil quality indicators

Datasets

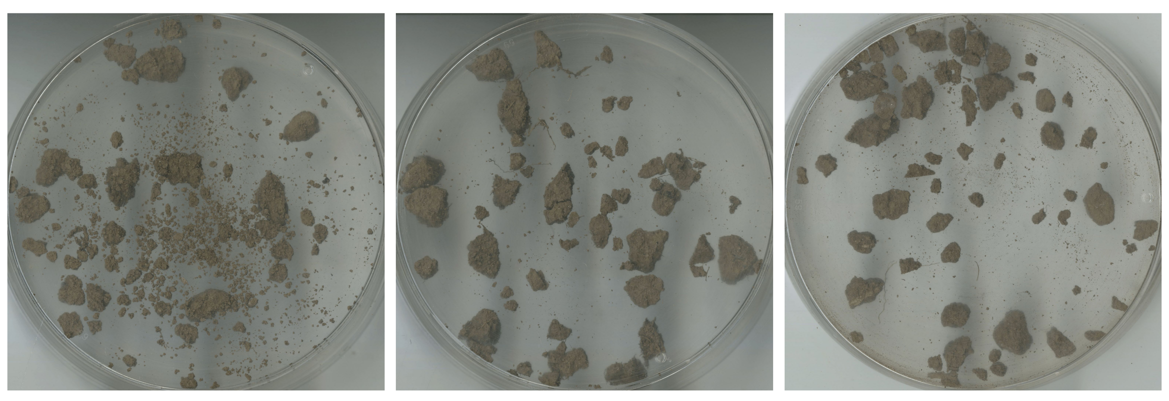
Dataset #1 - Soil Cores

- **315 core soil samples** from 63 fields around Scotland, with 5 samples per field
- The soil cores were imaged in collaboration with W.S.V. Lakshan under different moisture conditions:
  - **Saturated** with water
  - **Un-saturated**
  - **Oven-dried**
- Dry bulk density, gravimetric/volumetric water content, air filled/total porosity, water aggregate stability (WSA) values were provided per sample

WSA	:	28,90625
Dry Bulk Density	:	1,39
Total Porosity	:	0,47625
...		...

Dataset #2 - Petri Dishes

- **247 soil samples** from 2 fields: 68 and 179 samples from fields #1 and #2 respectively
- Oven-dried and sieved samples scanned in Petri dishes
- WSA values were provided per sample



WSA: 71.6 **WSA:** 58.96 **WSA:** 31.06

Methods Used

Convolutional Neural Networks

- Pretrained **VGG16**, **ResNet50**, **InceptionV3** and **DenseNet169** models with top layers removed and replaced with a pooling, dense, dropout and output layers
- Trained with **Adam** optimizer and **MSE** as a loss function
- Kerastuner implementation of Hyperband algorithm was used for tuning the number of dense units, dropout rate, and learning rate for each of the models
- **Data augmentation**: random rotation and horizontal/vertical flips
- **5-fold validation** was used during training
  - For Soil Cores, group k-fold split was used to keep the samples from the same field together to avoid data leakage
- Metrics used: **RMSE** and **MAE**

Manual Feature Extraction

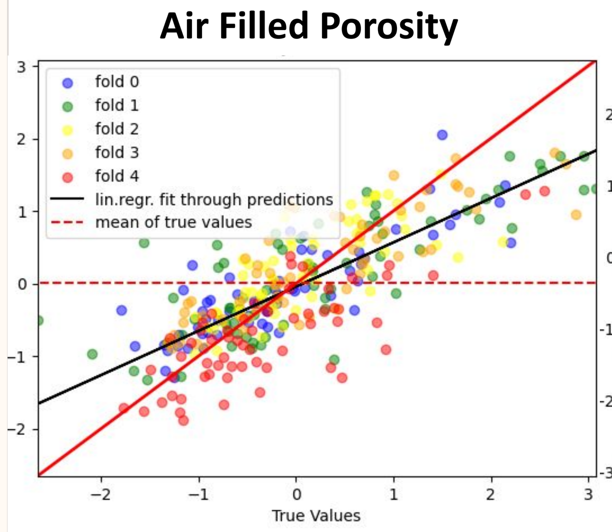
- **Petri Dishes:**
  - Aggregates were separated from the background using local Otsu thresholding and filtered by the mean pixel intensity
  - Extracted **shape/size** (perimeter, area, aspect ratio) and **texture** (Haralick features, local binary patterns) **features**
- **Soil Cores:**
  - Extracted **texture features** (Haralick features, local binary patterns)
- **XGBRegressor** and **RandomForestRegressor** used on the extracted features
- Grid Search for tuning the models' parameters
- **5-fold validation**
- Metrics used: **RMSE** and **MAE**

Total number of models trained across all data: 114

Soil Cores: Results

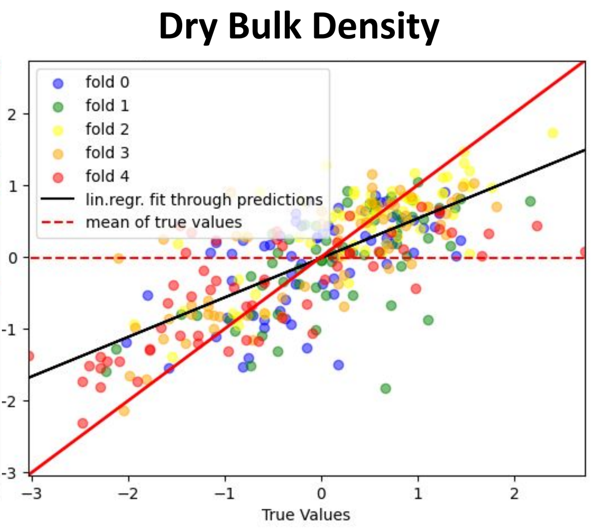
- All models demonstrated the most precise results with **Air Filled Porosity** across **all moisture levels**
- XGBRegressor and RandomForest performed on par with CNN models
- **Air Filled Porosity, Total Porosity, Dry Bulk Density** were predicted with a significantly smaller error than other quality indicators
- **Best performance**:
  - DenseNet169 on saturated samples and Air Filled Porosity values
  - XGBRegressor on unsaturated samples and Dry Bulk Density values

Air Filled Porosity



RMSE: 0.629 **MAE**: 0.482

Dry Bulk Density

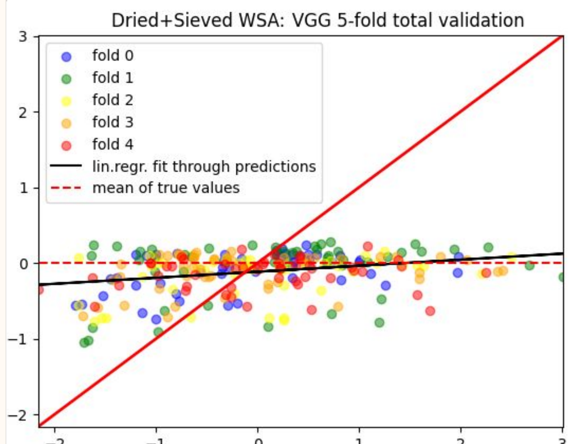


RMSE: 0.697 **MAE**: 0.534

Petri Dishes: Results

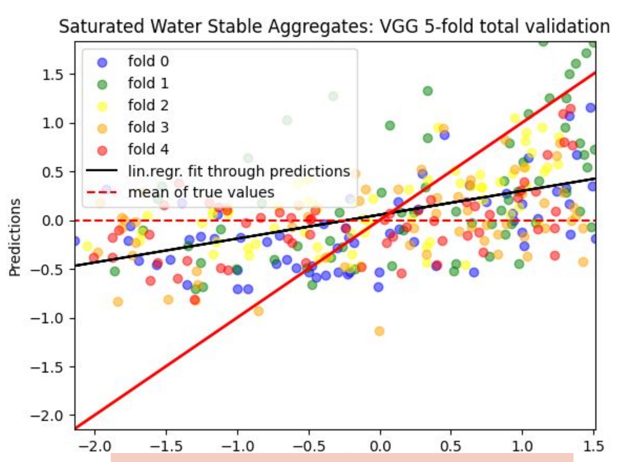
- None of the models were able to achieve satisfactory results
- XGBoostRegressor and RandomForestRegressor were able to achieve low RMSE/MAE values on the training set (unlike the CNN models), but were not able to generalise on the validation data (overfit)
- All WSA prediction results on this dataset are inferior to WSA prediction on Soil Cores of any moisture level

Best WSA prediction on Petri Dishes



RMSE: 0.97 **MAE**: 0.769

Best WSA prediction on Soil Cores



RMSE: 0.868 **MAE**: 0.715

Conclusions

- All methods used on Soil Cores produced inferior results on the oven dried samples compared to the same methods used on the saturated and unsaturated samples. Taking this and the results achieved on Petri Dishes into account, it might be assumed that the correlation between soil quality indicators and soil appearance is lower when the soil is oven-dried.
- The comparison across the results for all soil quality indicators for Soil Cores showed that air filled porosity, total porosity and dry bulk density were consistently achieving higher precision than gravimetric water content and water aggregate stability. None of the models were able to achieve reasonable precision in the case of volumetric water content. This might suggest that the latter quality indicators do not have a straightforward correlation with the visual characteristics of the soil.
- Poor performance on Petri Dishes dataset compared to the Soil Cores might be explained by low amount of data, no direct correlation between soil clod shape and WSA value, and not enough textural information that can be derived from the images.
- Both deep learning and traditional computer vision approaches achieved comparable results, which suggests that both techniques can be successfully applied on similar datasets, with the latter approach having the benefit of being less computationally expensive.

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