Challenges of Crop Classification from Satellite Imagery with Eurocrops Dataset

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Abstract. *Crops monitoring and classification on a nationwide level provide important information for sustainable agricultural management, food security, and policy-making. Recent technological advancements, followed by Earth observation programmes like Copernicus, have provided plenty of publicly available multispectral data. Combining these data with field annotations allows for continuous crop monitoring from publicly available data. In this paper, we present a solution for crop classification to determine crop type from Sentinel-2 multispectral data, utilizing machine learning techniques. Apart from presenting initial results, we discuss the challenges of crop classification on a Eurocrops dataset and further research directions.*
Keywords: *computer vision, multispectral imaging, remote sensing, crop classification*

1. Introduction

Crop classification using satellite imagery has been gaining more research attention recently, mainly utilizing publicly available data from Sentinel satellites and Landsat program [1]. Due to the massive amount of multispectral data, as well as the background of researchers, manually engineered features with phenological information are especially popular, replacing raw multispectral bands data. Authors in [2] combine data from heterogeneous sources: radar images from Sentinel-1 and multispectral images from Sentinel-2, with non-weighted accuracy reaching 0.85 for 23 crop types.

The research usually concentrates on a single country or even a small region, as the labelled data is scarce and diverse. Moreover, it usually covers only a small subset of cultivated crops that are especially relevant to the authors [3]. In this paper, a publicly available Eurocrops [4] dataset is used, and its usefulness for crop classification is analysed. The Eurocrops dataset provides field annotations for European countries along with ready-to-use multispectral data for each parcel. Figure 1 shows a small part of the dataset fields visualised in QGIS.

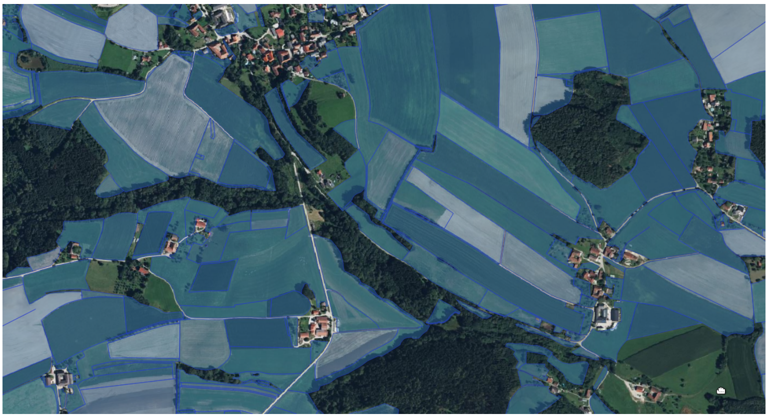

Figure 1. Fields from Eurocrops dataset with boundaries, visualized as semi-transparent blue polygons in QGIS on Bing Aerial Maps. Source: own work.

2. Materials and Methods

2.1. Dataset

Although the Sentinel-2 satellite has a resolution of 10 m and a revisits time of 10 days, the Eurocrops dataset provides for each field only a single representative pixel for each date, with 13 multispectral bands. Data are provided for each country individually. In this paper, due to the high amount of data, the training and testing focused on Austria, as data for this country were available at first, with 396600 annotated parcels in the training set, covering 44 crop types. The testing dataset is not a random subset of the training dataset, but it is a distinct geographic region of the country, specified in the Eurocrops dataset. The data provided by Eurocrops are from Sentinel-2 L1C products, which introduces significant bias due to the weather at a specific time point [5].

2.2. Data preprocessing

Dates when the images were taken are not consistent among the dataset. Therefore, before further processing, the data were resampled to common dates by taking the nearest data point for each date. Moreover, due to weather conditions, data are often obscured by clouds. Such data points could be potentially removed and resampled, e.g. with spline interpolation through time. Apart from using the raw pixel data, a simple yet effective vegetation indicator NDVI (Normalized Difference Vegetation Index) [6] was utilized, which is calculated based on near-infrared and red band values (bands 8 and 4 respectively). Example NDVI curves for a few selected crop types are presented in Figure 2. Using this index alone does not contain all information required for classification but seems to usually improve the model results.

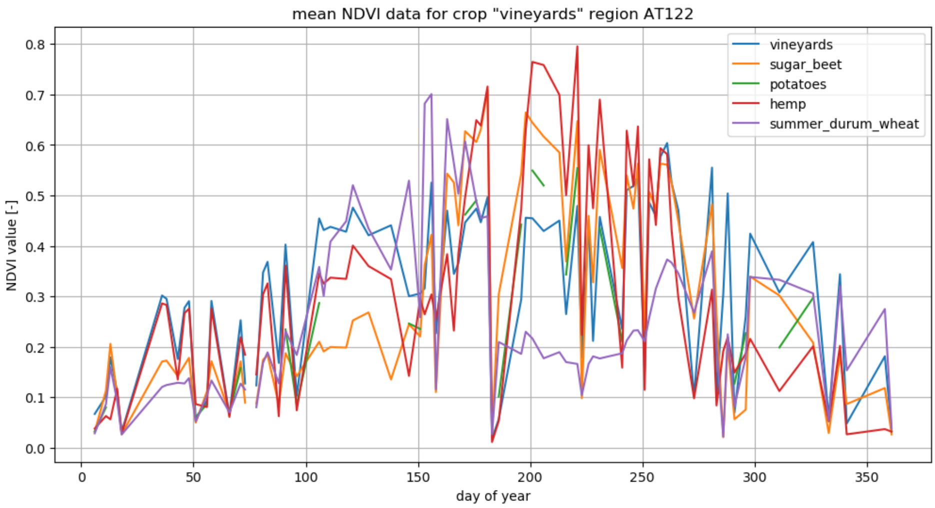

Figure 2. Average NDVI values through time for different crop types. One of the features used as model input, apart from the raw pixel values. Source: own work.

2.3. Algorithms

As there is no spatial information for a single parcel, the application potential for modern neural networks, including CNNs and transformers, is quite limited. Therefore, FCNN (Fully Connected Neural Network), as well as classical machine learning techniques, including SVM (Support Vector Machine) and random forest, were used. The input data consists of resampled and normalized pixel values with an additional NDVI feature. As it is a classification problem, the output data classes are different crop types. Due to high class imbalance, data were weighted by the number of samples in the training dataset.

2.4. Results

The best results on the testing set were achieved for FCNN, though the other methods were not significantly inferior. The best variant of the tested FCNN consists of four fully connected layers, with ReLU activation and batch normalization, and trained with cross-entropy loss. Table 1) shows the metrics achieved by the compared methods.

Table 1. Metrics achieved by the FCNN model on the test dataset for Austria, for all 44 crop types

Method	**Accuracy**	**Weighted accuracy**	**Precision**	**Recall**
FCNN	0.715	0.620	0.715	0.715
SVM	0.691	0.613	0.691	0.691
Random forest	0.694	0.431	0.692	0.692

Most of the crop types can be easily distinguished, but some crops (e.g. nuts and leguminous plants) have an accuracy not better than a random guess. Fig. 3 shows the confusion matrix trained for a few randomly selected crop types, which yields significantly better results.

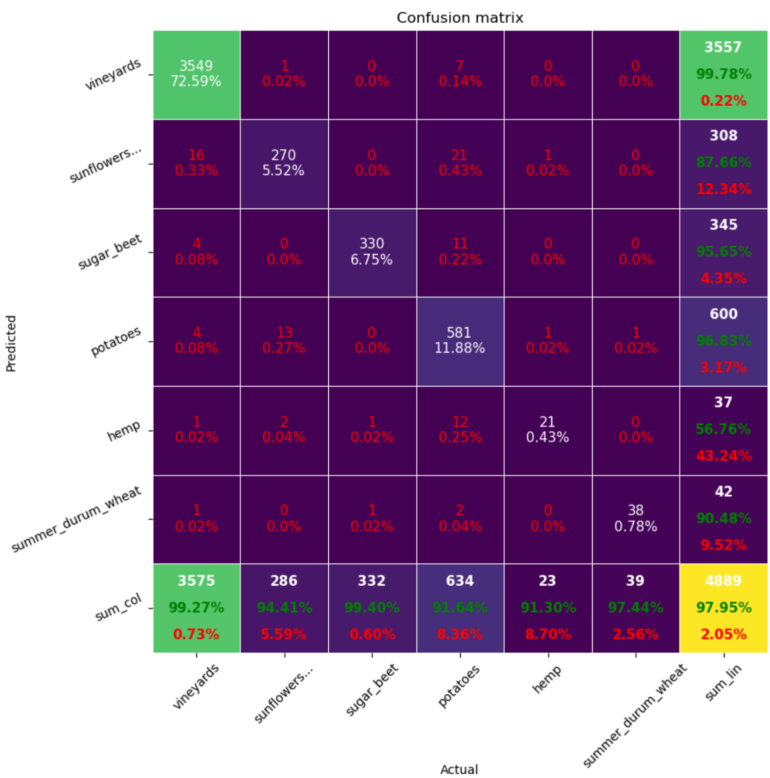

Figure 3. Confusion matrix for test dataset of crop classification, with a model trained only on a few selected crop types. To show high-class imbalance, the percentage of total predictions is shown in each cell (apart from the last row and column). Source: own work.

3. Conclusions

As presented in this paper, crop classification is achievable with the publicly available Eurocrops dataset, with weighted accuracy of 0.620 while training and testing on one country for all 44 crop types. Testing on fields from a different country than the training data yields significantly lower accuracy, possibly due to differences in climate, diverse vegetation processes, uncorrelated weather or even different subspecies for a specific crop, which is not covered by the dataset. Apart from including data from different countries in training, domain transfer with unlabeled data can be considered to tune the model to a different geographical region. The interoperability and accuracy of the model most probably could be improved by using Sentinel-2 L2A products with atmospheric correction and without cloudy data. Also, training the model to work only on a subset of crop types significantly improves the model's accuracy. Future work could involve analyzing all pixels within a parcel and not only a single representative pixel, allowing for spatial analysis. Another interesting research direction is the prediction from partial data without the full growing period.

Code available at `https://github.com/PUTvision/crop_classification_eurocrops`.

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