

# Machine learning classification methods in hyperspectral data processing for agricultural applications

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## ABSTRACT

In agricultural applications hyperspectral imaging is used in cases where differences in spectral reflectance of the examined objects are small. However, the large amount of data generated by hyperspectral sensors requires advance processing methods. Machine learning approaches may play an important role in this task. They are known for decades, but they need high volume of data to compute accurate results. Until recently, the availability of hyperspectral data was a big drawback. It was first used in satellites, later in manned aircrafts and data availability from those platforms was limited because of logistics complexity and high price. Nowadays, hyperspectral sensors are available for unmanned aerial vehicles, which enabled to reach a high volume of data, thus overcoming these issues. This way, the aim of this

paper is to present the status of the usage of machine learning approaches in the hyperspectral data processing, with a focus on agriculture applications. Nevertheless, there are not many studies available applying machine learning approach to hyperspectral data for agricultural applications. This apparent limitation was in fact the inspiration for making this survey. Preliminary results using UAV-based data are presented, showing the suitability of machine learning techniques in remote sensed data.

## CCS Concepts

• **Information systems** ~Geographic information systems • **Information systems** ~Data analytics • **Information systems** ~Process control systems

## Keywords

Agriculture; deep learning; hyperspectral data; machine learning; remote sensing.

## 1. INTRODUCTION

Hyperspectral data processing has significantly changed during the last decades. This fact was caused mainly because of the developments in new advanced sensors and processing equipment. Classification is usually the main goal of the hyperspectral data thus, most efforts have been put into this task and different approaches have been tested [1–5]. Lately, machine learning (ML) and deep learning (DL) approaches are becoming popular.

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New processing approaches allowed new applications in various fields, as in agriculture, which is the main scope of this paper. Monitoring of agricultural activities faces special challenges that are not common to other economic sectors, thus the use of remote sensing (RS) is necessary [6]. RS techniques facilitate to gather information over large areas with high revisit frequency, which is needed because of the strong seasonal patterns related to the biological lifecycle of crops [7]. The concept of monitoring and managing the crop production based on acquired data analysis is called Precision Agriculture (PA) also known as Precision Farming (PF) [8].

ML approaches applied to RS data are nowadays mostly used to crop identification or land use/cover classification [9–11]. However, in agriculture there are cases, like disease, weeds, or pest's detection, where regular multispectral images cannot provide the needed level of detail, and thus hyperspectral imagery needs to be used. Nevertheless, using hyperspectral data for this purpose has brought some challenges, like high number of bands, and need for advanced classification methods [12]. The connections between the need of more advance processing algorithms for very high dimensional data are highlighted in [13]. As previously mentioned, the focus of this study is applying ML to hyperspectral data acquired by using RS approaches for agricultural applications, since it provides the possibility to identify effected crops over large areas without the need of touching the ground and this kind of information will help farmers to make their crop management decisions more effective and increase their productivity. ML along with HSI has the potential to change the way we look at agriculture nowadays., Especially when developments in processing and data accessibility, caused mainly due to the miniaturization of hyperspectral components allowed their implementation on Unmanned Aerial Vehicles (UAV) platforms, whose operability is more flexible and less expensive than traditional platforms used for carrying the hyperspectral sensor, needed for accurate results, has increased.

## 2. HYPERSPECTRAL DATA

Hyperspectral data are acquired by passive optical sensors. It uses a fact that surface can reflect, absorb and transmit electromagnetic solar radiation [14]. The Sun is the primary source of radiation in a passive RS system. The solar energy modified by the atmosphere that was reflected gets back to the sensor where is converted into digital form [15]. The captured reflectance of light may then be decomposed into hundreds or thousands of contiguous spectral wavelength bands, for every pixel in the image ranging from ultraviolet to infrared, providing more detailed signatures [16]. An example of spectral signatures of selected materials can be seen in Figure 1.

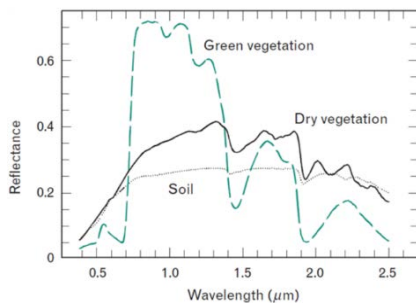


Figure 1. Spectral signatures of selected materials [17]

The signatures can be compared with spectral reflectance that were measured on materials with known compositions in laboratories or in the field, stored in spectral library. A combination of spectroscopy and image data acquisition by RS techniques, using different platforms (satellite, aircraft, UAV), is called hyperspectral imaging (HSI), known also as image spectroscopy. Each platform can be suitable for different applications depending on factors as coverage area or temporal resolution.

Hyperspectral images consist of hundreds or thousands of bands as opposed to multispectral images, that have usually from 5 to 12 bands [18]. The big number of spectral bands caused the emergence of third dimension to the spatial image resulting into 3D data cube. High dimensionality is special characteristics of hyperspectral images. In each band appears a unique brightness patterns or signatures of spectral bands. The rich spectral information available in the hundreds (eventually thousands) of narrow bands can possibly allow the accurate discrimination of different materials [3]. This fact makes hyperspectral data valuable. The biggest advantage of hyperspectral data, the high spectral dimensionality and resolution, is at the same time the biggest challenge to the processing and analyzing, arising the need for developing computationally efficient algorithms. In fact, standard parametric classifiers are not going to be sufficient anymore. ML appears to be a more suitable approach [19].

The problem with high dimensionality is known as “the curse of dimensionality”, introduced by Bellman [20], named as the Hughes phenomenon [21–23]. It is usually present because of limited training samples regarding the size of the feature space [24], resulting in hardly recognizable patterns of curse dimensional feature spaces [25]. Limited number of training samples and high number of features can decrease the average accuracy [26]. Other effects can be seen as distance between neighboring samples which is almost uniform. If the dimension is increased towards infinity, the distance between maximum and minimum samples, when it is normalized, the minimum goes to zero (equation 1). That means that all samples are somehow distributed equally and as a consequence of that, almost all samples are close to some border of the space [20].

$$\lim_{n \rightarrow \infty} \frac{dist_{max} - dist_{min}}{dist_{min}} \rightarrow 0$$

equation 1 Curse of dimensionality

To overcome the “curse of dimensionality” for hyperspectral data, the best technique for selecting the optimal dimensions needs to be chosen and preparation of sufficient training samples in the training phase of the classification needs to be done [26]. Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Convex Cone Analysis (CCA), Independent Component Analysis (ICA), Nonnegative Matrix Factorization (NMF), Kernels and sparse reconstruction are the most known techniques for dimension reduction.

## 3. MACHINE LEARNING

ML, as a part of artificial intelligence, allows to learn from input data and provides the ability to analyze complex data more effectively with higher classification accuracy than conventional processing methods [27], without being explicitly programmed [28]. The idea of applying ML into remote sensing was found in [29] back in 1990s. The ML approach in the study achieved highest accuracy compared to conventional methods at that time. After their great results and especially due to new advanced sensors that could produce data with higher quality in spatial and

spectral resolution, needed for accurate outputs, and the availability of the data, ML has become an important tool in remote sensing analysis.

A number of ML algorithms has been presented to RS image analysis during last years, e.g. artificial neural networks (ANN), decision tree (DT) classifiers, Random Forest (RF) and Support Vector Machines (SVM) [30–32]. The SVM are in general context considered as a state of the art method for HSI data classification, because they handle the curse of dimensionality issue well, thus it can be applied to high dimensional data with limited dataset samples [33].

Lately, Deep Learning (DL) methods has proven to be very effective at discovering intricate structures in high-dimensional data [34], thus suitable for hyperspectral data. DL outperforms the limitation of conventional ML techniques, which was the ability to process natural data in their raw form [34]. The huge potential of DL hyperspectral data processing mentioned Mou et al. [35]. Zhang et al. [36] have found that DL is actually everywhere in remote sensing (RS) data analyzing (e. g. image preprocessing, pixel-based classification, target recognition and recently in high-level semantic feature extraction and scene understanding), even though it did not provide the same impact on RS yet, as in detection in computer vision on RGB imagery [37].

DL is characterized by neural networks (NNs) with many hidden layers, that's why they are called deep [38]. Multiple hidden layers work to build an improved feature space. Higher layers make aspects of the input that are important for discrimination more relevant and suppress irrelevant variations. Second layer learns first order features, as edges; third layer learns higher order features (combination of first layer features, combinations of edges) [34].

Constructing a pattern-recognition or ML system required a deep knowledge for decades to build a feature extractor that could transformed the raw data into suitable internal representation or feature vector, from which the learning system could detect or classify patterns in input [34], but DL typically results in black-box solutions that give us little to no insight into how they are working and why we should trust them [37]. DL is using representation learning. This approach has been known for decades but, due to recent advancement in computational power, more available data and excellent results, the implementation of the technique started to grow big. According to [38] it has even the fastest-growing trend in big data analysis, and it was consider as one of the ten breakthrough technologies of 2013 [39].

## 4. APPLICATIONS

### 4.1 Agriculture applications

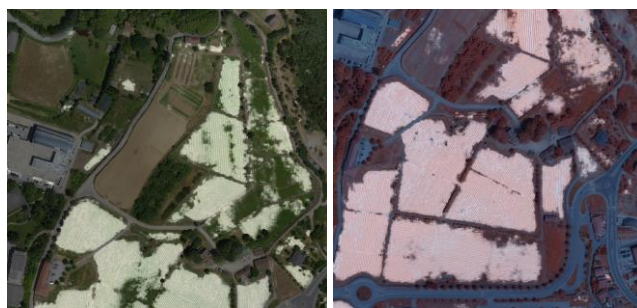
Yalcin [40] utilized AlexNet as a pre-trained CNN model for classifying different phenological stages of six plant classes. The classification performance of the fine-tuned CNN based approach was compared with results achieved by ML approach based on manually extracted features. Results from manually extracted features were outperformed by results where the features were learned from CNN model. Liu et al. [41] applied Learning Vector Quantization (LVQ) neural network classifier and PCA techniques for discriminating and classifying different fungal infection levels in rice panicles. The classification accuracies achieved great results and proved that with hyperspectral remote sensing data it is possible to discriminate different fungal infection levels of rice panicles by using NN approach. A comparison of ML methods on hyperspectral plant disease assessments carried out Yeh et al. [42]. In the study were tested

two hyperspectral image analysis methods: stepwise discriminant analysis (SDA), spectral angle mapper (SAM) and the proposed Simple Slope Measure (SSM) method. The outcomes of the research proved the suitability of using nondestructive methods to assess strawberry foliage Anthracnose symptoms in early stages. A comprehensive overview of ML tools for various biotic and abiotic stress traits applications can be found in [43]. Dutta et al. [44] provided a comparison of various supervised ML methods for a classification of salad leaf related disease. Fletcher and Turley [45] proved that by using combination of canopy hyperspectral narrowband data and random forest machine learning algorithm it is possible to differentiate cotton from Palmer amaranth, an invasive weed of cotton production systems. Ashourloo et al. [46] were applying ML regression techniques for the leaf rust disease detection using hyperspectral measurement. They found out that Gaussian process regression (GPR) can outperform other methods (partial least square regression, v support vector regression) in case of using smaller training dataset and that challenges in early detection of plant disease can be reduced by ML regression techniques.

### 4.2 Preliminary testing on vineyard detection

With the goal to detect vineyard plots, a first approach using CNNs was carried out. Data acquisition from vineyards located within the campus of University of Trás-os-Montes and Alto Douro (UTAD) was carried out. Imagery was acquired using the fixed-wing UAV senseFly eBee (senseFly SA, Lausanne, Switzerland), with a Canon IXUS 127 HS camera - operating in RGB and a Canon PowerShot ELPH 110 HS camera - for red-edge (RE) imagery acquisition, were used in two distinct flight plans. The flight height was ~175m resulting in 5 cm/px Ground Sample Distance (GSD). Both RGB and RE imagery were submitted to a photogrametric processing stage that enabled orthophoto mosaics computation.

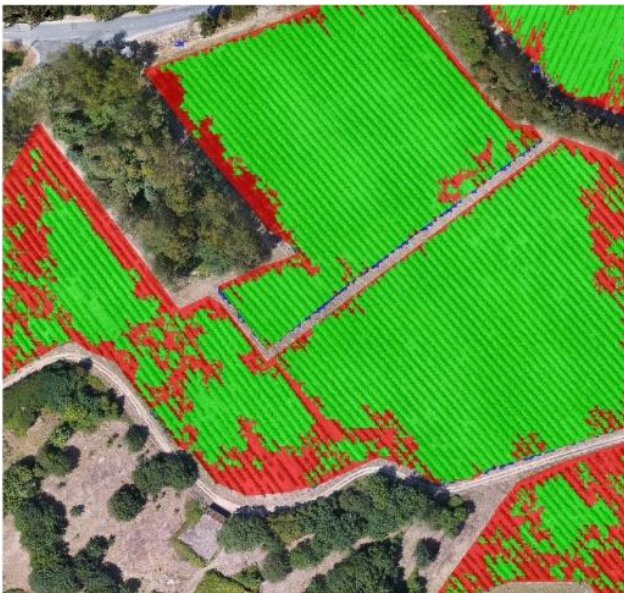
Afterwards, they were manually segmented in patches of 512 x 512 pixels with stride of 64 pixels that were used to train a CNN (U-Net [47]). The network was implemented using Keras with TensorFlow as backend, coded in Python 2.7. All experiments were performed on workstation with an Intel Xeon CPU E5-2650, 64GB RAM and a NVIDIA GTX-1080Ti GPU (11 GB memory) which was used to accelerate the CNN. The CNN was trained from scratch with training set (Figure 2, left) which was split randomly in 80% (12.109 patches) for training and 20% (3.002 patches) for testing. The training was made using Dice coefficient as cost function, in 3 cycles of 128 epochs with the Adam optimizer. The learning rate was 1E-4, 1E-5 and 1E-6 in each cycle, respectively. Validation using Dice Coefficient achieved 0.9953 and is graphically depicted (Figure 2, right).



**Figure 2. RGB (left) and RE (right) orthophoto mosaics of the vineyard used for training and testing with detected vineyard plots highlighted.**



The trained network was then applied to a different vineyard area for validation, with same parameters (patches and stride). The resulting image from classification was binarized by considering that all pixels with a value above zero correspond to vineyard plot. Then a set of morphological operations were applied to remove possible outliers and to provide a better understanding of the detected area. The morphological operations were applied in the following order: open, close, remove objects lower than 2000 pixels that correspond to potential outliers. For validation purposes, a pixelwise comparison with a manual segmented mask, which corresponds to ground truth, was performed. The result for exact detection was achieved with 85.07% accuracy, followed by 14.64% for under detection and 0.29% over detection. A visual interpretation of the obtained results is presented in Figure 3. It is noticeable a clear lack of detection in areas with strong shadow presence and less density of inter-row vegetation, being this non-detection related to the inexistence of such situations in the dataset used for learning.



**Figure 3. Results from the pixel-wise comparison of the detected vineyard plots against a manual segmented mask, with RGB orthophoto mosaic in the background. (red under detection, green exact detection and blue over detection).**

## 5. CONCLUSIONS AND FUTURE WORK

Hyperspectral remote sensing imaging along with ML can bring some benefits to agricultural industry. It is a non-invasive, less laborious, accurate method that can reduce the costs and field work operations. Not many studies that implemented ML into remote sensing applications using hyperspectral data were found, especially in agriculture.

As for the obtained results, the good classification accuracy and experience acquired from these preliminary experiments encouraged the application of this approach for hyperspectral data processing in near future, driven by the strong conviction that ML/DL-based classification has a big potential for high-dimensional data, which turns out to be justified by both literature and our experiments.

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