Decision-making Approach for Early Plant Stress Detection from Hyperspectral Images

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Abstract. Smart agriculture is based on advanced technologies such as artificial intelligence to enhance agricultural efficiency while minimizing the use of resources. Collecting multimodal data provides inputs for both predictive models and decision support. In this context, hyperspectral (HS) images aim to support crop monitoring, facilitate disease detection processes, and tackle water scarcity challenges by promptly identifying water stress. The domain of computer vision-assisted smart agriculture is continually progressing, marked by a substantial volume of recent scientific literature detailing advancements in this domain. This progression aligns with the numerous advancements achieved in the realm of deep learning over the past few years. The objective of this paper is to introduce a methodology for constructing a model that classifies the level of water stress using a dataset comprised of image series of water-stressed plants, eliminating the necessity for additional precise labeling. Once constructed, this model requires only a single hyperspectral image of a plant to ascertain the degree of water stress.

Keywords: smart agriculture · water stress · hyperspectral images · machine learning

1 Introduction

Smart agriculture refers to the use of advanced technologies such as artificial intelligence, sensors, drones, and data analysis to enhance the efficiency of the entire agricultural process. This approach aims to maximize yields while minimizing the required resources such as water, pesticides, and energy. By integrating real-time data, in-depth analysis, and automated systems, smart agriculture enables farmers to make informed decisions to optimize each step of the agricultural production. Especially, computer vision enables machines to process visual data from cameras, drones, and satellites. The main explored methodologies in computer vision approaches for smart agriculture are image segmentation, image classification, object detection, and object tracking. In livestock management, computer vision monitors animal health and automates tasks. The acquisition of images can be done in different ways: aerial, satellites, drones, spectral imaging. The integration of hyperspectral (HS) image analysis into the smart farming process aims to improve agricultural analysis. The hyperspectral image-based system will play an essential role in building sustainable, intelligent agricultural techniques in the years to come.

Water resources are increasingly scarce and insufficient to meet plant demand. Several studies have been carried out with the aim of accurately detecting water stress at an early stage, in order to remedy it. Water stress occurs when available water resources fall short of water demand. One of the consequences of water stress is increased susceptibility of the plant to pests and diseases. With limited/altered photosynthesis, the chemical reactions that the plant undergoes during its metabolism can be modified, leading to the synthesis of metabolites. Since metabolites are produced in a certain quantity and at a specific time in the plant's life, it becomes possible to observe them, allowing us to directly determine the stage of the plant's life.

The aim of this work is to study how to detect water stress and to propose a decision-making approach for early plant stress based on hyperspectral images. An application to automate this detection of water stress in Centella asiatica plants has been developed. This plant was chosen because it is a semi-aquatic plant that responds quickly to lack of water, which facilitate experimental conditions. The study presented in this paper is part of a research line with a wider scope, aiming at developing a platform for decision support and monitoring of intelligent greenhouses using multimodal data. To achieve our objective, we combine supervised and unsupervised methods to create a model capable of determining water stress levels from a single unlabeled hyperspectral image. We first perform unsupervised pixel-wise labeling of the senescence class in our hyperspectral image series. Subsequently, we reuse the pixel-wise labeling obtained earlier to train a classification model that associates features (spectrum) with their senescence class (supervised approach). Finally, we train a model that relates the distribution of senescence classes (pixels) in the image to the overall water stress level of the corresponding plant. The remainder of this paper is structured as follows: Section 2 introduces the related work. Following that, in Section 3, we outline the problem and expound upon our proposed approach. Section 4 is dedicated to presenting the results and their interpretation. Lastly, in Section 5, we conclude and discuss our future endeavors.

2 Related work

In this section, we first present the context and then an overview of the related research concerning hyperspectral images in smart agriculture along with our motivations and objectives.

2.1 Decision-making for smart agriculture

Smart agriculture aims to improve resource efficiency, productivity and quality, based on a better understanding of the spatial and temporal variability that is generally present in many farms. The acquisition of data on crops and soils is the starting point of the process. Making the right decision at the right time to apply the right amount of inputs is an important issue on which the economics and sustainability of agricultural production depend. In this sense, the digital revolution in agriculture is based on intelligent, easy-to-use systems that are adapted to farmers' needs, and help them to make decisions. In a previous works [8], a multi-factor prediction and parameters identification based on Choquet Integral (with smart farming application) and a fuzzy decision support environment for smart farming ensuring better data structuration extracted from farms, and automated calculations, reducing the risk of missing operations, have been proposed. Numerous studies have been conducted to propose sustainable irrigation management practices [7].

2.2 Hyperspectral images in smart agriculture

More specifically, if we focus on the use of hyperspectral images for smart agriculture, S. Sankaran & al. compare in [12] various classifiers : LDA (Linear Discriminant Analysis), QDA (Quadratic Discriminant Analysis), NB (Naive Bayes), and BDT (Boosted Decision Trees) to determine the health status from hyperspectral images of avocado leaves, containing pixel-wise reflectance spectra. The best accuracies are achieved with the QDA (92%) and BDT (99%). BDT yields the best results but has the highest computation time. The most relevant vegetation index for classification in their experiment are NDVI and SIR. In [13], A. Signoron & al. present a state-of-the-art overview of deep learning methods for hyperspectral images. The advantage of deep learning is its ability to effectively utilize both the spectral and spatial richness present in hyperspectral images. In [16], X. Zhang & al. introduce a method using a deep learning classification model (DCNN) with multiple Inception-ResNet layers to automate the detection of yellow rust disease from hyperspectral wheat images. It achieves an accuracy of 85%, which is higher than the 77% obtained with a Random Forest. Indeed, leveraging both spectral and spatial information leads to improved accuracy. In [15], L. Varga al. present a method for determining fruit maturity stages from hyperspectral images using a deep learning model specifically designed for hyperspectral image processing. There is no need for feature extraction preprocessing, the model autonomously decides which wavelengths are most important.

It achieves better accuracy with the entire spectrum (93.3% for avocados) compared to other machine learning models such as SVM and kNN, regardless of the preprocessing applied (RGB, PCA, full). It also outperforms other deep learning models that are not specifically tailored to hyperspectral images, such as ResNet-18 or AlexNet. The article also introduces methods for visualizing the ripening process, using an autoencoder with a 3-dimensional output before the deep learning model.

2.3 Status and hydric stress detection

Hydric or water stress refers to a lack of water and the reaction of the plant.It is one of the consequences of irregular precipitation, and becomes a constraint for plants. Hydric stress blocks the vegetative cycle, imparting color changes, defoliation,... In [5], the authors provide an overview of methods for specifically detecting water stress using hyperspectral images. In [6], K. Loggenberg & al. explain the influence of water stress on the plant spectrum. Random forest is used to determine the important features that lead to model predictions and provide valuable insights for the interpretability of machine learning models, as wavelengths are linked to the plant's biophysical properties. For labeling the images, in-field stem water potential (SWP) measurements were used, which were captured using a customized pressure chamber. When confronted with water stress conditions, plants respond by closing their stomata, resulting in a significant reduction in photosynthesis. This reduction is further compounded by a decrease in leaf surface area, stomatal conductance, and a decline in chlorophyll content. Behmann & al. presents in [1] an interesting approach for detecting early-stage water stress in barley using hyperspectral images. To achieve this, they combine an unsupervised method to first obtain pixel-level labeling of senescence status. Then, they train a linear support vector machine (SVM) ensemble using spectral features as input and the senescence class obtained through unsupervised means as labels. Finally, they train a model to determine the plant's water stress state based on the relative distribution of senescence stages in the image. They then demonstrated the generalability of their method by applying the same approach to maize.

3 Materials and Methods

This section outlines the methodology employed in conducting the study, encompassing three key facets: the utilization of Centella asiatica, the experimental materials, stress treatments employed, and the proposed methodology.

3.1 Centella asiatica

It can be interesting to deliberately place a plant in a situation of water stress because, with limited/altered photosynthesis, the chemical reactions that the plant will carry out during its metabolism can be modified and it will then synthesize metabolites. These metabolites are molecules which may be of interest in particular for the pharmaceutical industry, as is the case for the plant that we used during this experiment: *Centella asiatica*. *Centella asiatica* is a semi-aquatic herbaceous plant used as traditional medicine in several regions worldwide. It has has received relatively limited attention in the context of water stress research: the results in [2] suggested that plants irrigated to 100% pot water capacity showed highest growth and plant biomass production; the results also indicate that *Centella asiatica* tolerates relatively high water levels, as at 125% water supply compared to pot capacity, the plant exhibited characteristics quite similar to those at 70%. Next, [14] show that a 25% reduction in total water consumption irrigation schedule was considered as the optimal irrigation regime. Nevertheless, they include tests on a phenotyping platform with hyperspectral images to model the behavior of this plant under water stress conditions. Based on the present findings, *Centella asiatica* has relatively large leaves, which are advantageous for imaging purposes. Indeed, this reduces the need for extensive cropping or image enhancement before further work. Another interesting feature of *Centella asiatica* is that it produces numerous metabolites, especially when subjected to stress conditions. This study underscores the relevance of working with *Centella asiatica*, as it demonstrates the plant's effective response to changes in water supply.

3.2 Experimental material and stress treatments

The experiment was conducted at UniLaSalle Rouen. It involved growing *Centella asiatica* hydroponically, meaning on a neutral and inert substrate irrigated with a solution containing mineral salts and essential nutrients for the plant. Then, we collected plants and placed them in suitable containers, so that we could pass them through the phenotyping station. The experiment lasted eight hours. The plants were subjected to three different levels of water stress: grown with their roots submerged in water (Fig. 1), deprived of water at regular intervals (with water half the time of the experiment in intervals of 30 minutes), and completely deprived of water until necrosis occurred. For each of these conditions, two plants were used, totaling six plants analyzed. The plants were selected with relatively similar morphologies to avoid biasing the results. The materials used for the experiment were: a pot adapted for imaging support, clay beads, transparent containers, *Centella asiatica* plants, water sourced from the hydroponics platform, an imaging platform, a control monitor, and z hyperspectral camera Resonon Pika L. The hyperspectral camera Resonon Pika L works with CMOS sensor, 400-1000nm, pixel size 5.86µm, slit size 12µm, 900 samples, 499 lines, 300 spectral channels, 12-bit. The hyperspectral images acquired with this camera consist of 300 bands, covering the spectral range from 380 to 1020 nm. The protocol was as follows: first, similar plants were selected and individually placed in suitable containers, ensuring that their roots were not confined. To ensure the stability of the plants in the containers, clay pellets were added to fill any empty spaces. Then, the small containers containing the plants were placed in a large pot previously filled with clay pellets, creating a controlled environment

(Fig. 1 (b)). Before starting the experiment, all the containers were carefully watered to ensure uniform conditions. The containers were labeled from 1 to 6, with containers 1 and 2 representing stress-free conditions, receiving a continuous water supply. Containers 3 and 4 represented moderately stressed plants, receiving water for half of the experiment's duration at 30-minute intervals. Finally, containers 5 and 6 were intended for plants subjected to constant water stress, receiving no water supply throughout the experiment. Each plant was photographed 8 times, with a 1-hour interval between shots. Consequently, the duration of the experience is approximately 8 hours. Each hyperspectral image took approximately 5 minutes to capture on the platform, and the time of each capture was meticulously recorded.

Fig. 1: (a) Centella Asiatica plants maintained under optimal growth conditions (b) Experimental setup for hyperspectral data acquisition

3.3 Proposed approach

The biophysical alterations caused by water stress have an impact on the reflectance spectrum at diverse wavelengths. Notably, the spectrum in the visible range (400-700nm) is sensitive to leaf pigmentation, responding to water deficit, while the spectrum in the near-infrared range (700-1300nm) reflects changes in cellular structure associated with water stress [3]. Vegetations Index (VI), derived from combinations of reflectance values across different spectral bands, providing insights into various biophysical properties of the plant, such as leaf area index (LAI), total biomass, and vegetation vigor. Thus, VI are closely linked to the plant's water status and can aid in identifying plants experiencing water stress [11]. Among these indices, the Normalized Difference Vegetation Index (NDVI) stands out as the most used, to evaluate the plant's health status. The NDVI can be calculated using the following equation:

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{RED}}{\mathrm{NIR} + \mathrm{RED}} \tag{1}$$

with NIR representing near-infrared channel reflectance and RED representing red channel reflectance. NDVI is particularly effective in detecting water stress conditions [9]. Moreover, the combination of multiple VI often proves more informative than a single IV, enhancing the accuracy of water stress assessment [10].

Our approach combines supervised and unsupervised methods to create a model capable of determining water stress levels from a single unlabeled hyperspectral image. However, initially, we need a labeled dataset of hyperspectral image series depicting various levels of water stress to train our models. We first perform unsupervised pixel-wise labeling of the senescence class in our hyperspectral image series. Subsequently, we reuse the pixel-wise labeling obtained earlier to train a classification model that associates features (spectrum) with their senescence class (supervised approach). Finally, we train a model that relates the distribution of senescence classes (pixels) in the image to the overall water stress level of the corresponding plant (see figure 2).

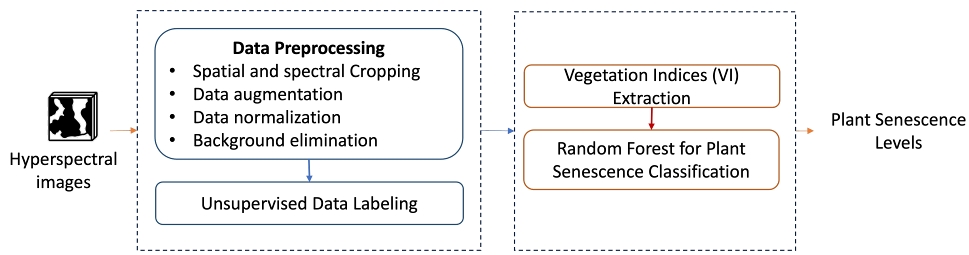


Fig. 2: Flowchart of the proposed method

Preprocessing In this step, we performed spatial and spectral cropping, data augmentation, and data normalization. Initially, we conduct spatial cropping to realign images onto the focal point of the plant and spectral cropping to solely keep wavelengths ranging from 380nm to 810nm to avoid interference from non-relevant wavelengths for water stress detection. Then we applied data augmentation techniques such as rotation at 90, 180, and 270 degrees, horizontal and vertical flipping, and random cropping to enhance robustness and improve the generalization capabilities of the model. Furthermore, an L2 Euclidean normalization was applied to standardize the data, ensuring that all features have a comparable influence on the model. In order to capture and isolate the pixels associated with the plants from the background, a K-means clustering was performed. Subsequently, clusters representing plants and those depicting the background are differenciated by setting the criterion that the mean NDVI within each cluster had to be > 0.4.

Unsupervised labelling For the first stage of unsupervised labeling, the objective is to obtain labeling for each pixel indicating the level of senescence, in order to subsequently train machine learning models based on these labels. As a reminder, leaf senescence is a continuous process, from tip to base. We leverage this information to perform clustering on plant images, and then sort the formed clusters to accurately represent this senescence process for observation. The chosen method for clustering is to use randomly initialized K-Means on all images in our dataset simultaneously. We aggregate our time series of images to perform clustering on all images (which fully describe the hydric stress). The number of clusters chosen is equal to 12 that is sufficient to capture the ordinal senescence process. For this stage, we hypothesize that clustering occurs based on different senescence stages, and the order of grouping reflects a clear senescence process in plants (the effectiveness of the clustering algorithm depends on the clarity of the senescence process). If the obtained clusters do not adequately represent the ordinal senescence process, then we sort the clusters based on the relevant vegetation index that accounts for the ordinal senescence process from tip to base.

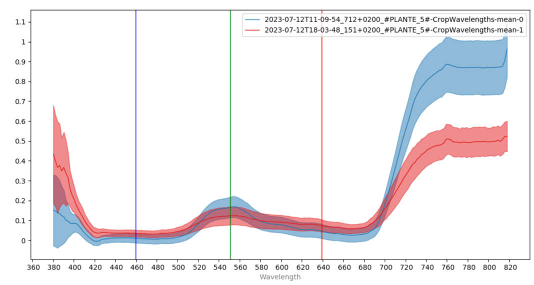
Training of classification models In this phase, we train a Random Forest classification model using the labeling obtained in the previous phase (12 plant senescence levels). This enables the model to determine the senescence level of the plant for each pixel based on the associated spectrum. Indeed, Random Forest is robust to overfitting and allows after the training to determine the importance of each features. To train our Random Forest model, we split our data into training and test sets. The filtered features and their corresponding labels were divided into an 80:20 ratio for training and testing, respectively. The random_state=42 parameter was set to ensure the reproducibility of results in each execution. We chose a Random Forest model with a number of estimators set to 100, a decision motivated by the pursuit of an optimal balance between prediction accuracy and computational efficiency. Setting the number of estimators to 100 means that our Random Forest consists of 100 individual decision trees.

To gain computational efficiency, we perform feature extraction. Instead of using the entire spectrum as input, we choose to keep only 11 relevant vegetation index for our problem according to the literature [4]: Normalized Difference Vegetation Index (NDVI), Modified Red Edge NDVI (mRENDVI), Plant Senescence Reflectance Index (PSRI), Sum Green Index (SG), Red Edge NDVI (RENDVI), Red Green Ratio Index (RGRI), Simple Ratio Index (SR), Carotenoid Reflectance Index 2 (CAR2), Carotenoid Reflectance Index 1 (CAR1). Then, in a second step, a regression algorithm (such as random forest regression could be used to associate the distribution of senescence levels in an image with the associated water stress level.

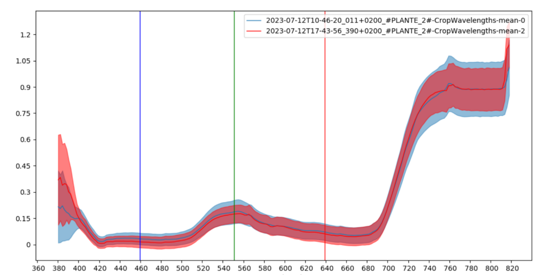
4 Experimental Results and discussions

During the experiment, it can be observed that the plant subjected to water stress wilts over time. The figure (Fig. 3) displays the evolution of the plant subjected to water stress, represented as an RGB reconstruction extracted from the hyperspectral image. Moreover, we can observe an important decrease of

Fig. 3: Color reconstruction from 3 RGB bands of the images of the plant subjected to water stress (chronologically : from left to right, then top to bottom)



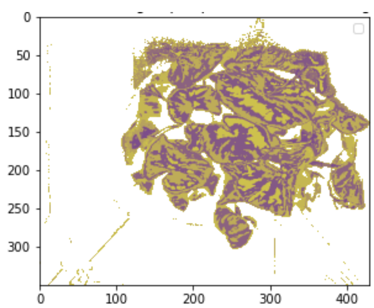
(a)



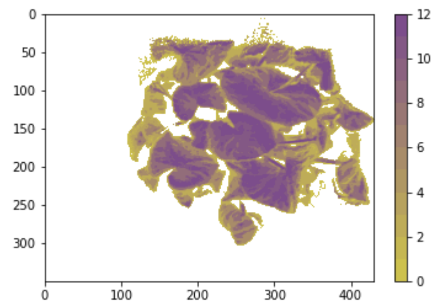
(b)

Fig. 4: Spectrum's of respectively day 1 (in blue) and day 8 (in red) of leaves of plant 5 subjected to water stress (a) and plant 2 not subjected to water stress (b)

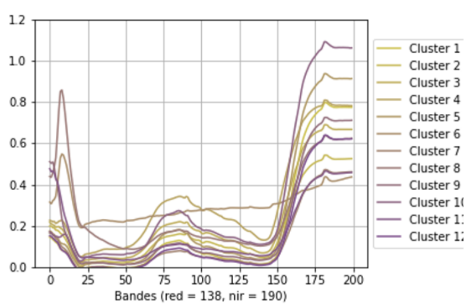
the spectrum in the near-infrared range as the experiment progresses for the plants subjected to water stress (Fig. 4a) while no significant changes are observed for plants not subjected to water stress (Fig. 4b). These differences of spectrum are significant enough to distinguish between the different treatments. This spectrum variation results in a decrease in the NDVI index whereas well-hydrated plants show very little variation. The number of clusters used for the background elimination is chosen experimentally. Indeed, if the number of clusters is too low, it fails to distinguish the plant from the background and when it's too high neither. Experimentally, we apply Kmeans with K=12.



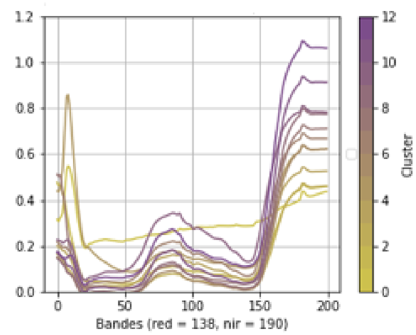
(a) Plant pixels grouped by clusters



(b) Plant pixels grouped by sorted clusters



(c) Spectrum of the centroids of the twelve clusters



(d) Spectrum of the centroids of the sorted clusters

Fig. 5: Unsupervised labeling based on K-means clustering of plant pixels with a number of clusters = 12. Obtained clusters are sorted according to their average reflectance value in the near-infrared (band 190, 780 nm) (y axis represents the pixel intensity).

In the unsupervised labelling step, the obtained clusters corresponding to senescence levels are not ordered (does not capture the gradual ordered leaf senescence process) (Fig. 5a, 5c). We then reassign the cluster numbers to match with the appropriate leaf senescence level. The clusters were sorted according to their average reflectance value in the near-infrared (band 190, 780 nm). Thus, we can observe the continuous process of senescence from the base to the tips of the leaves (Fig. 5b, 5d). Our Random Forest Classifier model provided an accuracy measure of 71,1%. Since the classes are ordinal, we are interested not only in the overall accuracy of predictions but also in accuracy within a tolerance of 1 or 2 classes. This means we are evaluating the model's ability to predict the correct classes while allowing a margin of error of one or two classes, respectively, considering the order of the classes. Thus, the accuracy within a tolerance of 1 and 2 corresponds to 78.8% and 85.3%, respectively. We can see the importance of the VI for determining the predictions of the random forest model on (Table. 1). We can see that the Sum Green Index (SG) and Simple Ratio Index (SR) are the most important features leading to the senescence level prediction.

Table 1: Importance of VI for random forest prediction model

SG	**SR**	**RENDVI**	**mRENDVI**	**RGRI**	**SR4**	**PSRI**	**NDVI**	**CAR2**	**CAR1**
0.222	0.142	0.095	0.084	0.073	0.071	0.067	0.057	0.055	0.053

5 Conclusion and future work

In this paper, a decision-making approach is proposed, composed of three main phases : data acquisition, data preprocessing/labeling and classification with a specific application to *Centella asiatica* plant under water stress. An experiment protocol is designed to systematically collect spectral data at different intervals in real conditions, which constitute the data acquisition phase. These images provide a complete perspective on the development of plant stress, providing important information on changes induced by water stress over time. The resulting dataset serves as a fundamental starting point for the design and building of water-stress prediction pipeline using hyperspectral images. During the labeling phase, the proposed approach performs unsupervised ML pixel-wise labeling and associate each pixel with a level of senescence based on expert knowledge and clustering techniques. Subsequently, trained a random forest classification model allow associating this distribution of senescence levels with an overall level of plant water stress. Experimental results show promising results and prove that Sum Green Index (SG) and Simple Ratio Index (SR) are the most important features leading to the senescence level prediction. Although deep learning approaches have shown significant efficacy in HyperSpectral Image (HSI) analysis, they require a large amount of labeled datasets to generalize well. Currently, we are focusing on Self-supervised deep learning approaches that has proven great promise for learning useful representations from unlabeled data.

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