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***Abstract*— Information from digital images can be automatically collected and analyzed using computer vision (CV), which allows to solve complex problems through self-learning given by artificial neural networks.**

The objective of this study was the evaluation of a dynamic strategy of nutrient solution management and the creation and validation of a ML algorithm to obtain a digital RGB image regressor for indoor-grown basil. The algorithm has the purpose of analyzing the images returning the prediction of the SPAD value, therefore a relative measure of the nutritional status of the plants. In commercial application, the regressor could allow fertilization to be remotely steered to avoid or remedy nutrient deficiencies. The experiment concerned the indoor growth of *Ocimum Basilicum* (cv. "Genovese"), for 22 days after transplanting. During the growth cycle, five nutritional regimens were applied: surplus (160% and 130%), optimal (100%) and deficit (70% and 30%) starting from a slightly modified Hoagland nutrient solution and the experimental scheme used was randomized blocks. The architecture of the regression algorithm has foreseen the implementation of 13 layers, four validation metrics have been foreseen, such as MSE, MAE, R^2 and r. The algorithm was trained for 1200 epochs with a learning rate of 0.001. Performance was encouraging, achieving low (dimensionless) MSE and MAE values of 2.92 and 1.32, respectively, and R2 and r coefficients of 0.94 and 0.97, respectively. The biomass analysis demonstrates the possibility of carrying out a dynamic strategy of nutrient management with a significant reduction in the use of fertilizers. The results obtained by the algorithm are promising, also in consideration of the discrete number of images in the dataset and the few layers, the computational lightness of which the algorithm is composed.

Keywords*— *computer vision, machine learning, image regressor, autonomous nutrition

I. INTRODUCTION

Optimal crop nutrition is an important prerequisite for high yield and good quality products, also in indoor cultivation. The automation and optimization of production inputs, such as nutrition, for crop plant development is becoming increasingly urgent for ecosystem sustainability and natural resource management [1].

Information received from digital images can be collected and analyzed automatically through the use of computer vision (CV) technologies, making the process faster and more accurate than manual methods [2]. CV is closely linked to sophisticated machine learning (ML) techniques such as artificial neural networks (ANN) that, through self-learning, are able to solve complex information processing problems [3]. Thanks to this, it is possible to have an indirect assessment of crop yield [4], predict the water status of plants [5] and especially the nutritional status of crops [6].

Accurate assessment of plant health and nutritional status is crucial for optimizing crop productivity and ensuring sustainable agricultural practices. Monitoring plant nutritional status traditionally involves time-consuming and laborious methods such as crop monitoring with SPAD-502 [7] or even destructive and expensive methods such as biochemical analysis of leaf tissue.

There are numerous studies confirming the positive relationship between SPAD values and the nutritional status of the plant, as stated by Liu et al. (2006) [8] on spinach or by Naiji and Souri (2018) [9] on basil.

In recent years, advances in machine learning techniques have opened up new possibilities for non-invasive plant health monitoring techniques. This experiment aims to propose an innovative approach that uses RGB image analysis combined with a regression algorithm to estimate the SPAD value, thus in a relative way, the nutritional status of basil plants.

This study has a twofold objective, the first is to analyse the biomass growth curve to determine the possibility of dynamically managing plant fertilisation throughout the growing cycle. The second objective is the creation and validation using specific metrics of a ML algorithm to obtain a RGB digital image regressor for basil plants grown indoors. This algorithm will process the input image and, thanks to its architecture and training, will return the prediction of the SPAD value. In this way, it will later be possible to send the output of the regressor to the fertiliser, dynamically and efficiently managing the nutrition of basil plants grown indoors.

II. MATERIAL AND METHODS

A. Experimental design

The experiment involved the indoor growth of *Ocimum Basilicum* (cv. 'Genovese'), for 22 days after transplanting (DAT). The study was conducted inside a climatic cell, located at DISTAL in Bologna. The cell is equipped with 27 independent steel boxes that provide insulation and avoid light contamination across treatments. The temperature and relative humidity conditions of the cell were respectively 23°C and 70% throughout the growth cycle. The basil was germinated for three weeks within the same cell and then transplanted into a tray with peat with a planting density of 285 meter^2 plants. The experimental design used was randomized blocks. In each compartment, plants were grown under a LED module with an R:B 3:1 spectral ratio and light intensity of 250 µmol $m^{-2}s^{-1}$ (PPFD), for 16/8 hours day^{-1} (light/dark).

In this experiment, five different nutrient treatments were applied, each replicated three times, for a total of 15 cultivated boxes. The nutrient solutions were prepared by starting with an optimal solution (EC: 2.4 mS cm^{-1}) and then diluting it to obtain a 70% (v/v) medium nutrient solution with water (EC: 1.9 mS cm^{-1}) and a 30% (v/v) low nutrient solution with water (EC: 1.2 mS cm^{-1}), then separately the 160% (EC: 3.5 mS cm^{-1}) and 130% (EC: 3 mS cm^{-1}) solution were prepared. The optimal solution was prepared following the concentrations of the standard Hoagland nutrient solution. Irrigation was carried out by sub-irrigation, keeping a film of water inside the cultivation tray at all times.

B. Data acquisition

During the entire vegetative cycle, non-destructive measurements including SPAD surveys and RGB image capture of the basil plants were carried out on a daily basis; in addition, four inter-cycle samplings and one final destructive sampling were performed.

The SPAD-502 is defined as a chlorophyll meter as it returns a dimensionless value closely correlated with the concentration of chlorophyll in the leaves [7].

RGB digital images are captured from above daily using a high-resolution digital camera of a mobile phone (model: Redmi Note Pro 9), trying to frame the entire tray shell below (Fig. 1). The dataset includes approximately 600 images that are always captured in the same way using a homemade metal stand that allows the camera to always be held in the same place. An important prerogative before taking the photo is to turn off the LED growth light, just in time of acquisition, therefore, the shot takes place only via the camera's flash. The actual measurements of nutritional status are obtained through measurements with the SPAD-502 (Konica Minolta - Instrument Measuring), obtaining 5 data per tray per day, where each data corresponds to the average of 5 measurements. The destructive measurements consisted of taking the fresh weight of stem and leaves, dry weight of the fresh sample after dehydration in an oven at 65°C for 72 hours, plant height and stem diameter. For each inter-cycle destructive sampling, 3 plants per box were collected, while for end-of-cycle sampling, 10 plants per box were measured.

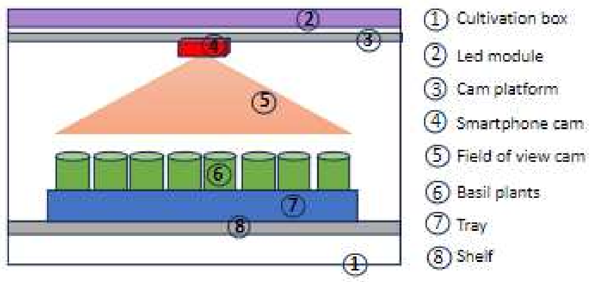

Fig. 1. Image acquisition setup during the experiment

C. Pre-processing and Feature Extraction

The dataset of RGB images is labelled according to the day the photo was taken. An image pre-processing algorithm was then implemented in order to increase the effectiveness and efficiency of the autonomous predictive models. This consisted of cropping the middle section of the photo to avoid colour alterations in the back of the photo, then a segmentation by thresholding using RGB values was applied in order to eliminate the background and all noise elements, bringing out only the region of interest (ROI) for the objective of this study, i.e. the leaves (Fig. 2).

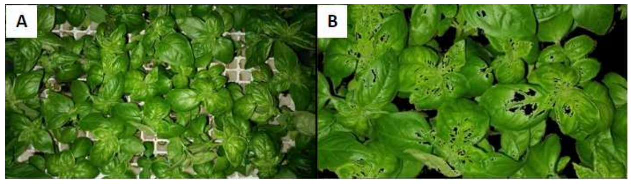

Fig. 2. (A) original image; (B) image processed with cutting and thresholding

Within this algorithm, a section was added to obtain from the ROI of the pre-processed images, the extraction of 17 vegetation indices (VIs) derived from 3 different colour spaces: RGB, CIELab and HSV (Table 1). Finally, all data are added into a dataset where each image is associated with its features such as the 17 VIs, the nutritional treatment, the DAT and the SPAD reading. This file will represent the input dataset for the ML regression algorithm.

The pre-processing and feature extraction algorithm is implemented with the OpenCV, Numpy and Pandas libraries of Python 3.11 using Visual Studio Code as the IDE (Integrated Development Environment).

Table 1. Vegetational indices (VIs) extracted from RGB images captured daily during cultivation.

Vegetation Indices	**Formula**	**References**
Mean red channel (R)	R	[10]
Mean green channel (G)	G	[10]
Mean blue channel (B)	B	[10]
Excess Green Index (EXG)	2G – R – B	[11]
Relative red (r)	R / (R + G + B)	[12]
Relative green (g)	G / (R + G + B)	[12]
Relative blue (b)	B / (R + G + B)	[12]
Normalized Green-red difference index (NGRVI)	(G - R) / (G + R)	[13]
Normalized Red-blue difference index (NRBVI)	(R - B) / (R + B)	[14]
Normalized Green-blue difference index (NGBDI)	(G - B) / (G + B)	[15]
Green leaf index (GLI)	(2G – R – B) / (2G + R + B)	[16]
Mean L* channel (L*)	L*	[17]
Mean a* channel (a*)	a*	[17]
Mean b* channel (b*)	b*	[17]
Mean H channel (H)	H	[18]
Mean S channel (S)	S	[18]
Mean V channel (V)	V	[18]

D. Training and validation

Different kinds of regression algorithms are currently available (e.g. Linear Regressor, Random Forest, Support Vector Regressor, etc.), for the task of our experiment a regression algorithm called Multi-Layer Perceptron (MLP) was chosen. The MLP is a feedforward type of ANN and is composed of several layers of artificial neurons organized in a hierarchical manner [19]. In particular, the architecture of the implemented algorithm is composed of 13 layers and four validation indices were considered: Mean Square Error (MSE), Mean Absolute Error (MAE), Coefficient of Determination (R^2) and Correlation (r).

The Mean Squared Error is a metric used to assess the goodness of a machine learning model in predicting continuous values. It is calculated (1) as the mean squares of the differences between the values predicted by the model and the actual values in the test data set. A lower MSE indicates a better fit of the model to the actual data.

$$MSE = (1/n)\ \Sigma(yi - \hat{y}i)^2 \qquad (1)$$

The Mean Absolute Error, or MSE, is another metric used to assess the accuracy of a machine learning model in predicting continuous values. Unlike the MSE, the MAE calculates (2) the average of the absolute differences between predicted and actual values. The MAE is less sensitive to outliers than the MSE, since the squares of the differences are not taken into account.

$$MAE = (1/n)\ \Sigma|yi - \hat{y}i| \qquad (2)$$

The coefficient of determination, also known as R-squared, is a metric that measures (3) the proportion of the variance in the output data that can be explained by the model. It takes values between 0 and 1, where 1 indicates a perfect fit of the model to the data and 0 indicates that the model does not explain the variance in the data. A negative value of R^2 indicates that the model is worse than a simple baseline model.

$$R^2 = 1 - (\Sigma(yi - \hat{y}i)^2 / \Sigma(yi - \bar{y})^2) \qquad (3)$$

The correlation coefficient is a statistical measure that evaluates the linear relationship between two variables. In machine learning, the Pearson correlation coefficient (r) (4) is often used, which measures the linear correlation between model predictions and actual values. It takes values between -1 and 1, where 1 indicates a perfect positive correlation, -1 indicates a perfect negative correlation and 0 indicates no linear correlation.

$$r = (\Sigma(xi - \bar{y})(yi - \hat{y}i)) / (\sqrt{(\Sigma(xi - \bar{y})^2)}\ \sqrt{(\Sigma(yi - \hat{y}i)^2)}) \qquad (4)$$

Before training the algorithm on the input data, the dataset is divided into training set (80%) and test set (20%) with a random state of 50% and only after normalization of the features, the dataset is ready for training. In this case, training continued for 1200 epochs before the metrics stabilized, with a learning rate of 0.001.

The algorithm architecture, training, testing and validation are implemented with Python 3.11 Numpy, Pandas and Scikit-learn libraries using Visual Studio Code as the IDE.

E. Statistical analysis

An ANOVA analysis was performed on the data collected from the destructive sampling, respecting the classical assumptions, to assess the differences in biomass between the five different nutrient treatments for each sampling date. This analysis is essential to assess the possibility of managing the nutrition of basil plants in indoor cultivation with a dynamic strategy, respecting the phenological stage of cultivation. The analysis was performed with R software (version 4.3.1) installed on a Windows 11 operating system and using Rstudio as IDE.

III. RESULTS

From the statistical analysis of data on fresh biomass (including leaves and stem) deriving from destructive measurements, as shown in the graph (Fig. 3), no particular statistical differences emerge for the first 11 days after transplanting. Subsequently, differences in biomass between the various treatments are accentuated, until the day of harvesting (22 DAT) where statistical differences are deduced only for the treatment at 30% (EC 1.2 mS cm^{-1}) which proves to be unfavorable, obtaining a reduction of 89% of the fresh weight of the epigeal part of the plant compared to the average among the other treatments (70%, 100%, 130%, 160%).

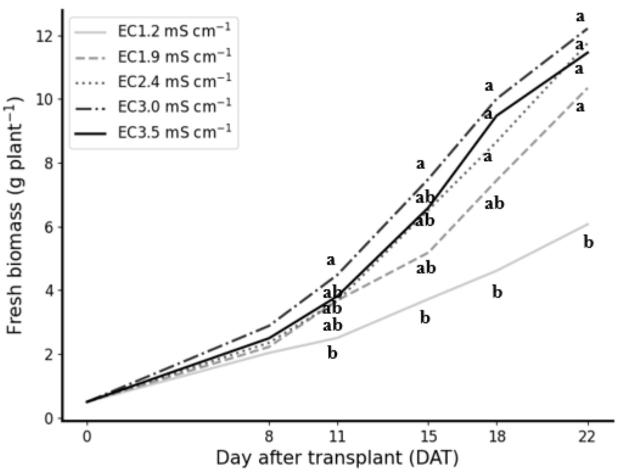

Fig. 3. Fresh biomass growth (g $plant^{-1}$) based on days after transplanting (DAT)

After training and testing the data collected during daily non-destructive measurements, the results showed that the regression algorithm proposed in this study achieved a high level of accuracy in predicting the nutritional status of basil plants grown indoors.

The model returns low MSE and MAE values of 2.92 and 1.32 and high R^2 and r values of 0.94 and 0.97 respectively (Fig. 4), demonstrating its effectiveness in estimating nutritional status based on RGB images. The values of the algorithm's performance metrics are dimensionless, as are the values obtained from SPAD readings.

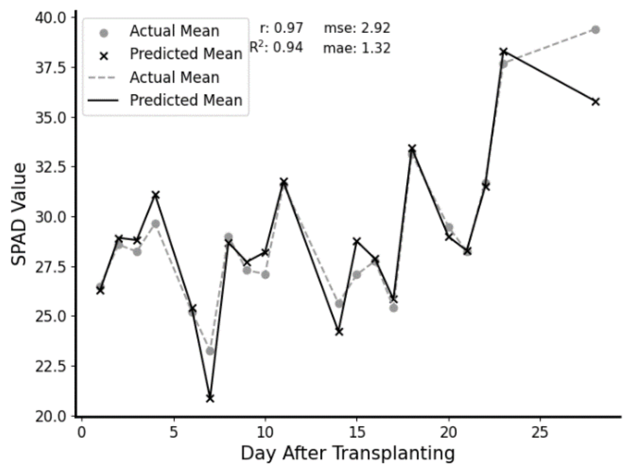

Fig. 4. Graph of the predicted SPAD values in relation to the measured values of the MLP regression algorithm [20].

IV. DISCUSSION

The analysis of fresh biomass allows us to lay the foundations for a dynamic management of the nutrition of basil plants for indoor cultivation. This study differs from the results of a similar experiment carried out by Hossaini and his research team [21], which obtain an advantage from a solution with EC equal to 1.2 to 0.9 mS cm^{-1}. Repeating the experiment becomes of crucial importance to strengthen the theory of dynamic management of fertilization. Considering the results of this experiment, a good nutritional strategy could be based on dividing the vegetative cycle into two phases, with the division point on the 11th day after transplanting. The dividing point indicates the day in which the first statistical differences on the fresh biomass are detected between the various treatments. Based on the results obtained from the statistical analysis during the first phase, a 30% (v/v) nutrient solution (EC 1.2 mS cm^{-1}) is recommended over the optimal fertilization (EC 2.4 mS cm^{-1}) without compromising the yield, proceeding with a more concentrated nutrition even at only 70% (v/v) (EC 1.9 mS cm^{-1}). This process would allow a considerable reduction in the use of fertilizers with a double environmental and economic advantage.

The use of RGB image monitoring combined with machine learning algorithms offers several advantages over traditional methods of plant nutrition assessment [22]. This approach allows a non-destructive and real-time evaluation, allowing timely interventions to correct nutrient deficiencies and optimize fertilization strategies [23]. Furthermore, the method can be scaled for large-scale crop monitoring, simplifying precision farming practices.

V. CONCLUSIONS

This study demonstrates interesting results regarding the dynamic management of indoor fertilization, but more investigations are needed to identify with precision and robustness the best dynamic fertilization strategy.

The results, however, obtained by the algorithm are encouraging considering the discrete number of images in the dataset and the few epochs with which the regressor was trained and validated. Furthermore, the architecture of this algorithm is quite short and computationally light, which results in a fairly accurate and very fast analysis.

Finally, the last step to make plant nutrition autonomous will be to connect the output of the image regressor to a fertilizer that will convert the value obtained into a time function in which the dosing pump will have to deposit the nutrient solution. This study is intended to be a starting point for the whole task of automating plant nutrition, with the future aim of collecting more data to make the regressor increasingly accurate.

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