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A fast analysis approach for crop health monitoring in hydroponic farms using hyperspectral imaging

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Abstract

Hydroponic farming is considered as a more sustainable solution in comparison to conventional farming. Most of the hydroponic farms rely on manual visual inspection for crop monitoring, which can be subjective, time-consuming, and tedious, especially in the case of large area farms. Hyperspectral imaging (HSI) is a promising technique for automated sensing and monitoring. Though several automated systems based on HSI have been developed recently for crop monitoring, these tend to be computationally complex and demand significant processing power and time, especially when handling extensive data from large farms. In this context, we explore an approach using spectral ratios for crop growth monitoring and the detection of early-stage nutrient stress. The early detection of the nutrient stress can enable effective crop, resource, and time management in large hydroponic farms. A sensitive nutrient deficiency index, named normalized nutrient deficiency index (NNDI), has been formulated for the early-stage detection of nutrient deficiencies. Evaluating these indices is computationally simple and quick. A methodology for crop growth monitoring and nutrient deficiency stress using these indices is demonstrated on Lactuca sativa L. crops. It is envisaged that the proposed quick, non-destructive imaging technique can enable future automation possibilities and serve as an invaluable tool in indoor hydroponic farms.

Keywords: hyperspectral imaging, crop monitoring, vegetation indices, NDVI, green lettuce, smart agriculture

1. INTRODUCTION

Sustainable agriculture focuses on improving crop production without comprising the needs of future generation. The key determinant factor for successful crop growth depends on several parameters such as lighting, temperature, nutrient intake, humidity, etc. Variations in any of these factors from the optimal conditions could affect the crop yield and hence a continuous monitoring of these parameters are essential. Recently, controlled environment agriculture (CEA) have gained much attention for the year-round production of leafy greens to meet the rising consumer demand [1]. CEA regulates most of the environmental conditions such as lighting, temperature, humidity, and nutrients. One of the most common methods employed to grow leafy greens using CEA is hydroponics based vertical farming, where the use of land, water, and nutrients are optimized.

Most of the vertical farms rely on manual visual inspection for crop monitoring, which can be quite subjective, time-consuming, and tedious, especially in the case of large farms [2]. Hyperspectral imaging (HSI) is a promising non-destructive technique for automated sensing and monitoring in biomedical [3-5], agriculture [6-9], marine [10-12], pharmaceutical [13] and remote sensing applications [14, 15]. There are methods that offer automated systems based on HSI for crop monitoring using advanced digital image processing and artificial intelligence (AI) [16]. However, such techniques are computationally sophisticated and require large processing power and time when dealing with big data from large farms [17]. Hence, there is a need for fast and efficient methods for automated growth monitoring. To address this challenge, an approach based on normalized spectral ratios known as hyperspectral vegetation indices, which are primarily used in remote sensing applications, can be employed. Evaluation of these vegetation indices are computationally simple and fast [18].

Furthermore, there is a crucial need to analyze the biochemical changes in crops with respect to time to promptly detect nutrient deficiencies and enhance crop growth for better resource utilization, and time management in farms. In this manuscript, we introduce fast and non-destructive approaches utilizing HSI to monitor crop growth and nutrient deficiencies. These approaches identify nutrient deficiencies by assessing biochemical changes linked to variations in internal structure and pigment levels, offering improved potential for early-stage detection. The key feature of these techniques is their non-destructive nature in detecting crop nutrient stress, which can enable automation possibilities.

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2. SYSTEM DESCRIPTION

2.1 Experimental setup

The schematic of the setup used for monitoring crop growth is shown in Fig. 1. The HSI camera employed monitors the reflected spectrum in 400 – 1000 nm wavelength region and a broadband light source covering this wavelength region is used for illumination. For this investigation, samples of green lettuce (Lactuca sativa L.) crops were grown in a commercial hydroponic system (P-Com, Panasonic). Seeds of green lettuce were initially sown into rockwool and germinated at 20-24 °C. The photoperiod was maintained such that the plants received 16 hrs of light per day. The investigation is conducted in two steps. In the first part of the study, a sample area of 15 × 6 cm was chosen from tray 1 (see Fig. 1) for performing the proof-of-concept demonstration.

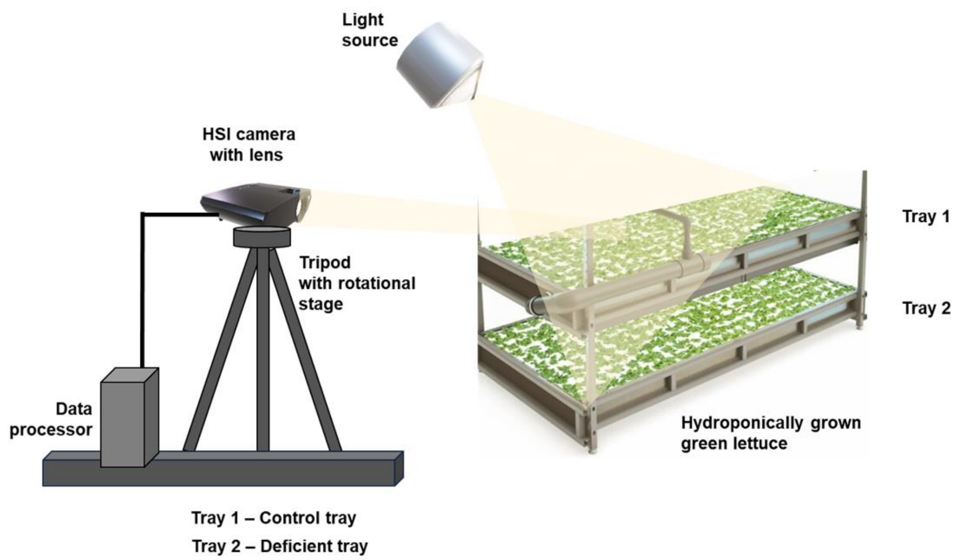

Figure 1. Schematic illustration of the proposed automated crop growth monitoring method.

In the second part, the crops were grown in two trays. The crops in tray 1 were grown with optimum nutrient composition and is designated as the control tray. The crops in tray 2 (indicated as deficient tray) received a nutrient composition deficient in multiple components (such as 78% deficient in Ca, 65% deficient in K, & 95% deficient in Fe.). The difference in the growth of the crops in these two trays has been investigated utilizing the proposed vegitation indices based approach. The life cycle of a crop typically consists of three main phases: germination, growth, and senescence. The growth phase can be subdivided into subphases such as log (exponential growth), maturity (steady growth) and flowering phase (harvest time). Our investigations specifically concentrate on the growth and senescence phases.

3. RESULTS AND DISCUSSION

In the first part of the investigation, two remote sensing indices, namely normalized difference vegetation index (NDVI) and modified chlorophyll absorption ratio index 2 (MCARI2) were used for evaluating the growth of the plants. NDVI is an indicator of live green vegetation. Values of NDVI varies between -1 and +1. NDVI is defined as [19]:

$$\text{NDVI} = \frac{R_{NIR} - R_{red}}{R_{NIR} + R_{red}} \tag{1}$$

where R_{NIR} represents reflectance at 800 nm and R_{red} represents reflectance at 680 nm.

MCARI2 is an index that is sensitive to the relative abundance of chlorophyll, defined as [20]:

$$\text{MCARI2} = \frac{1.5 * (2.5 * (R_{NIR} - R_{red}) - 1.3 * (R_{NIR} - R_{Green}))}{\sqrt{(2 * R_{NIR} + 1)^2 - (6 * R_{NIR} - 5 * \sqrt{R_{red}}) - 0.5}} \tag{2}$$

where R_{NIR}, R_{red}, and R_{Green} represent reflectance at 800 nm, 670 nm, and 550 nm, respectively.

NDVI and MCARI2 maps generated from the hyperspectral datacubes recorded using the HSI camera are shown in Fig. 2a. The computational time taken for generating these maps from datacubes of 7 GB size was only 1 s on a portable laptop computer with Intel i-7 quad core processor running at 1.9 GHz speed with 32 GB random access memory (RAM). Growth curves based on NDVI and MCARI2 along time (growth phase) are shown in Fig. 2b and 2c, respectively.

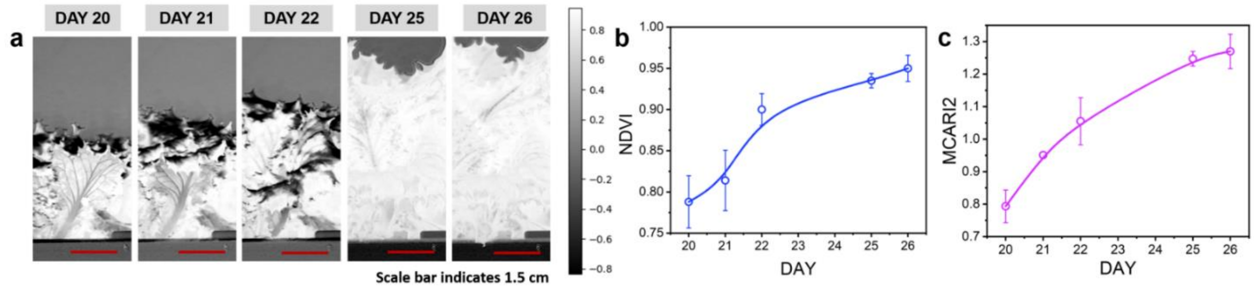

Figure 2. a. NDVI maps for the captured crop area at day 20, 21, 22, 25, and 26 from the seeding date, b. Growth curve based on NDVI c. Growth curve based on MCARI2. The line is only a guide to the eye.

Both the growth curves based on NDVI and MCARI2 show an increasing trend with respect to the growth over a time period. Standard reference growth curves are created for normal plant growth. Abnormalities in the plant growth can be identified by comparing the real time data to these reference growth curves.

In the second part of the investigation, images of *Lactuca sativa* L. grown in tray 1 (control tray) and tray 2 (deficient tray) were acquired using the HSI camera on different days along the crop life cycle (referred to as days after planting (DAP)). Evaluating the variation of vegetation indices during nutrient deficiency can provide insights on the nutrient deficiency progression. In this context, a term named as spectral index is defined as given in Equation 3, which is equal to the normalised difference ratio between reflectance at two wavelengths given by,

$$\text{Spectral index} = \left(\frac{R_{\lambda_A} - R_{\lambda_B}}{R_{\lambda_A} + R_{\lambda_B}}\right) \quad -(3)$$

$R_{\lambda A}$ and $R_{\lambda B}$ represents reflectance at wavelength A (λ_A) and B (λ_B), respectively. A normalised contrast map is plotted by substituting the spectral values from the control and deficient trays at DAP 38 (in senescence phase) in Eq. (3) to identify the optimum wavelength coordinates for defining the spectral index (See Fig. 3a and b).

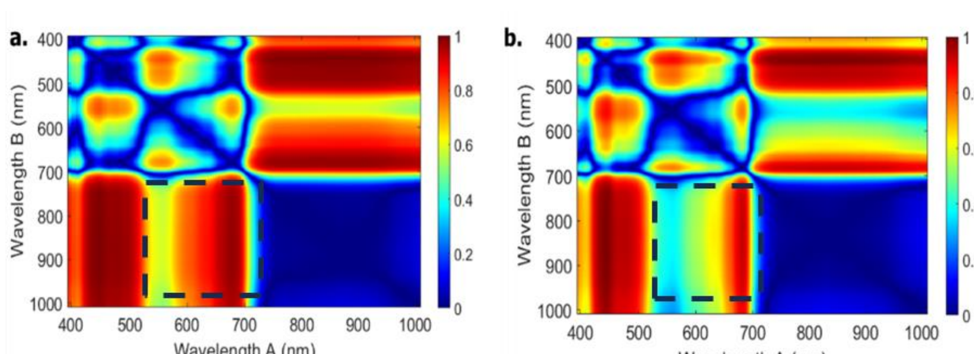

Figure 3. Normalized spectral index contrast map for crops grown a. control tray b. deficient tray at DAP 38 (in senescence phase). Color bar represents the normalized spectral index value along the wavelength coordinates A (λ_A) and B (λ_B)

The contrast map of spectra extracted from the recorded datacubes for the crops in the control and deficient tray showed a notable deviation from 0.8 to 0.45 along wavelength ranges of 540 nm – 710 nm, and 700 nm –1000 nm for wavelength A and B, respectively (the regions marked in black dotted lines in Fig. 3). For the selection of optimum wavelength in NIR window, certain bands with water absorption are avoided due to the inconsistent variations in the ambient atmosphere. Based on the results from the normalized spectral index contrast map shown in Fig. 3, a sensitive nutrient deficiency index, named normalized nutrient deficiency index (NNDI), has been formulated for the early-stage detection of nutrient deficiencies in hydroponically grown lettuce, as given by Equation 4:

$$\text{NNDI} = \left(\frac{R_{\lambda_{705}} - R_{\lambda_{800}}}{R_{\lambda_{705}} + R_{\lambda_{800}}}\right) \qquad - (4)$$

Difference plots for normalised spectral index contrast map for crops grown in the control and deficient trays at DAP 22 (in growth phase) and DAP 38 (in senescence phase) were generated to evaluate the sensitivity of the index (see Fig. 4a and b).

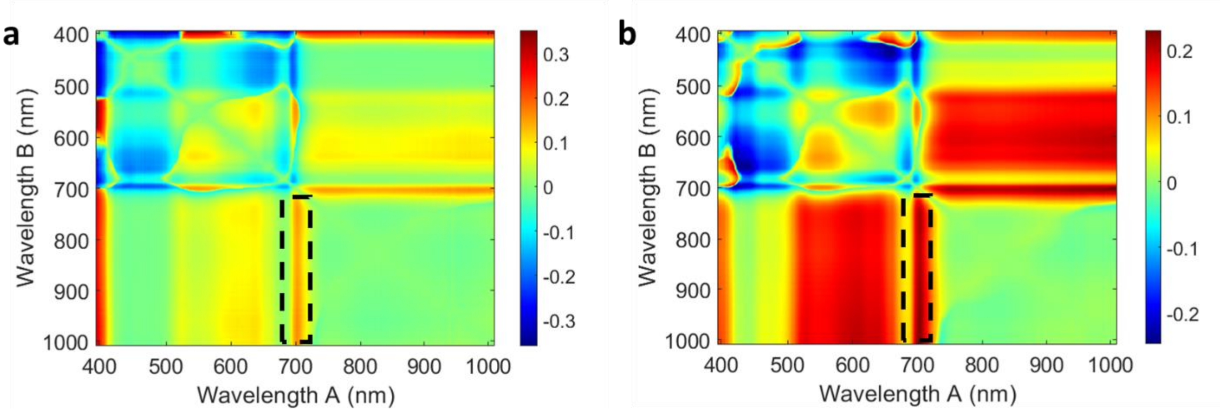

Figure 4. Difference contrast map of normalized spectral indices for crops grown in control and deficient trays at a. DAP 22 (in growth phase) and b. DAP 38 (in senescence phase). Color bar represents the difference of the normalized spectral indices along the wavelength coordinates A (λ_A) and B (λ_B).

It is seen from the difference contrast space that the differences are highest for the band centred at 705 nm compared to the band centred at 680 nm (see the areas marked by black dotted lines in Fig. 4). Hence, the sensitivity at space coordinates of NNDI (705 nm, 800 nm) is observed to be higher compared to space coordinates of NDVI (680 nm, 800 nm).

Plots depicting the variation of the two normalised spectral indices, NDVI and NNDI, w. r. t time for crops grown in control and deficient trays are shown in Fig. 5.

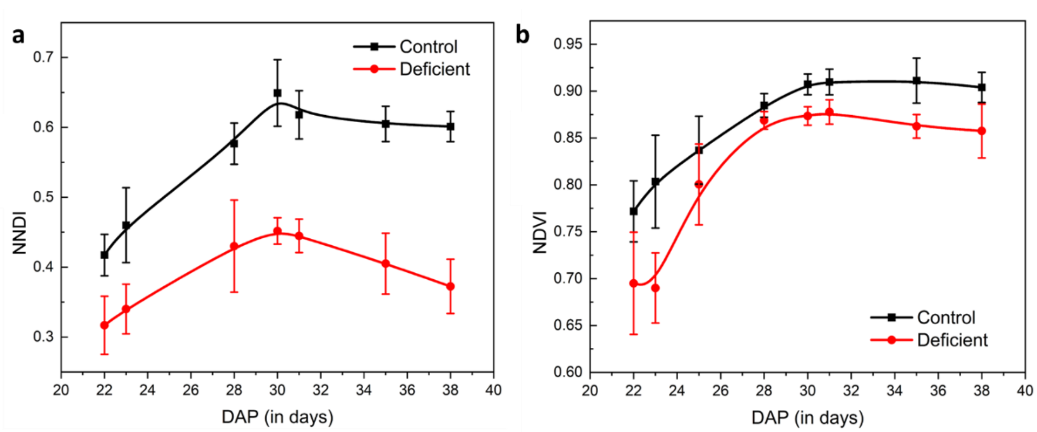

Figure 5. Plot depicting the normalized spectral indices for crops grown in control and deficient trays a. NNDI and b. NDVI. Note that the dotted line is only a guide to the eye.

From the plots shown in Fig. 5, it can be seen that the spectral indices NDVI and NNDI can help in the identification of nutrient deficiencies in lettuce crops. The corresponding NDVI and NNDI maps at DAP 25 (in growth phase) and DAP 33 (in senescence phase) for the deficiency and control trays are depicted in Figs. 6 and 7. It is seen that the crops grown in the control and deficient tray has NNDI values in the range of 0.41 to 0.65 and 0.32 to 0.42, respectively.

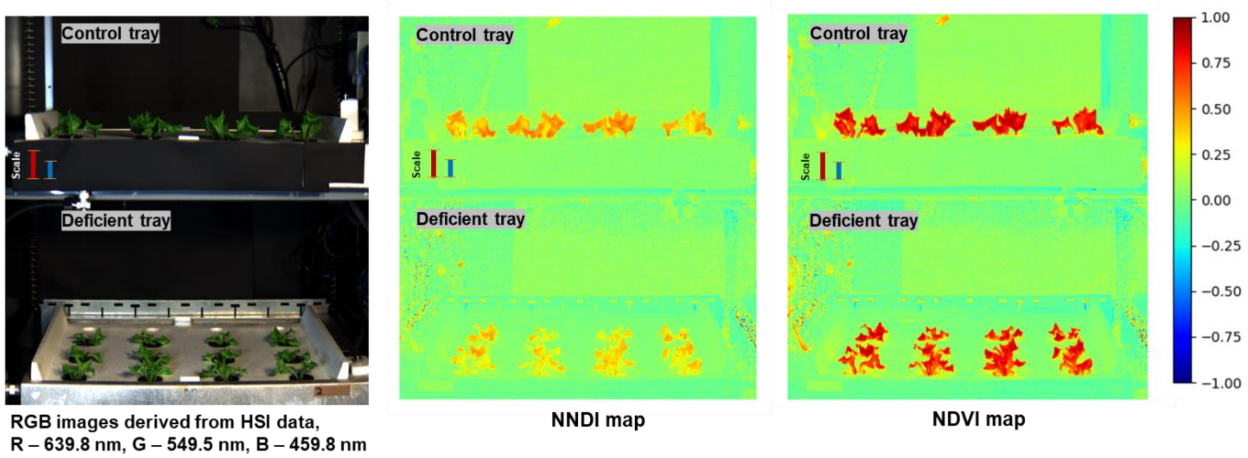

Figure 6. RGB image of the green lettuce crop and corresponding NNDI and NDVI maps at DAP 25. Red and blue scale bars in the RGB image indicates 4 cm in control and deficient trays, respectively.

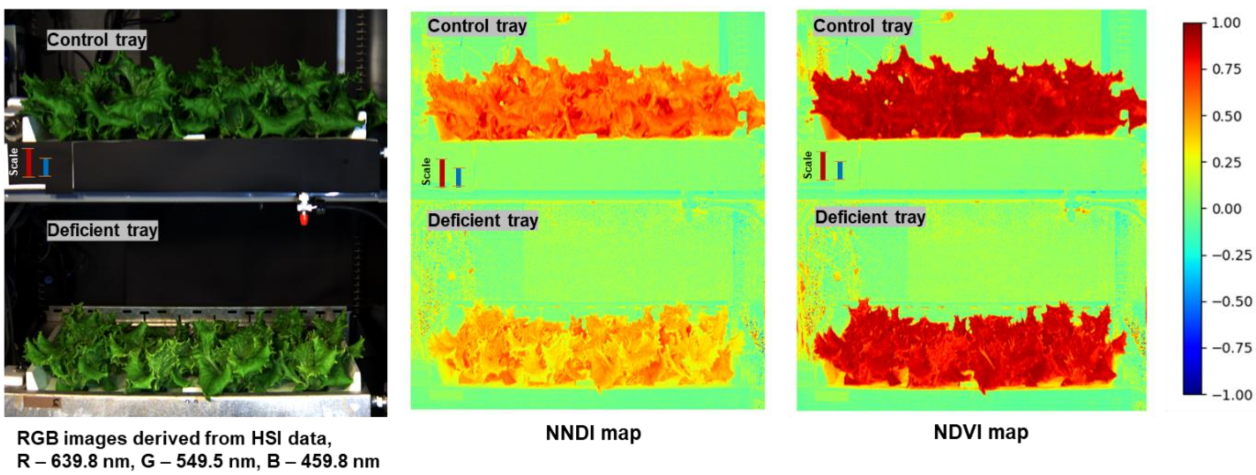

Figure 7. RGB image of the green lettuce crop and corresponding NNDI and NDVI maps at DAP 35. Red and blue scale bars in RGB image indicates 4 cm in control and deficient trays, respectively.

It is evident from these figures that vegetation indices such as NDVI and NNDI can help in identifying the nutrient deficiencies in green lettuce. In addition, it is also observed that the newly defined spectral index, NNDI, is more sensitive in comparison to NDVI for deficiency detection both in growth and senescence phases. As this developed technique can enable early identification of plant stresses before visible symptoms appear, a possible implementation strategy to operate in real time is visualised for implementing in future sustainable farms and is shown in the Fig. 8.

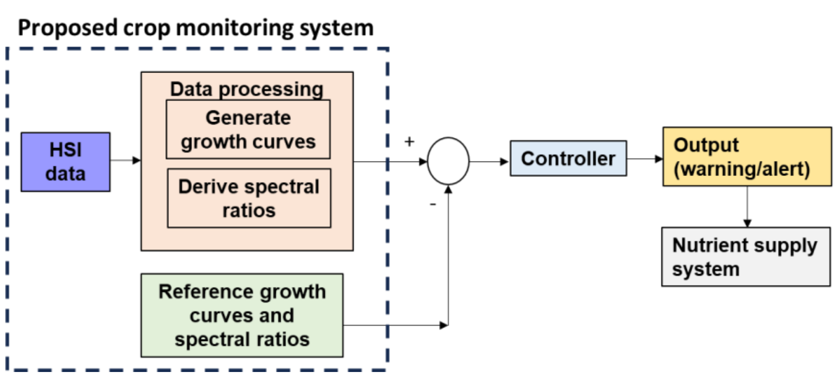

Figure 8. Proposed implementation strategy of the developed technique in future sustainable farms.

The control feedback from the crop monitoring system to the crop nutrient supply system could aid in compensating the nutrient deficiency at an early stage, which will help in reducing crop losses. It is envisaged that the adoption of such monitoring technologies could assist in ensuring maximum yield with minimal wastage, contributing to sustainable agricultural practices.

4. CONCLUSION

Simplified crop growth monitoring models using vegetation indices are illustrated. Different vegetation indices were investigated for their applicability in the detection of nutrient deficiencies. The results show that among the various indices discussed, NNDI offers better sensitivity in extracting symptoms of multi-nutrient deficiencies. The proposed method requires minimal computational time (~ 1s) and allows quick classification of growth stages. These fast analysis approaches introduced to monitor crop health and detect nutrient deficiency at an early stage can help in minimizing crop loss. Such systems can also offer a comprehensive insight into crop health and environmental variables, facilitating more effective and sustainable agricultural methods.

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