NITROGEN ESTIMATION SYSTEM IN LETTUCE USING MULTISPECTRAL CAMERA ON EDGE DEVICE

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Abstract: Farmers can improve their decision-making by accurately diagnosing nutrient deficiencies, resulting in more efficient fertilizer use and reducing the environmental impact of over-fertilization. This study presents an automated system detecting nitrogen stress in lettuce through multispectral imaging, running on an edge device. The system estimates nitrogen levels in leaves using a machine learning algorithm, calibrated against reference measurements taken in the field, achieving a mean squared error of 0.4 and R^2 of 0.98. Based on threshold values determined through ground-truth experiments, plant health data is transmitted to a cloud database, which can be accessed via a web or desktop application. The proposed method guarantees efficient monitoring and regulation of nitrogen levels in crops.

Keywords: Leaf Nitrogen Concentration, Machine Learning, Multispectral Image, Edge Device, Lettuce.

I. INTRODUCTION

Lettuce (Lactuca sativa, L.), a member of the Asteraceae family, is a significant vegetable crop cultivated globally in both open-field and greenhouse environments [1]. It is low in calories, fat, and sodium but rich in fiber, folate, vitamin C, and essential minerals such as iron [2]. Lettuce cultivation poses challenges due to susceptibility to numerous diseases, sensitivity to climate conditions, and specific nutritional requirements. Numerous studies have investigated the influence of plant nutrients on lettuce yield and quality, establishing that certain nutrients are essential for optimal production [3]. Nitrogen is a macronutrient required in large quantities for plant growth [4], significantly impacting the chlorophyll content in leaves. The nitrogen content in leaves serves as a critical indicator for nitrogen fertilizer application [5], particularly during early growth stages. This parameter is closely linked to the final leaf quality at later growth stages, making it valuable for managing nitrogen application effectively to ensure both high yield and quality.

Over the past decade, researchers have increasingly focused on examining agricultural products using non-invasive methods known as remote sensing. This technique has gained significant popularity in precision agriculture due to its ability to monitor crop growth rapidly and non-destructively. Remote sensing has diverse applications in agriculture, such as crop identification, yield forecasting, rangeland surveys, and early detection of insect or disease pressures [6]. A key method within remote sensing is multi-spectral imaging, which allows for calculating various vegetation indices. These indices are particularly useful for managing nitrogen content in crops. Despite their broad coverage, satellite images often lack the spatiotemporal resolution required for precise monitoring of nitrogen status [7]. While capable of capturing high-resolution images, manned airborne platforms face limitations due to operational complexity and high costs. Remote sensing has revolutionized precision agriculture by providing essential data for informed decision-making.

Although ground-based remote sensing platforms can achieve high accuracy in monitoring nitrogen status, they often face limitations in providing immediate measurements. To address this challenge, a novel system was designed for in-field analysis of nitrogen status in lettuce. The proposed system integrates a MapIR Survey3W multispectral camera with a Raspberry Pi single-board computer to automatically capture and process images directly in the field. The system autonomously collects and processes these images on-site and uploads the analyzed data to a Firestore database, making it accessible for visualization through a computer application. The method for estimating nitrogen levels is based on Instance Multiple Instance Regression (Instance-MIR) [8]. Additionally, the collected data undergo calibration using reference measurements from field-based instruments to enhance the precision of nitrogen estimates. The system sets specific thresholds for nitrogen sufficiency or deficiency, enabling timely alerts to users when intervention is required, thus ensuring effective nutrient management based on real-time field conditions. This paper is organized as follows: Following this introduction, the next section presents the system's implementation, including its structure, algorithms, and software components. The third section provides test results; the final section offers conclusions and discusses future work.

II. MATERIALS AND METHODS

A. System design

Figure 1 presents the block diagram of the proposed system, designed to efficiently capture, analyze, and

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transmit agricultural data through a well-integrated setup. The core of the system is the Capture and Analysis Node, which comprises a MAPIR Survey3W multispectral camera coupled with a Raspberry Pi 4B embedded computer, enabling real-time image processing and analysis.

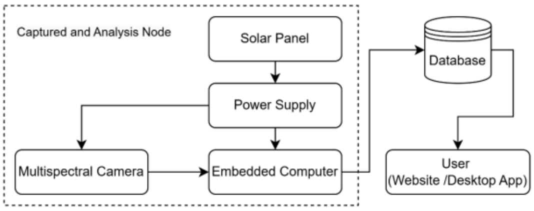

Figure 1. The system block diagram.

The system is powered by a solar panel connected to a power supply unit to sustain continuous operation even in remote places. This improves the system's autonomy and reduces downtime caused by power limits. After capturing the images, the embedded computer processes and analyzes the data and transmits the results to a centralized database - Google Firebase - used in this study as the primary data storage hub.

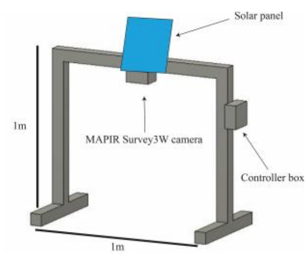

Figure 2. The physical design system.

Additionally, Figure 2 illustrates the system's physical design as deployed in the field. The design features a robust frame that supports both the MAPIR Survey3W camera and the solar panel at an optimal height of one meter above the ground. The camera is centrally positioned to maximize its field of view, ensuring comprehensive coverage of the crops. The frame also includes a controller box mounted on the side, which houses the embedded computer (Raspberry Pi) and other essential electronic components.

B. Nitrogen Estimation and Calibration

In this study, the Instance-MIR method was combined with Support Vector Regression (SVR) from previous research to estimate the nitrogen levels in lettuce using multispectral data (see Fig. 3) [8]. After using the MAPIR Survey3W camera, these captured images were processed to calculate vegetation indices such as the Normalized Difference Vegetation Index (NDVI), Green Normalized Difference Vegetation Index (GNDVI), and Normalized Difference Red Edge Index (NDRE). Although NDVI correlates with chlorophyll content and green biomass (see Formula 1), its sensitivity to variations in leaf nitrogen concentration can be limited especially during later growth stages [9]. By utilizing green/red-edge and near-infrared wavelengths, GNDVI (see Formula 2) and NDRE (see Formula 3) are sensitive to the changing nitrogen concentration in leaves, suitable for later growth stages where NDVI may saturate [10]. The formula for NDVI is:

$$NDVI = \frac{NIR-RED}{NIR+RED} \quad (1)$$

with NIR as near-infrared and RED as red wavelengths. The formula of GNDVI and NDRE are:

$$GNDVI = \frac{NIR-GREEN}{NIR+GREEN} \quad (2)$$

$$NDRE = \frac{NIR-RED\ EDGE}{NIR+RED\ EDGE} \quad (3)$$

with GREEN and RED EDGE are green and red-edge wavelengths, respectively.

Each lettuce plant is represented as a "bag" containing multiple image instances, with the nitrogen content measured through laboratory analysis serving as the reference value for the bag. During training, the SVR model with a Gaussian kernel learns the relationships between the spectral features of individual instances and the nitrogen reference values. In the prediction phase, the trained model processes new data by estimating nitrogen content for each image instance within a bag. The final nitrogen estimate for the plant is obtained by averaging the instance-level predictions. This instance-based prediction approach enables the model to aggregate information while effectively maintaining high prediction accuracy.

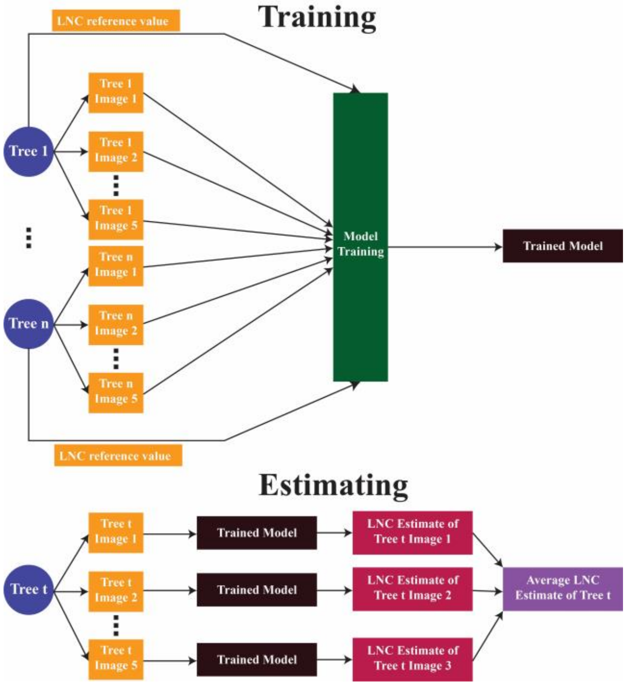

Figure 3. The Instance Multiple Instance Regression Paradism [8].

After applying the Instance-MIR method for the initial nitrogen estimation, the study further calibrates these predictions using direct measurements of Leaf Nitrogen Concentration (LNC) collected from the field. LNC refers to the amount of nitrogen in a plant's leaf tissue. This calibration process is essential to refine the model's predictions and enhance its accuracy. The calibration data, obtained by using a SPAD-502 meter (Minolta Camera Co., Osaka, Japan) [11], is used to fine-tune the model, ensuring that the estimated nitrogen levels closely align with the actual nitrogen concentrations in the lettuce leaves. The SPAD value is an index obtained from the meter representing the relative chlorophyll content in plant leaves. These SPAD readings were then converted to LNC using a predefined conversion formula (see Formula 4) [12], ensuring that the estimates were accurate and could be used to guide data-driven decisions in precision agriculture.

$$SPAD = LNC \times 0.067 + 31.6 \quad (4)$$

The study of Xiong *et al.* carried out extensive experiments measuring SPAD values and corresponding LNC across several dicot species. The study used statistical regression analysis plotting SPAD values against corresponding LNC measurements. This process aimed to identify the precise relationship specific to dicot species under standardized conditions. In this study, the slope 0.067 is the proportional contribution of nitrogen to SPAD readings which indicates for every unit increase in LNC, the SPAD value increases by 0.067 units. The intercept 31.6 represents the baseline SPAD value when LNC in lettuce is negligible. This two-step approach of prediction followed by calibration enables a more precise and reliable assessment of nitrogen status in the crops, supporting effective nutrient management strategies in agriculture.

C. Requirement of Desktop and Web Applications

Both desktop and web programs were created with particular criteria suited to precision agriculture to improve the monitoring and analysis of nitrogen status in lettuce growing. The primary objective of the desktop application is to provide an accessible and straightforward tool for analyzing the nitrogen status of lettuce plants. It features an intuitive user interface that allows users to seamlessly import images of lettuce plants or retrieve historical data from the database. Upon importing an image, the application processes it and presents a clear result indicating whether the lettuce is "Good" or "Nitrogen Deficient". This straightforward approach ensures that users with varying levels of technical expertise can effectively utilize the application, thereby streamlining the analysis process and facilitating prompt decision-making.

In addition to the desktop application, a web application was developed to complement its functionality by providing remote monitoring capabilities and leveraging Internet of Things (IoT) technologies. The web application was built using the ThingsBoard platform, an open-source IoT solution renowned for its scalability and flexibility in managing IoT devices and data. Users can access the application from any location via a web browser, enabling continuous monitoring of lettuce crops and facilitating timely interventions when necessary. The web application presents data through interactive charts, graphs, and dashboards, assisting users in effectively interpreting trends and patterns. It maintains a user-friendly interface consistent with the desktop application to enhance the overall user experience. The platform is designed to be scalable, accommodating additional sensors and data sources as the agricultural operation expands.

III. RESULTS AND DISCUSSION

A. Field Deployment and Testing

For sixty days, the proposed system was established in an open field located in Tay Tuu Commune, Bac Tu Liem District, Hanoi City, Vietnam. Two distinct groups were formed: one group received normal nitrogen levels, while the other experienced a significant nitrogen deficiency, with an 80% reduction in nitrogen supply. The system was placed one meter above the crops to collect precise multispectral data for nitrogen monitoring (Figure 4). Sampling was captured every day between 12:00 and 13:00 to ensure the best reflectance circumstances during the brightest hours. This timing improved the quality of the multispectral camera's reflectance data and increased the precision of the system's nitrogen stress estimation.

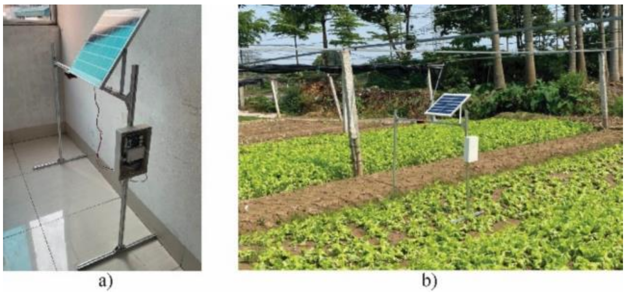

Figure 4. (a) Indoor prototype setup, (b) Field deployment of the system.

B. Measured vs. Estimated Leaf Nitrogen Content

To evaluate the accuracy of the nitrogen content estimates produced by our model, we compared them with the measured Leaf Nitrogen Concentration (LNC) obtained using the SPAD-502 meter (see the blue line in Figure 5). In the left panel of Figure 5, both the estimated and observed nitrogen concentrations for nitrogen-sufficient plants exhibit a similar downward trend over time. The calculated values generally remain close to the actual nitrogen levels, with only slight deviations from the SPAD

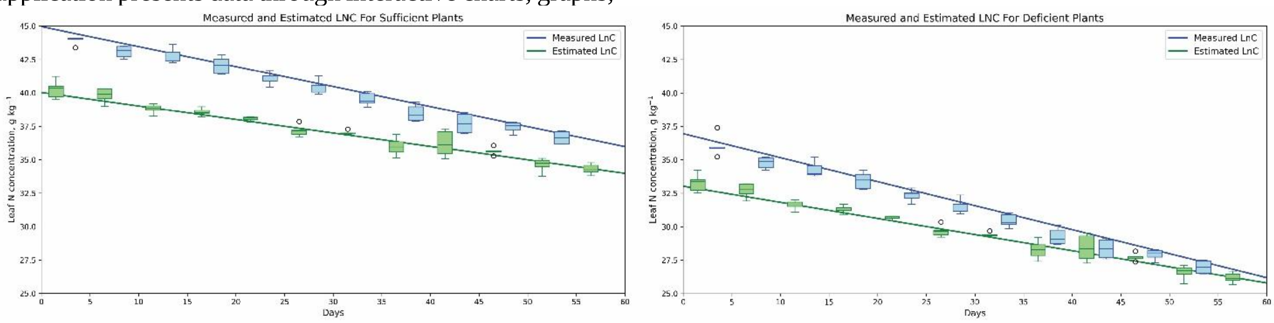

Figure 5. Over time, the measured and estimated Leaf Nitrogen Concentration (LNC) for plants.

measurements. Conversely, the right panel of Figure 5 indicates a noticeable difference between the estimated LNC values from the model and the SPAD measurements for nitrogen-deficient plants. Although both the estimated and observed patterns show a decrease in nitrogen concentration over time, the estimations consistently underestimate the nitrogen content compared to the actual data. The model's strong performance in predicting LNC is confirmed by a mean squared error (MSE) of 0.4 and R^2 of 0.98. The relatively high MSE can be attributed to the variability in measured LNC values across different observation days. This natural fluctuation in the actual data introduces higher differences between measured and predicted values, contributing to the elevated MSE. However, the high R^2 value of 0.98 indicates that the model effectively captures the overall trend and variability in the data. This demonstrates that, despite the larger error margins for specific predictions (as reflected in the MSE), the model explains a significant proportion of the variance in LNC and maintains a high level of predictive accuracy for plants receiving adequate nitrogen throughout the observation period.

C. Nitrogen Level Classification Thresholds

Based on the statistical analysis and the box plots presented in Figure 8, a clear threshold for LNC was established to differentiate between these two categories (see Formula 4). The observed LNC and the estimated LNC distributions show distinct patterns that support the determination of this threshold. From the box plot analysis, it is evident that LNC values greater than 37.5 indicate a "sufficient" nitrogen level, whereas values equal to or below 37.5 are classified as "deficient." This threshold was derived by examining the distribution of LNC values across both categories, focusing on the separation point that minimizes overlap while maximizing classification accuracy.

$$Nitrogen\ levels = \begin{cases} sufficient, & LNC \geq 37.5 \\ deficient, & otherwise \end{cases} \quad (5)$$

The "sufficient" category demonstrates higher LNC values with a median and interquartile range that consistently exceed the 37.5 threshold, as shown in the observed and estimated LNC box plots. In contrast, the "deficient" category displays lower LNC values, with the median and majority of the data falling below this cutoff. This statistical separation ensures that the threshold is both practical and reliable for field application. This classification threshold enables actionable insights for managing plant nitrogen levels, guiding fertilization strategies, and optimizing crop health and productivity.

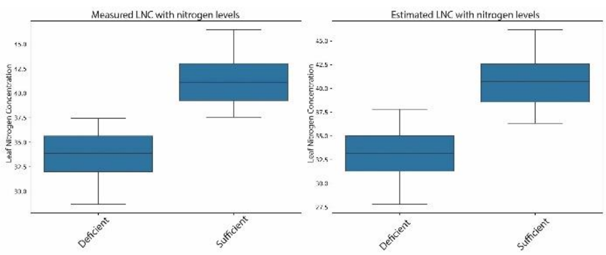

Figure 6. Measured and Estimated Leaf Nitrogen Concentrations for Nitrogen Level Classification.

D. The Desktop and Web Applications

The desktop application was developed in Python using the Tkinter library, which offers robust support for graphical user interfaces. The application successfully analyzed nitrogen levels from image inputs, as demonstrated in Figure 7. In subfigure (a), the system detects and classifies the plant as "Nitrogen Deficient," as indicated by the clear segmentation in the processed image and the status display. Conversely, in subfigure (b), the system recognizes a "Good" nitrogen status for the plant, again verified by the segmentation results. The application provides users with a simple interface, allowing them to import images, analyze nitrogen status, and store the results efficiently. These findings demonstrate the desktop application's capability to detect real-time nitrogen status with clear outputs.

In parallel, the web application (shown in Figure 8) was developed using the ThingsBoard IoT platform. This platform enables real-time monitoring of various environmental parameters associated with lettuce crops. The system is capable of tracking the status of sensors deployed across different locations, as seen in the sensor map for areas such as Bac Tu Liem, Cau Giay, and Gia Lam. The time-series data provided for each sensor offers detailed insights into plant status over time, facilitating continuous monitoring. The web interface displays sensor activity and status in a clear, organized manner, enabling users to track and manage their agricultural operations remotely.

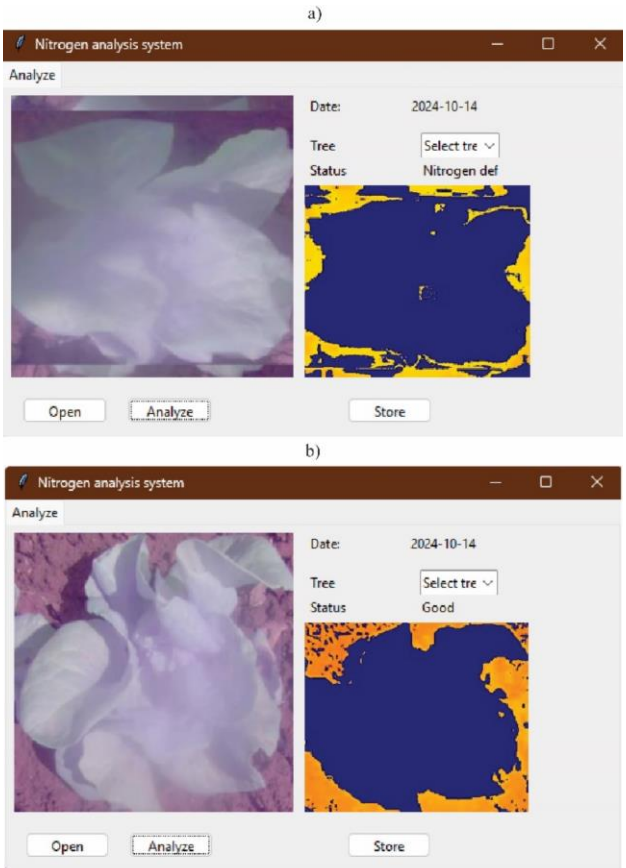

Figure 7. The desktop application with (a) Nitrogen Deficient Plant, and (b) Nitrogen Sufficient Plant.

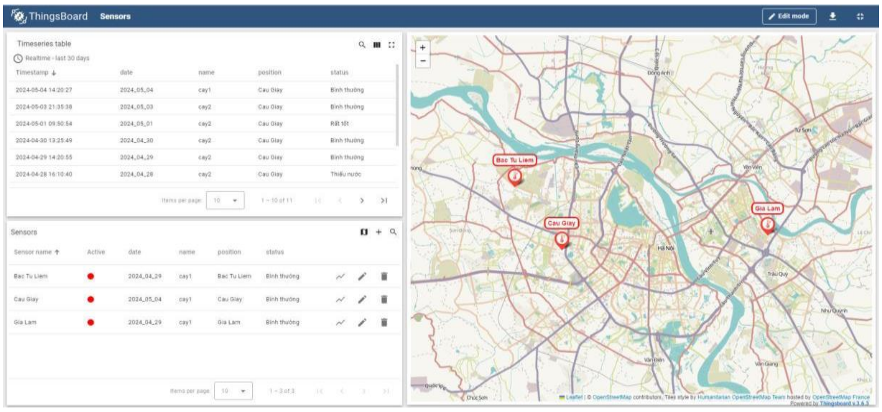

Figure 8. The web application on the ThingsBoard platform.

IV. CONCLUSION AND FUTURE WORKS

In this study, we developed an automated system that combines multispectral imaging, real-time image capture and machine learning algorithms to detect nitrogen stress in lettuce. The system accurately estimates nitrogen levels, achieving an MSE of 0.4, and includes a desktop tool for immediate analysis and a web platform for remote monitoring. These features enhance precision agriculture practices and promote efficient fertilizer management. However, the system has limitations, including reliance on a small dataset, leading to discrepancies in nitrogen level estimates, and a binary classification of nitrogen status that lacks nuance. The weather conditions and soil type also affect the precision of the threshold.

Future work will focus on expanding the dataset with various weather conditions and soil types for improved calibration and incorporating more detailed classifications. Enhancements to both the desktop application and the web platform, along with the integration of advanced machine learning, real-time weather data, and soil moisture levels, will contribute to a more comprehensive nutrient management approach. Ultimately, scaling the web application for multi-farm use will establish this system as a vital tool for modern precision agriculture.

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HỆ THỐNG ƯỚC TÍNH HÀM LƯỢNG NITƠ TRONG XÀ LÁCH SỬ DỤNG ẢNH ĐA PHỔ TRÊN THIẾT BỊ BIÊN

Tóm tắt: Nông dân có thể tăng tốc việc đưa ra quyết định của mình bằng cách chẩn đoán chính xác sự thiếu hụt dinh dưỡng, từ đó giúp việc sử dụng phân bón hiệu quả hơn và giảm thiểu tác động môi trường do việc bón phân quá mức. Nghiên cứu này giới thiệu một hệ thống tự động phát hiện tình trạng căng thẳng do thiếu nitơ ở cây xà lách thông qua hình ảnh đa phổ và được vận hành trên thiết bị biên. Hệ thống này ước tính mức độ nitơ trong lá bằng cách sử dụng một thuật toán học máy được hiệu chỉnh dựa trên các phép đo tham chiếu thực hiện tại hiện trường, đạt sai số trung bình bình phương (MSE) là 0,4 và R^2 là 0,98. Dựa trên các giá trị ngưỡng được xác định thông qua các thí nghiệm thực địa, dữ liệu sức khỏe cây trồng được truyền đến cơ sở dữ liệu đám mây và có thể truy cập thông qua ứng dụng web hoặc máy tính để bàn. Phương pháp đề xuất này đảm bảo việc giám sát và điều chỉnh hiệu quả mức độ nitơ trong cây trồng.

Keywords: Lượng nitơ trong lá, Máy học, Ảnh đa phổ, Thiết bị biên, Xà lách.

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