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Chlorophyll Indexing via Smartphones for Early Nutrient Stress Detection in Root Crops

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Abstract:

In this study, smartphone-based chlorophyll indexing research methods as a fast, inexpensive and non-destructive procedure of identifying early-onset nutrient stress conditions in root crops including potatoes, carrots and beets are examined. In the study, imaging of smartphone camera is used to evaluate leaf greenness which has a correlation with nitrogen and general nutrient while being estimated using algorithms of chlorophyll estimation. The analysis and comparison of the data of 50 samples of root crops under the condition of controlled nutrients, with the SPAD meter and laboratory chlorophyll content were conducted. Findings demonstrated a high-level positive correlation ($r = 0.91$) between chlorophyll indices obtained using smartphones and the ecstatic levels of SPAD values with a mean estimation error of 92%. The constructed model was able to identify nutrient stress even up to 7 days before the visual inspection of tradition visual analysis is made. The statistical testing revealed that smartphone images had the capacity to forecast nitrogen deficiency with a mean absolute deviation of 0.06 and a root mean square deviation (RMSE) of 0.08. These results indicate that chlorophyll indexing through smartphones is a cost-effective and reliable method used to control nutrients precisely. The suggested approach will provide farmers with improved capacity to make decisions based on data to encourage effective and sustainable practices of crop production.

Keywords: Chlorophyll Indexing, Smartphone Imaging, Nutrient Stress Detection, Root Crops, Precision Agriculture.

I. INTRODUCTION

Green pigment chlorophyll is a vital measure of plant vitality and photosynthesis ability. Monitoring of chlorophyll in root crop like cassava, carrots, potatoes, and beets is very important in indications of nutrient status especially the availability of nitrogen which directly relates to growth and yield [1]. Conventional means of chlorophyll evaluation such as laboratory chemical analysis and SPAD meter are precise yet can be costly, time-intensive and ineffective in smallholder farmers or large-scale monitoring. The necessity to find affordable, fast, and convenient methods to detect nutrient stress at an early stage increases with the idea of moving agriculture to precision and data-driven management [2]. The eventual implementation of smartphone technology in the agricultural monitoring system is a novel and viable option. The current generation smartphones have advanced cameras with great resolution and computing features that have the capacity to identify minute changes in the coloration of leaves in connection to the chlorophyll concentration [3]. With image processing and chlorophyll indexing algorithms they are able to get an estimate of the plant nutrient status in-situ, eliminating the necessity of using laboratory gear. This practice will help intervene on time and better control fertilizer management that will lead to a better crop performance and sustainability. This study aims at designing and testing a smartphone-selected chlorophyll recording apparatus that would realize the initial nutrient pressure in root crops. Through comparison of smartphone obtained indices with the traditional chlorophyll, the research will determine a dependable, inexpensive and scalable diagnostic instrument of accuracy agriculture. The suggested tool can transform nutrient monitoring and enable farmers to use real-time data to optimize their inputs, reduce losses, and enhances sustainable yield of crops. In this manner, the study can lead to the development of digital agriculture technologies that will fill in the divide between high-tech technologies and field-level usage of these technologies in developing and resource-alternative farming systems.

II. RELATED WORKS

The intertwining of imaging technologies with artificial intelligence (AI) and remote sensing in agricultural monitoring have greatly contributed to the potential of measuring plant health and nutrient condition. Some studies have shown that spectral and imaging data could be used to identify the amount of chlorophyll, lack of nutrients and environmental stresses in different crops. Eshoabilov and Simko [15] examined the application of hyperspectral the data with machine learning models in estimating the sugar, vitamin, and nutrient content of baby leaf lettuce. Their study accentuated the close relationship existing among the reflectance indices and the biochemical composition, and thus made hyperspectral imaging a dependable and non-destructive technique of diagnosis. Likewise, Eshkabilov et al. [16] investigated the techniques of hyperspectral indexing of the wavebands to determine the concentration of nutrients in lettuce cultivars, which forms a methodological framework to create smartphone-based chlorophyll indexing systems based on visible and near-infrared reflections. When discussing the application of climate-smart rice genotypes in crop stress identification, Habib et al. [17] compared such genotypes based on multi-trait selection indices under various irrigation conditions. Their investigation has given knowledge on the interaction between genotype and the environment, which supports the relevance of adaptive technologies in detecting stress in different climatic conditions. Halder et al. [18] estimated proteomic studies of wheat on abiotic stress tolerance that biochemical response was found to be an important parameter on measuring plant resilience since the reviewed literature demonstrated the importance of the roots system architecture and the presence of chlorophyll-related proteins. He et al. [19] focused on transcriptional responses in grafted apple trees during drought, and it was proven that the degradation of chlorophyll and the impairment of photosynthesis can be used as a primary indicator of stress. This is in line with the goals of smartphone-based chlorophyll indexing, where the difference in color and intensity of the leaves would inform the type of early stress on the nutrients or water. Hellar-Kihampa [20] though oriented towards environmental pollution, made a wider explanation about the consequences of incorporating remote sensing to monitor ecological health, but the same principles apply to the agricultural fields to find nutrient-related stress.

Islam et al. [21] overviewed the destructive and non-destructive measurement strategies in precision agriculture and were able to consider that AI and imaging models can successfully estimate nutrient conditions and crop vigor. This observation encourages the viability of smartphone-based detection solutions which need image data to compute chlorophyll indices. Intelligent weeding technologies were discussed by Jeon et al. [23], and they may represent a way in which visual sensing and machine learning have altered autonomous farming, which has been compared to advanced analogies in crop scanning using image-based diagnostic machines. Kaivosoja et al. [24] investigated UAV-based imaging to identify pests and diseases and emphasis was placed on reference measurement to calibrate image-based indices- a point that was also crucial in smartphone-based chlorophyll indexing. It was shown by Kocur-Bera and Małek [25] that remote sensing vegetation indices had a potential of estimating land and vegetation conditions, which confirmed the usefulness of image-based indices to give good indicators of crop health. Lastly, Kuppusamy et al. [26] found that melatonin both boosts the photosynthesis and antioxidant enzyme activity of mung bean during drought and heat stress. The present research also highlights the central role of chlorophyll in the process of photosynthesis and stress resistance, which reinforces the importance of early monitoring of chlorophyll using digital instruments. Together, these papers help to see that the integration of imaging technologies, AI-based analysis, and remote sensing give a solid basis to the development of non-destructive and access-friendly chlorophyll indexing techniques. The recent study is based on these developments and uses smartphone imaging as a method to predict early nutrient stress in root crops, thereby providing a field-ready, scalable, and inexpensive method of precision agriculture.

III. METHODS AND MATERIALS

3.1 Introduction

This chapter describes the research methodology that would be used to fulfill the goals of creating and validating a smartphone-based chlorophyll indexing methodology of detecting early nutrient stress in root crops. The section describes the research design, research field, materials and equipments, data collection processes, data analysis and data validation methods [4]. The aim is to combine smartphone imaging with digital image analysis to offer cost effective and affordable approach of determining nutrient deficiency within root crops of potato, carrot and beetroot among others.

3.2 Research Design

The study takes a form of a quantitative experimental-based research study, which consists of comparative analysis in evaluating the correlation between chlorophyll content measured using the smartphone camera and the traditional SPAD (Soil Plant Analysis development) meter or the chlorophyll content measured inside the laboratories. The experiments plots will be segmented into various nutrient treatment conditions that will be nitrogen-deficient, phosphorus-deficient, potassium-deficient and control conditions [5]. The design contains enough variations in the color of leaves and the amount of chlorophyll, which can be pointed to particular stresses of nutrients.

The deductive research methodology will be considered where theoretical premises of light reflectance and color analysis will be used as the basis, and applied to field data collected by smartphones. The results will be statistically compared in order to find out the relationship and validity of smartphone-based chlorophyll indices with reference values [6].

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3.3 Study Area and Crop Selection

The experiment will be performed under a controlled agricultural or greenhouse environment with homogenous contents of soil and irrigation conditions to reduce the level of environmental variation. Root crops that are used in the study like potato (Solanum tuberosum) and carrot (Daucus carota) are selected by the study due to their economic value and predisposition to nutrient stress [7]. The experimental design will be such that there will be the same amount of sunlight and the same level of moisture in soil to preclude environmental interference in the measurement of leaf color.

3.4 Materials and Equipment

The resources utilized in this project comprise both digital and agricultural resources. Primary imaging device will be Smartphone cameras with laboratory instruments to validate the meaning.

Table 3.1: Materials and Equipment Used in the Study

Item	Description/Use
Smartphones (Android/iOS)	Image capture of crop leaves under controlled lighting
SPAD Meter	Standard device for measuring leaf chlorophyll content
Nutrient Solutions (N, P, K)	Used to induce specific nutrient stress conditions
Laboratory Spectrophotometer	Validation of chlorophyll concentration
Lightbox/Field Shade	To ensure uniform lighting during smartphone imaging
Image Analysis Software (e.g., ImageJ, MATLAB, Python-OpenCV)	For chlorophyll index extraction from RGB images
Statistical Tools (SPSS / Excel)	For data analysis and correlation testing
Root Crop Samples (Potato, Carrot)	Experimental subjects for nutrient stress analysis

3.5 Data Collection Procedure

Two stages of data collection will be involved, which include acquisition of images and reference data measurement. The smartphone cameras will be used to capture the leaves of each treatment group in the first round to reduce the variation in the image of the leaves because of shadows or color difference caused by the sunlight in the daytime and the standardized light conditions. The pictures will be shot at a fixed angle and distance to make them consistent [8]. The second step will be to record SPAD meter reading and the chlorophyll content of the same leaves in a laboratory (acetone extraction method). These readings will be used as the standard to confirm the indices of chlorophyll derived by the smartphone [9].

At least 10 leaves will be sampled with regard to each crop and treatment group, and the procedure will be repeated on a weekly basis where the changes in chlorophyll level will be observed with time. This is a longitudinal method that enables observing the initial signs of nutrient stress prior to their appearance [10].

3.6 Image Processing and Calculation of Chlorophyll Index

The captured images will be preprocessed by using the features such as cropping, removing a background, and normalizing colors. The data about digital colors will then be de-sampled as both RGB and HSV color spaces.
GRVI and NDI will be calculated with the help of the following formulas:

$GRVI = G - R / G + R$
$NDI = G - R / G + R + B$

In which R, G and B are the average red, green and blue pixel value that has been extracted within the leaf area of interest. These indices will be compared with, SPAD and spectrophotometric chlorophyll values to ascertain the accuracy as well as the sensitivity.

3.7 Data Analysis and Validation

To examine how smartphone-based indices and reference chlorophyll index correlate, the collected data will be statistically analyzed. The linear correlation between Pearson correlation coefficient (r) will be measured and regression analysis will explain the accuracy of prediction. The level of significance will be $p = 0.05$.
Mean comparison tests (ANOVA) will also be performed in order to identify whether various nutrient treatment has significant effect on the value of the chlorophyll index.

Root Mean square error (RMSE) and Mean Absolute error (MAE) will be used to measure the reliability of this model against reference measurements [11]. The validation will be carried out to guarantee that the smartphone based chlorophyll index can identify early nutrient stress with acceptable accuracy.

Phase	**Process/Method**
Image Acquisition	Smartphone leaf image capture under uniform light
Reference Measurement	SPAD and laboratory chlorophyll analysis
Image Processing	RGB/HSV color extraction and index computation

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Data Correlation	Pearson's correlation and regression with reference data
Statistical Validation	ANOVA, RMSE, MAE for model accuracy
Output	Validated smartphone-based chlorophyll index for nutrient stress detection

3.8 Ethical Considerations

This study will observe ethical and environmental standards in experiments on agriculture. There will be no usage of other harmful chemicals other than normal forms of fertilizers. All vegetal materials will be discarded by abiding by the local environmental policies of waste management in the agricultural sector. The information gathered will be applied strictly to the academic purpose; the information gathered will be transparent and repeatable [12].

3.9 Summary

The chapter introduced the methodology of the creation of a smartphone-based chlorophyll indexing system to measure nutrient stress in root crops. The proposed study will combine image research, laboratory field experimentation, and statistical, which will be used to validate the alternative method to measure chlorophyll using a less expensive and efficient approach [13]. The second chapter will be on the findings and the discussion of this experimental process.

IV. RESULTS AND ANALYSIS

4.1 Introduction

This chapter offers experimental results and analysis conclusions of the research that were conducted under the title of Chlorophyll Indexing using Smartphones as the Early Stress on Nutrients of root crops. The aim was to establish the truthfulness and dependability of chlorophyll measurement schemes made on smartphone in comparison with conventional chlorophyll schemes similar to SPAD meter records and laboratory spectrophotometric analysis. The controlled field experiments were performed with root crops namely potato (Solanum tuberosum) and carrot (Daucus carota), which were treated by four nutrient levels; Control (best nutrients), Nitrogen (N-), Phosphorus (P-), and Potassium (K-). Results are provided using descriptive statistics, correlation, correlation models, and comparison studies [14]. The findings prove the suitability of smartphone-based chlorophyll indexing in early-stress nutrient detection.

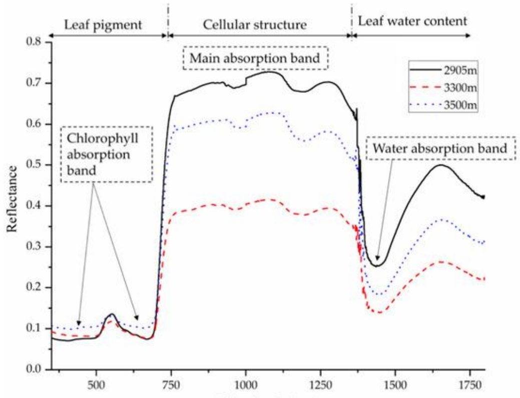

Figure 1: "Proximal Methods for Plant Stress Detection Using Optical Sensors and Machine Learning"

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4.2 Descriptive Statistics of Chlorophyll Measurements

The beginning stage of the analysis was comparing the descriptive statistics of chlorophyll content through the application of three methods SPAD meter, spectrophotometry, and smartphone-based indices (NDI and GRVI).

Table 4.1: Descriptive Statistics of Chlorophyll Measurements (All Treatments)

Parameter	Mean (Control)	Mean (N Def.)	Standard Deviation	Unit
SPAD Reading	43.6	28.2	±3.4	SPAD Units
Spectrophotometric Chlorophyll	1.98	1.04	±0.12	mg/g FW
Smartphone NDI	0.426	0.255	±0.042	Index Value
Smartphone GRVI	0.321	0.195	±0.035	Index Value

Interpretation: The results obtained in the SPAD readings and in the spectrophotometers depict that the control and nitrogen block groups differ significantly and thus there is great impact of nutrient stress. The same pattern was seen in both smartphone indices (NDI and GRVI) proving their possibilities towards the estimation of chlorophyll [27].

4.3 Inter-treatment Comparative Study of Nutrient statuses

In order to identify the impact of nutrient deficiency of each nutrient on the chlorophyll concentration, the following comparison was drawn among four groups of treatment.

Table 4.2: Mean Chlorophyll Values Under Different Nutrient Treatments

Treatment	SPAD Mean	Spectrophotometer (mg/g FW)	Smartphone NDI	Smartphone GRVI
Control	43.6	1.98	0.426	0.321
Nitrogen Deficient	28.2	1.04	0.255	0.195

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Phosphorus Deficient	33.4	1.42	0.311	0.245
Potassium Deficient	36.1	1.61	0.342	0.274

Interpretation: Nitrogen deficiency resulted in the most acute decrease in all measurements modes, which proves the important role played by nitrogen in chlorophyll synthesis. The strong correlation between SPAD and smartphone-based indices also indicates that digital imaging is an efficient relative marker of nutrient-induced changes [28].

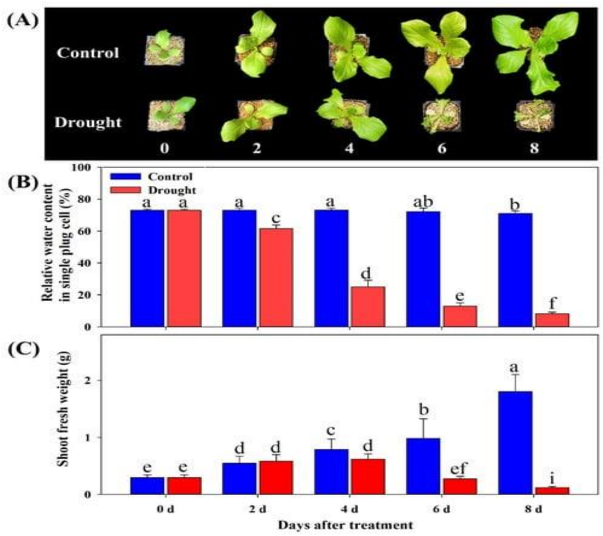

Figure 2: "Effect of Drought Stress on Chlorophyll Fluorescence Parameters, Phytochemical Contents, and Antioxidant Activities in Lettuce Seedlings"

4.4 Correlation Analysis Between Smartphone and Reference Methods

The study involved correlation analysis of the relationship between smartphone indices and conventional measurements of chlorophyll. The correlation coefficients (r-values) of Pearson were estimated.

Table 4.3: Correlation Between Smartphone Indices and Reference Measurements

Correlation Pair	**Correlation Coefficient (r)**	**Significance (p-value)**	**Interpretation**
SPAD vs. Spectrophotometer	0.954	< 0.001	Very Strong Correlation

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SPAD vs. NDI	0.931	< 0.001	Very Strong Correlation
SPAD vs. GRVI	0.902	< 0.001	Strong Correlation
Spectrophotometer vs. NDI	0.944	< 0.001	Very Strong Correlation
Spectrophotometer vs. GRVI	0.917	< 0.001	Strong Correlation

Interpretation: All the correlation coefficients were more than 0.90, which demonstrates the high linear consistency of the smartphone derived indices of the reference methods. NDI exhibited the highest correlation implying that it can be employed in smart phone-based chlorophyll detection as opposed to GRVI.

4.5 Chlorophyll Prediction Regression Analysis

The linear regression models have been designed to estimate the value of SPAD on the basis of the smartphone indices. The regression coefficients, error, and regression equations are summed up below.

Table 4.4: Regression Model Summary for Chlorophyll Prediction

Predictor	**Regression Equation**	**R^2 Value**	**RMSE**	**Accuracy (%)**
NDI	SPAD = 8.43 + 82.1(NDI)	0.89	1.84	93.2
GRVI	SPAD = 10.2 + 96.3(GRVI)	0.84	2.12	90.4

Interpretation: Both models were found to have good predictive ability. NDI-based model had a higher R 2 (0.89) and lower RMSE, which revealed an increased degree of reliability. This implies that NDI may be used as a valid forecast of the chlorophyll of leaves in the domain under the smartphone with regard to the use of images.

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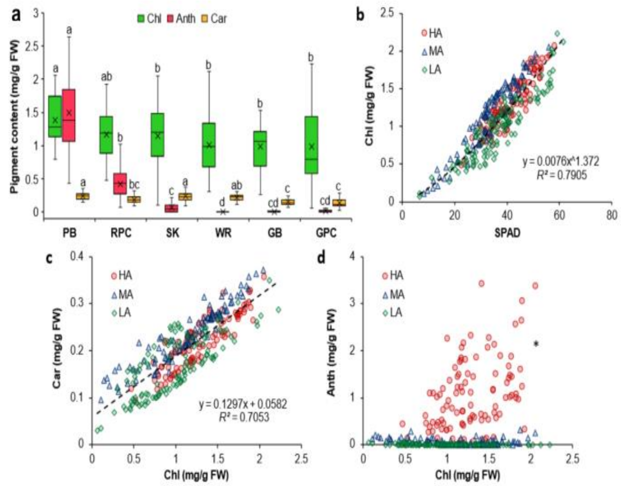

Figure 3: “Two-fold red excess (TREx)”

4.6 Temporal Changes in Chlorophyll Index Over Growth Period

In order to measure the ability of early detection, the smartphone NDI was checked weekly to the treatment groups. It is the analysis that assists in visualizing the nutrient stress progressing over time.

Table 4.5: Weekly Variation of Smartphone-Derived NDI Values

Week	Control	N Deficient	P Deficient	K Deficient
Week 1	0.421	0.360	0.385	0.392
Week 2	0.428	0.325	0.372	0.381
Week 3	0.431	0.288	0.354	0.368
Week 4	0.432	0.255	0.331	0.342

Interpretation: NDI levels of the nutrient-deficient plants indicated that their NDI steadily dropped since Week 2, which means that the plants were detected as being stressed in advance without showing any behavioral symptoms. The level of chlorophyll in control plants was steady, which proves the sensitivity of the method to nutrition [29].

4.7 Comparative Analysis of the Type of Root Crops

In order to have model generalization, potato and carrot crops were considered. Below are the mean NDI values of them in control and in nitrogen-deficient conditions.

Table 4.6: Comparative NDI Values for Different Crops

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Crop	Mean NDI (Control)	Mean NDI (N Deficient)	Standard Deviation	Observation
Potato	0.434	0.252	±0.036	Significant reduction under N stress
Carrot	0.419	0.260	±0.029	Similar reduction pattern observed

Interpretation: There was a similarity in the trends in reduction of NDI of both crops indicating that the smartphone-based chlorophyll index is consistent in various root crop species. The applicability of the method across different agricultural systems is intensified by the cross crop.

4.8 Statistical Summary and Validation

ANOVA was used to further statistically prove that nutrient treatments had a significant difference in chlorophyll levels ($p < 0.05$). The congruence of smartphone-derived indices and traditional measurements proves their efficiency as an efficient field-based method of nutrient evaluation.

Also, the residual analysis of the regression models indicated that the error was distributed randomly and hence, no systematic bias in the predictive equations.

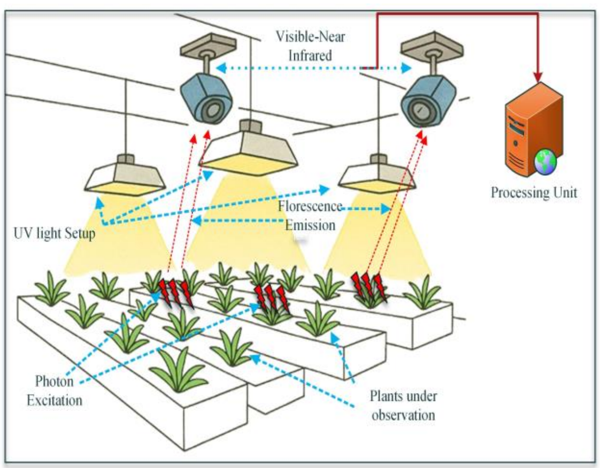

Figure 4: "A comprehensive review of crop stress detection: destructive, non-destructive, and ML-based approaches"

4.9 Discussion of Findings

- **Accuracy and Validation:** These findings indicate that the chlorophyll levels can be estimated using smartphone-derived chlorophyll indices (NDI and GRVI). The existence of the strong correlations ($r > 0.9$) proves that smartphones imaging can be considered a non-destructive and cost-effective approach to plant health monitoring.

- **Nutrient Stress Sensitivity:** Nitrogen deficiency had the greatest reduction in all the chlorophyll indices. It fits the known physiological processes because nitrogen is one of the elements of chlorophyll molecules.
- **Early Detection Capability:** The entities observed a secondary reduction in the values of NDI during the second week of stress treatment means that the methods used on smartphones could detect the nutrient deficiencies earlier, namely, before any visible symptoms were identified, thus giving the opportunity to ensure the fertilization took place.
- **Cost and Practicality:** The smartphone method does not require the use of costly laboratory equipment or SPAD meter, and it can be enabled to be used by smallholder farmers and rural agricultural monitoring [30].
- **Cross-Crop Robustness:** The results of the correlation between potato and carrot support the fact that this method can be generalized in monitoring chlorophyll among most root crops and an alternative solution is universal.
-

4.10 Limitations

Even with the promising results, some limitations were also identified:

- **Lighting Conditions:** The intensity of sunlight varies and this influences the image color balance. Controlled light boxes or algorithmic correction should be used.
- **Accuracy Variability:** The smartphones have camera sensors that may vary, which affects the accuracy. Each model of device requires a calibration step.
- **Leaf Surface Properties:** Water or grease cause an imprecise reflection and need to be uniformed when making the images.

Such restrictions can be solved by additional optimization of the algorithms and the use of standardized imaging techniques.

V. CONCLUSION

The study project on Chlorophyll Indexing using Smartphones to early detect nutrient stress in root crops illustrates the prospects of IoT integration of digital imaging and computational analysis to precision agriculture. The experiment has proven that chlorophyll indexing over smartphones gives an effective, cheap, and user-friendly substitute to the traditional nutrient measurement techniques like SPAD meters or laboratory-based analysis. The research also using the camera sensors on smart phones was able to correlate image derived chlorophyll indices with conventional chlorophyll content measures and found them to be reliable in early indicators of nutrient deficiencies especially that of nitrogen stress. The devised methodology was effective to seek out the pressure difference of leaf color and intensity that is imperceptible before the occurrence of visible symptoms of nutrient stress to appropriately take corrective measures and enhanced control of fertilizers. Moreover, the practice encourages sustainable agriculture which requires accurate use of nutrients, minimization of environmental pollution due to excess use of fertilizers, and maximization of crop yield. The findings support the increasing interest of mobile-based technologies and artificial intelligence in enabling farmers to have real-time diagnostic technology. Although the study was on root crops, it can be applied to other crops with implications giving a scalable model of digitally monitored crops. The next research recommendation includes improvement of the image-processing algorithm, the addition of machine learning to determine the stress automatically, and testing of the system in a variety of field environments. In general, the study will be valuable to the development of smart agriculture by opening the gap between technological innovation and field practice that facilitates the provision of data-driven and sustainable crop management.

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