Green Insight: A Novel Approach to Detecting and Classifying Macro Nutrient Deficiencies in Paddy Leaves.

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Abstract*— Macro nutrient deficiency in paddy leaves is a critical concern in agriculture that impacts crop yield, food security, and sustainable farming. Addressing nutrient deficiencies in paddy plants is vital for ensuring these concerns. This research focuses on automating the detection and classification of common macro-nutrient deficiencies, specifically Nitrogen (N), Phosphorus (P), and Potassium (K). Utilizing image processing techniques, the study identifies distinct color patterns associated with each deficiency, providing a non-invasive and efficient approach. The analysis involves pixel ratio calculations within defined HSV color ranges and threshold values. A modular workflow encompasses preprocessing, horizontal partitioning, pixel ratio computation, and deficiency classification. The innovative methodology we introduced demonstrates promising outcomes, achieving a 96% accuracy rate in identifying nitrogen deficiency, along with 90% accuracy for phosphorus deficiency and 92% accuracy for potassium deficiency detection. While the methodology showcases promise, certain limitations, such as the requirement for leaf symmetry and single-deficiency identification, are recognized. These findings lay the groundwork for more accurate and automated nutrient deficiency detection, and the future work aims to address the identified limitations and generalize the solution for broader applications in real-world agricultural settings.

Keywords*— *Nutrient Deficiencies, Image processing, Color Analysis, Classification, HSV

I. INTRODUCTION

Rice (*oryza sativa*) stands out as one of the most vital crops worldwide, ranking second only to wheat in terms of production and food-related production. It plays a critical role in ensuring food security, particularly in Asia, where approximately 90% of global rice production and consumption occurs [1]. Within the context of Sri Lanka, rice holds exceptional significance as both a staple crop and a livelihood source. The contribution of rice production to the country's agricultural GDP is around 7%, supporting the livelihoods of roughly 1.8 million farming households [2]. Given its importance, fluctuations in rice production can have far-reaching impacts on the welfare of the population.

However, a worrisome trend has surfaced recently – a notable 40% decline in rice harvest over the preceding two years has been taking place around the world [3]. This decline is attributed to a convergence of factors, including the proliferation of diseases due to extreme climatic fluctuations, inadequate nutritional conditions, and the prevalence of harmful pathogens in cultivation regions. Consequently, both the quantity and quality of harvested rice have suffered.

Rice plants are susceptible to a variety of diseases such as Bacterial blight, leaf smut, Brown spots Blast, Sheath rot, False smut, and Leaf scald [4]. These diseases affect different parts of the plant and cause substantial harm. While some diseases are caused by bacterial and fungal activity, others stem from deficiencies in essential nutrients like Nitrogen, Potassium, Phosphorous, Calcium, and Magnesium etc. [4].

This study is primarily centered on the identification and categorization of common macro-nutrient deficiencies in rice plants, specifically focusing on nitrogen, phosphorus, or potassium deficiencies. The challenge posed by nutrient deficiencies in paddy plants represents a significant concern for both farmers and researchers. These deficiencies can lead to decreased crop yields, compromised crop quality, and increased vulnerability to pests and diseases. Traditional methodologies employed to detect nutrient deficiencies involve manual inspection and analysis, which is a process that is not only labor-intensive but also time-consuming. Furthermore, the outcomes of these techniques may not always be consistently accurate, as they can be influenced by the skill level of the individual conducting the analysis. As a result, there is an urgent need for a more accurate, efficient, and automated approach to identifying nutrient deficiencies in paddy plants.

Recent researches have demonstrated that image processing and machine learning techniques can be used to identify and detect nutrient deficiencies in crops, including paddy plants. Although these studies demonstrate the potential of detecting nutrient deficiencies in paddy crops, there are still challenges to overcome in the development and implementation of these techniques for nutrient deficiency detection in paddy plants [5] - [17]. Based on the review of research papers, it is observed that the shape of paddy leaves can be intricate and varied, making it challenging to extract meaningful features for nutrient deficiency analysis [5]. There is a lack of differentiation among nitrogen, phosphorus, and potassium deficiencies in paddy crops. These deficiencies often exhibit similar features, which make it challenging to accurately diagnose and address them individually using existing solutions [6]. Additionally, there is a clear need for user-friendly and cost-effective tools that can be utilized by farmers and researchers in real-world agricultural settings to detect nutrient deficiencies in paddy plants. Therefore, color pattern analysis has emerged as a more effective approach

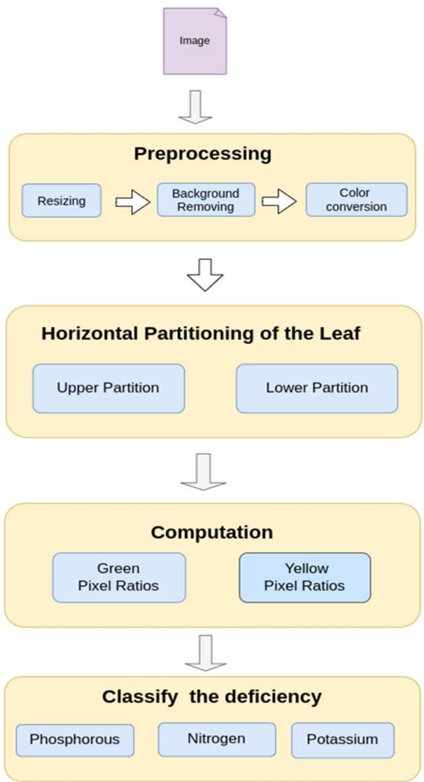

Fig. 1. High level diagram of the proposed solution

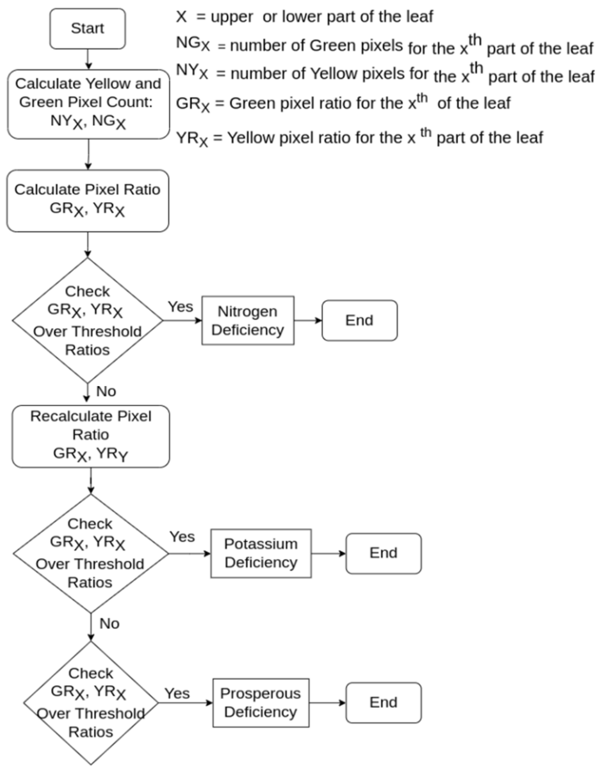

Fig. 2. Flow diagram of the computational process

in this context [7]. Additionally, it has been noted that while machine learning techniques are powerful in various applications, they can be computationally demanding. Training ML models on large datasets and complex neural network architectures can necessitate significant processing power and memory resources. This may pose practical challenges, particularly when deploying the models on devices with limited resources or in real-time applications [7]. Consequently, it has been found that color analysis, which focuses on scrutinizing color variations and patterns in the leaves, offers valuable insights into nutrient deficiencies [8].

The subsequent sections will delve into the methodology, color pattern analysis, result, and discussion and limitations sections respectively. The study concludes with a summary of the results and potential directions for future research.

II. Method

A. Proposed Solution

1) High-level diagram

The high-level diagram (Fig.1) encapsulates the systematic approach employed in identifying nutrient deficiencies within paddy leaves. At the outset, the leaf images undergo preprocessing operations. This includes resizing the images, removing background noise, and converting the color space to HSV [9]. These preparatory steps ensure that the subsequent analysis is conducted on standardized and optimized images. The next step involves dividing the leaf image into two distinct sections: the upper and lower partitions. This partitioning facilitates focused analysis on both segments, contributing to the comprehensive assessment of color patterns. Within the computation phase, critical computations are performed. The process encompasses defining HSV color ranges that best encapsulate the color behavior of nutrient-deficient leaves. Alongside, threshold values are established to identify variations in pixel ratios. Greenish and yellowish pixel ratios are calculated, providing valuable insights into color distribution within the partitions. Armed with the data, the system proceeds to classify nutrient deficiencies. By closely examining the calculated ratios against predetermined thresholds and color ranges, the system excels at identifying specific deficiencies such as nitrogen, potassium, and phosphorous. This classification represents the culmination of the analytical process, precisely determining the exact deficiency displayed by the leaf.

In summary, the high-level diagram encapsulates a comprehensive process that spans preprocessing, partitioning, computation, and classification. This methodical approach harmonizes each step, culminating in precise nutrient deficiency identification based on color patterns, contributing to the advancement of research in the field of agriculture using image processing.

2) Flow diagram

The above flow diagram (Fig.2) illustrates the sequential computational process for identifying nutrient deficiencies, specifically nitrogen, phosphorus, and potassium. The process initiates by calculating the percentages of greenish and yellowish pixels, integral to the leaf's color makeup. The next step involves assessing the presence of a nitrogen deficiency based on these percentages. If a nitrogen deficiency is confirmed, the process concludes at the nitrogen deficiency stage.

However, if a nitrogen deficiency is not identified, the process reiterates by recalculating the percentages of greenish and yellowish pixels. This recalibration leads to the evaluation of a potential phosphorus deficiency. If the greenish and yellowish percentages indicate a phosphorus deficiency, the process concludes at the phosphorus deficiency stage.

Fig.3. Macro deficiencies of paddy leaves. (Phosphorus, Nitrogen and Potassium deficiencies respectively)

In instances where neither nitrogen nor phosphorus deficiency is detected, the process advances to examine the possibility of a potassium deficiency. By considering the precomputed greenish and yellowish percentages, the system identifies a potassium deficiency if the criteria are met, subsequently concluding at the potassium deficiency stage. This systematic approach ensures an accurate classification of nutrient deficiencies through the analysis of greenish and yellowish pixel percentages.

B. Dataset

The dataset obtained from Kaggle played a crucial role in both the training and testing phases of this research study. In total, the dataset consisted of 426 images. To ensure a balanced distribution for threshold values identifying dataset and testing dataset, a 7:3 ratio was adopted for image splitting. Consequently, each deficiency category was allocated 100 images for the thresholding phase, while the remaining 42 images were reserved for the testing phase.

Visible symptoms associated with nutrient deficiencies in nitrogen, potassium, and phosphorus are often observed in the upper level of a moderate stage paddy leaves. These symptoms include changes in leaf color and alterations in leaf morphology.

- Nitrogen Deficiency: A higher concentration of yellow color compared to green color is generally observed in the paddy leaf, suggesting reduced chlorophyll content due to insufficient nitrogen levels.
- Phosphorus Deficiency: A prominent yellowish-brown coloration is typically observed in the tips of the leaf, indicating a lack of phosphorus. Conversely, the lower part exhibits a higher proportion of greenish color.
- Potassium Deficiency: The leaf may demonstrate a similar greenish color, albeit with a slight presence of yellow. However, the overall greenish color remains higher than the yellow color.

C. Preprocessing

The images of the dataset primarily featured elongated paddy leaves with a higher resolution, which introduced complexities during preprocessing and analysis stages.

The original images were resized with dimensions of 300 pixels in width and 3000 pixels in height, resulting in a standard aspect ratio for paddy leaves. This elongated shape posed difficulties when resizing the images. Resizing the images to smaller dimensions resulted in distortions, as the inherent shape of the paddy leaves was not preserved. Consequently, critical details were lost, leading to compromised accuracy in subsequent operations, such as feature extraction and classification. Therefore, 300 * 3000 was selected as the appropriate dimensions.

During the process of attempting background removal using popular libraries like OpenCV and PIL, difficulties were encountered due to the similarity between the background and foreground of the images. Consequently, the results of the background removal process were unsatisfactory, leading to image distortion. To address this issue, alternative solutions were explored, and Removebg, an online service specializing in automated background removal, was discovered. Their API was integrated into the applications. By harnessing the capabilities of Removebg, more accurate and effective background removal for the images was achieved. This online service overcomes the challenges posed by the similarity between the background and foreground elements in the images.

In the preprocessing phase, the HSV (Hue, Saturation, Value) color space conversion was chosen as it enhances image analysis by separating color information into Hue, Saturation, and Value components. Unlike RGB, HSV separates luminance and chrominance, making it less sensitive to lighting changes. This is crucial for accurately detecting nutrient deficiency symptoms in leaves under varying lighting conditions. HSV also offers intuitive color manipulation through Hue and Saturation adjustments, aiding precise identification of color variations linked to nutrient deficiencies. Given that nutrient deficiency symptoms often manifest through color changes in leaves, utilizing HSV color space facilitates robust and accurate analysis of color patterns, contributing to effective nutrient deficiency assessment in paddy leaves.

D. Image Capturing

The acquisition of images for input into the system follows a specific criterion. It is essential that the captured images of deficient leaves exhibit horizontal symmetry in their visual attributes as shown in Fig. 4. This entails encompassing the leaf tip and the upper portion of the plant body within the image frame. Additionally, each image must capture a signal leaf. This meticulous approach ensures that the input images maintain a consistent and standardized format, enabling accurate and reliable analysis of nutrient deficiency symptoms.

E. Horizontal Partitioning of the Image

As depicted in Fig .4 the research employed a technique involving the horizontal partitioning of paddy leaf images.

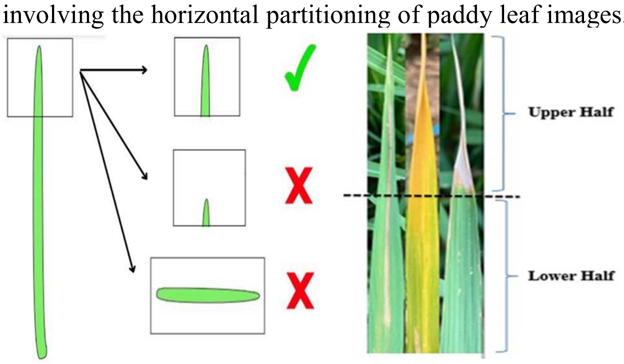

Fig. 4. Image Capturing Process and Horizontal Partitioning of the paddy leaf (include K, N, P deficiencies respectively)

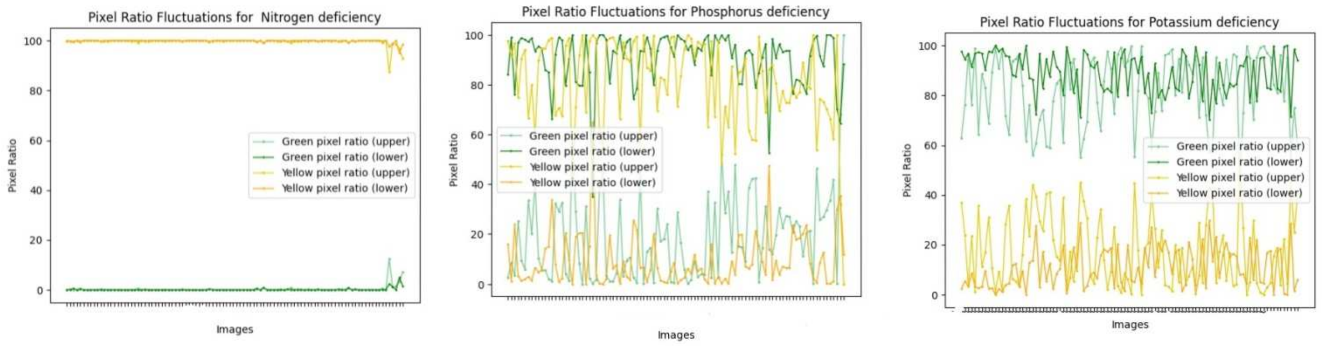

Fig. 5. Green and Yellow Pixel ratio Fluctuations for 100 test images per each nutrient deficiency (Nitrogen, Phosphorus, Potassium respectively) based on identified HSV color ranges.

This method entails the division of each leaf image into upper and lower halves, leveraging the assumption of horizontal symmetry within the leaf structure. By segmenting the leaf into symmetrical halves, the study capitalizes on the inherent consistency in leaf structure. Changes in color patterns on either side of the leaf due to nutrient deficiencies can be systematically examined. This technique allows for a separate and more precise identification of deficiency symptoms based on color features on each side of the leaf.

III. Color Pattern Analysis

A. *Defining HSV color ranges*

In the analysis of color using the HSV model for identifying each deficiency in paddy leaves, specific color ranges play a pivotal role. The HSV perspective entails a breakdown of the color ranges as follows:

1) Identifying HSV color ranges for nitrogen deficiency:

Greenish Color Range: This range is determined by the subsequent values:

Lower Limit: Hue = 50, Saturation = 40, Value = 40

Upper Limit: Hue=138, Saturation = 255, Value = 255

The Hue value range of 50 to 138 signifies the color spectrum associated with green. Saturation spans from 40 to 255, signifying intensity, and Value ranges from 40 to 255, indicating brightness.

Yellowish-brown Color Range: This range is defined by the subsequent values:

Lower Limit: Hue = 20, Saturation = 40, Value = 40

Upper Limit: Hue = 50, Saturation = 255, Value = 255

The Hue range from 20 to 50 represents yellow Hues. Saturation values, spanning 40 to 255, denote varying intensities, while Value, ranging from 40 to 255, represents different levels of brightness.

This color range facilitates distinct identification of greenish and yellowish color pixels, contributing to the precise detection of nitrogen deficiency in paddy leaves.

2) Identifying HSV color ranges for phosphorous and potassium deficiencies:

Greenish Color Range: This range aids in identifying both phosphorus and potassium deficiencies. The range is defined as follows:

Lower Limit: Hue = 36, Saturation = 65, Value = 125

Upper Limit: Hue = 138, Saturation = 255, Value = 255

In this range, the Hue component spans from 36 to 138, encompassing green hues. Saturation values from 65 to 255 denote intensity, and Value ranging from 125 to 255 signifies brightness.

Yellow Color Range: This range, applicable to phosphorus and potassium deficiencies, is outlined as:

Lower Limit: Hue = 0, Saturation = 0, Value = 20

Upper Limit: Hue = 29, Saturation = 255, Value = 255

Within this range, the Hue component covers 0 to 29, representing yellow Hues. Saturation values from 0 to 255 signify intensity, and Value from 20 to 255 indicates Brightness.

These HSV color ranges facilitate the targeted identification of deficiencies related to phosphorus and potassium in paddy leaves, utilizing distinct HSV levels.

B. *Defining threshold ratios:*

The color analysis methodology encompasses a comprehensive examination of the distribution of greenish and yellowish-brown pixels within specific regions of both the upper and lower segments of paddy leaves. To accomplish this, well-defined HSV color ranges correspond to nutrient deficiencies. By scrutinizing the behavior of these greenish and yellowish-brown pixels and observing their percentages for each deficiency, statistically significant trends are extracted.

The procedure yields threshold ratios for pixel proportions, particularly focusing on the Green / Yellow ratio. For instances of nitrogen deficiency, distinctive patterns emerge: the yellowish pixel ratio within the upper half of the leaf consistently exceeds 90%, while in the lower half, it consistently remains below 1%. Simultaneously, the greenish pixel ratio in both the upper and lower halves of the leaf maintains levels below 1%. For phosphorus deficiency, a discernible trend involves a yellowish pixel ratio surpassing 35% in the upper half, while staying under 30% in the lower half. Correspondingly, the greenish pixel ratio remains consistently below 65% in the upper half and below 75% in the lower half. Regarding potassium Deficiency, the identified patterns stipulate that the yellowish pixel ratio in the upper half consistently exceeds 50%, whereas in the lower half, it remains above 30%. Simultaneously, the greenish pixel ratio demonstrates a persistent threshold of below 55% in the upper half and below 70% in the lower half.

This systematic assessment of pixel ratios within distinct segments of paddy leaves, guided by defined color ranges accurately identifies and classifies nutrient deficiencies based on well-established and quantifiable thresholds.

C. Calculation of Pixel Ratio:

In the context of analyzing pixel ratios for the upper and lower halves of a leaf, the calculation involves a straightforward process. Specifically, the pixel color ratios for both greenish and yellowish-brown colors can be determined as follows: the count of greenish pixels or yellowish pixels is divided by the total number greenish pixels and yellowish pixels of pixels in the respective region as depict in Equation (1). This computation yields a quantitative representation of the prevalence of greenish or yellowish colors within the given segment of the leaf.

$$Pixel\ Ratio = \frac{No.Green\ or\ YellowPixels}{Total\ No.Green\ and\ YellowPixels} \times 100\%$$

Equation 1: Symbolic Representation of Pixel ratio Calculation

The procedure entails the computation of pixel percentages by utilizing the established pixel ratios. This calculation offers a succinct indicator of color distribution within the scrutinized leaf regions. Through the conversion of ratios into percentages, the prevalence of greenish and yellowish colors obtains measurable form. The calculation of pixel percentages for each color within each respective half is carried out as follows:

The equations incorporate the following variables:

x = Upper or Lower part of the leaf.
i = Initial pixel.
n = n^{th} pixel.
GR_x = Greenish pixel ratio for the x^{th} part of the leaf.
YR_x = Yellowish-brown pixel ratio for the x^{th} part of the leaf.
NG_x = Number of Green pixels for the x^{th} part of the leaf.
NY_x = Number of Yellowish pixels for the x^{th} part of the leaf.

- Greenish pixel ratio for the x^{th} part of the leaf

$$GR_X = \frac{\sum_{i=0}^{n} NG}{\sum_{i=0}^{n} NG + \sum_{i=0}^{n} NY} \times 100\%$$

Equation 2. Calculation of Greenish pixel ratio for the x^{th} of the leaf

- Yellowish-brown pixel ratio for the x^{th} part of the leaf

$$GR_X = \frac{\sum_{i=0}^{n} NY}{\sum_{i=0}^{n} NG + \sum_{i=0}^{n} NY} \times 100\%$$

Equation 3. Calculation of Yellowish pixel ratio for the x^{th} of the leaf

D. Exploring the Variations in Pixel Ratios for Each Color Across Defined HSV Color Ranges and Threshold Values.

Through image analysis, it becomes feasible to ascertain how the percentage of pixel ratios for each color within each deficiency corresponds to the defined HSV color ranges and established threshold values.

When considering nitrogen deficiency, both the upper and lower sections of the leaf consistently display pixel ratios that align with the defined HSV color ranges. Specifically, the yellowish-brown pixel ratio presents a substantial presence, ranging from 97% to 99%, while the greenish pixel ratio ranges from 2% to 0.99%. However, the pixel ratio percentages of other deficiencies do not reveal a straightforward correlation within the relevant predetermined HSV color range and threshold values.

It is possible to differentiate both phosphorus and potassium deficiencies within the same HSV color range, by employing distinct threshold values. However, the pixel ratios for nitrogen deficiencies exhibit an irregular relationship around the identified color range. Fig 5 depicts a clear trend emerges wherein approximately 75-95% of green pixel ratios for both the upper and lower sections of the potassium deficiency leaves align within the HSV color ranges. Moreover, the yellow pixel ratios for the upper and lower halves of the leaf span between 0.99% and 25% and 30% to 45% respectively. When considering phosphorus deficiency, the upper half of the leaf displays yellowish pixel ratios ranging from 1% to 50%, while the lower half exhibits ratios spanning from 1% to 30%. In contrast, the pixel ratios for greenish color range from 50% to 97% for the upper half of the leaf and from 70% to 98% for the lower half.

IV. RESULTS

In the evaluation of the approach, it is observed that nitrogen deficiencies are identified with an impressive accuracy of 96%. However, there is a slight misclassification rate, with 3% of nitrogen images being mistakenly classified as phosphorus and 1% as potassium. Similarly, for phosphorus deficiencies, the system performs well, achieving a 90% identification rate. Nevertheless, there are misclassifications, with 6% of phosphorus images being wrongly labeled as nitrogen and 4% as potassium. Potassium deficiencies also show strong identification accuracy, standing at 92%. However, there are instances of misclassification, with 5% of potassium images being mistakenly categorized as phosphorus and 3% as nitrogen. These findings, along with an overall accuracy of 94%, shed light on the system's performance and highlight areas for potential refinement in future iterations.

Ref. [10] employing support vector machine (SVM) with the integration of K-Means and Fuzzy C-Means clustering. Utilizing the RGB mean value function and Regionprops. Through the collaborative use of SVM classifier, K-Means, and Fuzzy C-Means clustering, the method achieves accuracies of 85% and 92% in identifying mineral-deficient leaf images of rice crops, respectively. The [8] research proposed an algorithm based on pattern recognition combined with RGB color property examination for detecting nutrient deficiencies in paddy leaves, achieving a testing accuracy of 90%. However, our proposed solution employs the HSV color model, providing enhanced accuracy and effectiveness in nutrient deficiency identification compared to the RGB color model utilized in the mentioned study. Unlike the proposed methodology, which utilizes a single model for identification, the approach of [11] employs separate models for different nutrient deficiencies (InceptionV3, ResNet50, VGG16, and CNN.). CNN exhibited the best performance (96% accuracy) in predicting phosphate deficient leaves, with VGG16 performing well in identifying N deficiency (91% accuracy), and ResNet50 recommended for potassium deficient leaf identification (92% accuracy). The drawback of their method lies in using multiple models, potentially making it more complex and resource-intensive compared to the simplicity of a unified model, as in this approach. Another study utilized six transfer learning architectures, including Xception, DenseNet201, InceptionResNetV2, InceptionV3, ResNet50V2, and VGG19, to diagnose rice plant deficiencies[12]. The highest performance was achieved with InceptionResNetV2 (90%) in the Kaggle datasets. Also the [6] research on nutrient deficiencies in rice crops, while achieving a notable accuracy of 96%, is associated with substantial computational demands, relying on an Intel Core i5-3320 2.6 GHz CPU, 16 GB RAM, and 8x NVIDIA V100 GPU. In contrast, the proposed nutrient deficiency classification approach for rice crops, with a slightly lower accuracy of 94%, stands out for its resource efficiency and minimal computational requirements. This highlights a significant advantage of the proposed approach over [6], as it achieves commendable accuracy with reduced resource intensity.

In contrast, the utilized methodology demonstrated an overall performance accuracy of 94%, showcasing its effectiveness in attaining superior performance levels. This approach excels not only in achieving a commendable accuracy but also in its efficiency with more streamlined computational requirements. While other models may boast higher accuracies, the proposed methodology strikes a balance by offering competitive accuracy along with resource efficiency, making it a practical choice for nutrient deficiency classification in rice crops.

V. DISCUSSION AND LIMITATIONS

The proposed approach gives promising results for clearly identifying macro nutrient deficiencies using images of plant leaves utilizing color analysis which has been a challenging task to differentiate between different macro nutrient deficiencies. This can be integrated to precision agriculture systems to enable farmers to make decisions regarding nutrient supplementation.

While this study has made significant progress in identifying and categorizing nutrient deficiencies in paddy plants using pixel ratio analysis, certain limitations warrant consideration. Firstly, the effectiveness of the module relies on capturing leaf symptoms in the moderate stage of its life cycle, potentially restricting its applicability to other growth phases. The scope of the module is defined to detect only N, P, or K deficiencies, deficiencies beyond the scope are not capable enough to detect. Moreover, the module's current design is limited to identifying only one of the above nutrient deficiencies per analysis, which may not encompass complex scenarios involving multiple deficiencies. The requirement for horizontal symmetry in leaf appearance further constrains the module's applicability to leaves displaying such characteristics. As a result, future work should address these limitations by exploring methods to expand the module's capability to detect multiple deficiencies simultaneously, considering various growth stages and enhancing its adaptability to a broader range of leaf appearances. Furthermore, the inclusion of more comprehensive datasets and the incorporation of advanced image processing techniques could potentially mitigate the impact of external factors, ensuring greater accuracy and reliability in nutrient deficiency detection. Overall, the study bridges the gap between traditional practices and innovative technologies, offering a promising path to enhance crop productivity, improve food security, and contribute to agricultural sustainability.

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