



An Approach to Develop a Model to Detect the Phosphorus and Potassium Deficiency in Paddy Crop on Agriculture Farm Using DIP & ML

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Abstract

Excessive use of fertilizers harms the environment and disrupts plant habitats, while also raising costs for farmers. Proper timing and amounts of nutrients are crucial for plant health and environmental balance. The greenness of rice leaves indicates their chlorophyll and nutrient levels. Agronomy studies show rice plants need 10 nutrients, including primary ones like Nitrogen (N), Phosphorus (P), and Potassium (K), and secondary ones like Iron (Fe), Manganese (Mn), Copper (Cu), Zinc (Zn), Boron (B), Molybdenum (Mo), and Chlorine (Cl). Leaf nitrogen concentration (LNC) is highly correlated with chlorophyll content. There are several tools on LEAF+ to measure it, such as leaf color (LCC), SPAD, chlorophyll or nitrogen. Since these tools are cost-effective and not available to all farmers, LCC offers farmers the ability to estimate plant nitrogen needs in real-time for efficient fertilizer use and increased rice yield. Notable innovation in agriculture is the Leaf Color Chart (LCC), developed by Japanese experts. It measures chlorophyll levels in rice plants and aids in nitrogen management without harming the plant. Today, LCC is used globally to improve production efficiency and optimize nitrogen application rates. The remaining 2 major nutrients potassium and phosphorus can also be measured by experimentally expanding the available database of LCC, as has been done in the two models developed in this research paper.

Keywords: Leaf color Chart (LCC); Nutrients Management in crops; Precision Agriculture; Agriculture Farm Monitoring; Machine Learning for Crop Health; Agricultural Machine Learning Models; Soil Nutrient Monitoring

1. Introduction

These days, a global issue is that the world's population is growing while the land remains stationary. As a result, per capita agricultural productivity has decreased, and it was predicted that between fifty and seventy percent more grain would be needed. After 20 years, the global population of over 900 million people will require large quantities of nitrogen fertilizers to feed them, even though crop nitrogen recovery efficiency has improved [1]. However, excessive use of fertilizers can damage crops, so it is crucial to have accurate information about the nutrients in the crops. This ensures that fertilizers are used in precise amounts. The Leaf Color Chart (LCC) technique is very useful for this purpose, as it provides accurate information about the nutrients in the crops through the color of the leaves [2]. Using fertilizers according to this information can prevent crop damage, save unnecessary fertilizer use, and save money (Islam et al., 2007) this is a serious caution regarding food safety, since hunger and malnutrition are increasingly the cause. The rise in food production has decreased dramatically because of overpopulation, creating a huge imbalance between supply and demand [3]. As a result, the more fertile our land, the more we must increase output, which we can only accomplish with the aid of new techniques. A modern agricultural concept known as "time bound exactitude agriculture" uses technology to maximize crop output

and resource management within a set amount of time [4]. Contrary to conventional farming practices, which frequently depend on physical labor and broad-spectrum indicators, crop data-driven decision-making and increasing input, fertilizer, and pesticide usage are popular. This indicates a major shift in the field of space exploration, influenced by drones, sensors, data analytics, jeepneys, and advancements in the exploration of space travel aspects [5]. Farmers can precisely oversee and monitor their farms with the use of these instruments.

2. Literature Review

The main drawback of precision agriculture is time-consuming: It takes time to collect data using sensors, drones, satellites and other technologies to monitor the environment, soil characteristics, crop minerals components and crop health (Takebe & Yoneyama, 1989). There are a number of existing methodologies for presenting literature reviews. However, the methodology needed to achieve the purpose of this review is systematic review methodology. Therefore, I have summarized all the literature reviews of this paper in Table 3 according to the systematic review methodology.

Table 1: Review Comparative Table

S. No.	Title of Paper & Author	Publication Year	Methodology	Author Contribution
1	Evaluation of Leaf Colour Chart for Nitrogen Management in Hybrid Maize (ZEA MAYS L.) under Irrigated Ecosystem of Vertisols (Jyothsna et al., 2024)	2024	Machine Learning Leaf colour chart (LCC), Computer vision and agriculture, Hybrid Maize (ZEA MAYS L.) under Irrigated Ecosystem of Vertisols	Specific Nutrient Management (SSNM), Nitrogen Management
2	Architecting lymphoma fusion: PROMETHEE-II guided optimization of combination therapeutic synergy (Ansar, S.A., Arya, S., Soni, N. et al.)	2024	PROMETHEE-II technique, Multi Criteria DSS	Evidence-based decision-making toward an improved outcome of treatment in lymphoma.
3	Smart Zoos, Healthy Animals: SAHMT's Non-Invasive Healthcare Model (Praveen, S., Khan, A. H. J. et al.)	2024	IoT and Artificial Intelligence	Smart Animal Health Monitoring Tunnel (SAHMT)
4	1 Intelligent Hybrid Tourist Recommendations: Unifying Data Analysis and Machine Learning	2024	KNN and CNN with decision tree algorithms using the Statistical Package for the Social Sciences (SPSS)	Developed a Decision Tree Algorithm for novel hybrid tourist recommendation system
5	Analysis and design a framework identifying crop nutrients using KNN Approach: A systematic review (Rathod & Deepak, n.d.)	2022	Machine Learning, Digital Image Processing, KNN Approach, Artificial Intelligence	Systematic Review for identifying crop nutrients
6	Blockchain Technology for Healthcare Record Management (Faisal, M., Sadia, H., Ahmed, T., Javed, N. 2022).	2022	DBMS with Digital ledger	Blockchain technology in general and electronic medical record management of healthcare in particular

7	DVAEGMM: Dual VariationalAutoencoder With Gaussian Mixture Model for Anomaly Detection on Attributed Networks (W. Khan, M. Harron et al.)	2022	Network Attribute, Gaussian Mixture Model and Deep Learning	DVAEGMM to detect anomalies on attributed networks.
8	Development of LR- PCA Based Fusion Approach to Detect the Changes in Mango Fruit Crop by Using Landsat 8 OLI Images (H. C. Verma, Ahmed, T. et al.)	2022	Image Processing in Fusion of log-ratio (LR) and principal component analysis (PCA)	Images to extract meaningful information and detect temporal changes in the mango fruit crop areas with high change detection accuracy.
9	Nitrogen Deficiency Mobile Application for Rice Plant through Image Processing Techniques (Patel & Singh, 2022).	2022	Specific Nutrient Management (SSNM), Leaf colour chart (LCC), Computer vision and agriculture Machine Learning	Specific Nutrient Management (SSNM), Nitrogen Deficiency Mobile Application for Rice Plant through Image Processing Techniques
3	<u>Smart Zoos, Healthy Animals: SAHMT's Non-Invasive Healthcare Model</u> (Praveen, S., Khan, A. H. J. et al.)	2024	IoT and Artificial Intelligence	Smart Animal Health Monitoring Tunnel (SAHMT)
4	1 Intelligent Hybrid Tourist Recommendations: Unifying Data Analysis and Machine Learning	2024	KNN and CNN with decision tree algorithms using the Statistical Package for the Social Sciences (SPSS)	Developed a Decision Tree Alogrith for novel hybrid tourist recommendation system
5	Analysis and design a framework identifying crop nutrients using KNN Approach: A systematic review (Rathod & Deepak, n.d.)	2022	Machine Learning, Digital Image Processing, KNN Approach, Artificial Intelligence	Systematic Review for identifying crop nutrients
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7	DVAEGMM: Dual VariationalAutoencoder With Gaussian Mixture Model for Anomaly Detection on Attributed Networks (W. Khan, M. Harron et al.)	2022	Network Attribute, Gaussian Mixture Model and Deep Learning	DVAEGMM to detect anomalies on attributed networks.
8	Development of LR- PCA Based Fusion Approach to Detect the Changes in Mango Fruit Crop by Using	2022	Image Processing in Fusion of log-ratio (LR) and principal component	Images to extract meaningful information and detect temporal changes in the mango

	Landsat 8 OLI Images (H. C. Verma, Ahmed, T. et al.)		analysis (PCA)	fruit crop areas with high change detection accuracy.
9	Nitrogen Deficiency Mobile Application for Rice Plant through Image Processing Techniques (Patel & Singh, 2022).	2022	Specific Nutrient Management (SSNM), Leaf colour chart (LCC), Computer vision and agriculture Machine Learning	Specific Nutrient Management (SSNM), Nitrogen Deficiency Mobile Application for Rice Plant through Image Processing Techniques
10	Interaction among Multiple Intelligent Agent Systems in web mining(A. Ali and M. F. Farooqui).	2022	Web Technology, Complex networks, Web mining	Write aAlgorithm for developed multi-specialist framework.
11	A comprehensive review on automation in agriculture using artificial intelligence (Jha et al., 2019)	2019	Fuzzy logic artificial neural networks (ANN), Neuro-fuzzy logic Expert systems	A smart agriculture system based on deep reinforcement learning
12	Detection of plant leaf diseases using image segmentation and soft computing techniques (V. Singh & Misra, 2017)	2017	Color co-occurrence methodology, Image processing, Artificial Neural Network	Image Processing Techniques, color co-occurrence technology
13	Combined application of Artificial Neural Networks and life cycle assessment in lentil farming in Iran (A. Singh & Kaur, 2021).	2021	Artificial Neural Network (ANN),	Case study region and data collection, Energy balance in lentil cultivation
14	Wireless data management system for environmental monitoring in livestock buildings (Elhami et al., 2017).	2017	Wireless Sensor Networks (WSNs)	Implications for the wireless data management system design
15	Preserving apple (Malusdomestica var. Anna) fruit bioactive substances using olive wastes extract-chitosan film coating (Gray et al., 2017).	2017	Reagents and solutions, Microbial strain and media	Film forming solution, Apple fruits coating applying
16	Computer vision-based apple grading for golden delicious apples based on surface features (Gray et al., 2017).	2017	Support Vector Machine (SVM), MLP and K-Nearest Neighbor (KNN)	Computer vision-based algorithm for golden delicious apples grading
17	Applicable properties of the bio-fertilizer spent mushroom substrate in organic systems as a byproduct from the cultivation of Pleurotus spp (Moallem et al., 2017).	2017	Statistical analysis	Mushroom Cultivation, Find out Agro-substrates, Physical properties of agro-substrates, Chemical properties of agro-substrates

18	Modern Leaf Color Chart Successfully Prepared and Used in Crop Production of Sindh, Pakistan (Moallem et al., 2017).	2017	Nitrogen Management from Leaf colour chart (LCC)	Find out Nutrient management Computer Vision Technology and Machine Learning.
19	Using a simple leaf color chart to estimate leaf and canopy chlorophyll a content in Maize (Zea Mays)(Leghari et al., 2016).	2016	DIP, ML, DL, SPAD	Detecting crop nutrients
20	Apple and pear nutrition (Nguy-Robertson et al., 2015).	2015	Optimization	Detecting crop nutrients

Computer vision systems are already widely used in several industrial food production sectors and in agricultural agriculture. They can be used in potato, wheat, maize, soybean, pea, and lemon grading systems. It is justified to use due to its benefits [6]. It has been observed that most research projects look at how AI, ML, and IOT are used in tasks related to food processing and water management. Regarding the advancement of technology for detecting plant illnesses and shortcomings in agriculture, study is still necessary [7]. It was found that there are still gaps in the development of smart devices that work with agricultural equipment and use artificial intelligence and computer vision to automate tasks in the field. One potential option for future research might be to expand the use of advanced artificial intelligence [8]. For instance, a computer system intended to simplify and lower the cost of categorizing gluten-containing grains from pictures may benefit cultivars of wheat, oats, and rice [9]. Research is still needed, nevertheless, to build technologies that can detect plant illnesses and deficiencies in agriculture (Radhamani et al., 2016).

The current study discusses how technology is improving to identify plant diseases and agricultural deficiencies [10]. Following the justification, the present research aims to illustrate several machine learning, image, and video processing applications and techniques to encourage future researchers to apply them to address contemporary agricultural problems. [11] When paired with an examination of previous research and the problems it attempted to solve, new advances in artificial intelligence and computer vision can lead to creative solutions for agriculture that increase food security, quality, and production [12]. Applications based on the technology discussed in this paper will eventually be developed, allowing us to rapidly and inexpensively learn about the health of plants by only using our cellphones to scan their images (Liu et al., 2022).

Upon reviewing this assessment, data may be acquired to generate a leaf coloration chart (Nitrom) for oneself, which will improve output at the lowest possible cost [13]. There is an urgent need to promote the expansion of agriculture, thus we must investigate new study areas. It seems that incorrect nitrogen application is often the reason for low yield. Labs are now available to farmers for soil testing and plant N insufficiency [14]. Hence, providing farmers with access to LCCs means bolstering the agriculture industry and enabling them to independently control nutrients [15]. They could find the exact and right amount of fertilizer to use, and they might see a rise in crop yields benefit that will ultimately help those who depend on agriculture (Nguy-Robertson et al., 2015).

3. Contemporary Nutrient Detection Methods

There are many methods available to find the nutrients in agricultural crops. Some of the popular methods are mentioned here:

A. Soil Test

A soil test is an essential agricultural process used to evaluate the nutrient content, composition, and other characteristics of soil [16]. It provides critical information about the soil's pH level, organic matter, and concentrations of key nutrients such as nitrogen (N), phosphorus (P), and potassium (K). The main goal of a soil test is to guide farmers, gardeners, and land managers in optimizing crop yields by identifying nutrient deficiencies and recommending appropriate fertilizer applications (Rathod & Deepak, n.d.).

Here is an overview of key components in a soil test:

A.1. Soil Sampling

The accuracy of a soil test largely depends on proper soil sampling [17]. Samples are typically collected from different areas of a field or garden at varying depths (often 6-8 inches for agricultural purposes). These samples are then mixed and sent to a laboratory for analysis.

A.2. pH Measurement

Soil pH is crucial as it affects the availability of nutrients to plants [18]. A pH scale ranges from 0 to 14, with lower numbers indicating acidic soil and higher numbers indicating alkaline soil. Most crops thrive in slightly acidic to neutral soil (pH 6-7). If the pH is too low (acidic) or too high (alkaline), it can lead to nutrient deficiencies or toxicities.

A.3. Nutrient Levels

The test measures the presence of essential macronutrients:

- Nitrogen (N): Necessary for plant growth and photosynthesis.
- Phosphorus (P): Important for root development and energy transfer.
- Potassium (K): Vital for water regulation and overall plant health.

Micronutrients like calcium (Ca), magnesium (Mg), and sulfur (S) are also analyzed. The test identifies any deficiencies, helping guide the type and amount of fertilizer needed to replenish the soil (Li et al., 2023).

This method is labor-intensive, time-consuming, and costly (Rs. 3000 to Rs. 8000 per kilogram of soil; the machine costs between Rs. 1.5 lac and Rs. 3 lac). It requires traveling to the farm and gathering soil samples from various locations.



Figure 1. Soil Testing Lab

B. Soil Plant Analysis Development (SPAD)

The Soil Plant Analysis Development (SPAD) meter is a handheld device used in agriculture and horticulture to measure the relative chlorophyll content in plant leaves [19]. This provides valuable insights into the nitrogen status of plants, helping farmers and researchers optimize fertilizer application, monitor plant health, and improve crop management. SPAD meters are particularly useful for assessing real-time plant nutrient needs without the need for destructive sampling or lab testing (Jyothsna et al., 2024).

B.1. How the SPAD Meter Works:

The SPAD meter operates by emitting light at two specific wavelengths—one that is absorbed by chlorophyll and another that is not [20]. The device measures the difference in light absorption between these two wavelengths to estimate the chlorophyll content in the leaf [21]. Since chlorophyll concentration is closely related to the nitrogen content in plants, SPAD readings offer an indirect assessment of the plant's nitrogen status (Pal et al., 2024).

Here is an overview of key components in a soil test:

B.2. Applications in Agriculture:

- **Crop Monitoring:** SPAD meters are commonly used in crops like rice, wheat, maize, and other cereals to assess nitrogen levels and improve crop performance.
- **Nutrient Deficiency Detection:** The device helps identify early signs of nitrogen deficiency, allowing farmers to take corrective actions before yields are affected.
- **Precision Agriculture:** In modern precision farming, the SPAD meter plays a crucial role in fine-tuning nutrient applications, minimizing waste, and promoting sustainable farming practices.

B.3. SPAD Readings and Interpretation:

SPAD readings typically range between 0 and 100. A higher SPAD value indicates more chlorophyll and, by extension, higher nitrogen levels [22]. However, the interpretation of SPAD readings can vary depending on the crop species, growth stage, and environmental conditions. Calibration against local field conditions or reference curves is often required to translate SPAD values into actionable nitrogen recommendations (Bright, 2005b).

SPAD Chlorophyll meter is highly expensive (between Rs. 2 and Rs. 5 lacs) Soil Plant Analysis Development (SPAD) Chlorophyll meter measures just the quantity of chlorophyll in the plants and may be used to determine the crop's nitrogen composition.



a. SPAD reading of Chlorotic variety b. SPAD reading moderate variety c. SPAD reading of green (Non-chlorotic) variety

Figure 2. Chlorophyll Measuring by SPAD meter

C. Leaf color chart (LCC) Method:

The Leaf Color Chart (LCC) is an easy-to-use diagnostic tool for assessing the nitrogen status of plants, particularly in crops like rice, maize, and wheat [23]. It consists of a series of colored panels, typically ranging from light yellow green to dark green, that represent different levels of leaf chlorophyll content [24]. Since chlorophyll is closely related to nitrogen, the LCC helps farmers make decisions about when and how much nitrogen fertilizer to apply.



Figure 3. (Leaf Color Chart)

(Sari, Yuslena&Maulida, Mutia&Maulana, Razak&Wahyudi, Johan &Shalludin, Ahmad.(2021). Detection of Corn Leaves Nutrient Deficiency Using Support Vector Machine (SVM). 396-400. 10.1109/IC2IE53219.2021.9649375.)

C.1. Key Features of the Leaf Color Chart:

- **Simple and Low-Cost:** The LCC is a very affordable tool, often made of plastic or laminated paper, with a set of green color shades. It is highly accessible for smallholder farmers in developing countries who may not have access to advanced technologies.
- **Non-Destructive:** Like the SPAD meter, the LCC allows for non-destructive measurement. Farmers can visually compare the color of the crop's leaves to the chart without harming the plant.
- **Immediate Field Use:** The LCC provides real-time data by allowing farmers to directly assess leaf color in the field. This helps them quickly determine if the plants need additional nitrogen.

C.2. How the LCC Works:

- The process of using an LCC is straightforward. Farmers hold the chart next to the leaf they want to evaluate (usually the youngest, fully developed leaf) and visually match the leaf color to the closest shade on the chart [25]. Each color on the chart corresponds to a certain range of nitrogen levels in the plant. If the leaf color matches the lighter shades, it indicates a nitrogen deficiency, and fertilizer may need to be applied.
- The LCC is especially effective during critical growth stages, such as the tillering and panicle initiation stages in rice, when nitrogen demand is highest. By regularly checking leaf color with the chart, farmers can apply nitrogen at the right time to prevent over- or under-fertilization.

C.3. Benefits of the Leaf Color Chart:

- **Efficient Nitrogen Use:** By using the LCC, farmers can apply nitrogen only when the plant shows signs of deficiency, reducing the risk of excessive nitrogen use. This ensures that plants receive the right amount of nutrients for healthy growth, leading to better yields.
- **Environmentally Friendly:** Reducing over-application of nitrogen helps to minimize nutrient runoff into water bodies, which can cause environmental problems such as water pollution and eutrophication.
- **Cost Savings:** Optimizing nitrogen application using the LCC can lead to reduced fertilizer costs, particularly in resource-constrained settings.
- **Adaptable to Local Conditions:** The LCC can be easily calibrated or adjusted to different crop types, soil conditions, and growing environments, making it a flexible tool for a wide range of agricultural practices.

C.4. Limitations:

- **Subjectivity:** The accuracy of the LCC depends on the user's ability to match leaf color to the chart, which can be subjective. Variations in light conditions during observation can also affect the results.
- **Limited to Nitrogen:** The LCC primarily helps with nitrogen management, so it does not provide information about other nutrient deficiencies or overall soil health.

C.5. Applications in Precision Agriculture:

The LCC is widely used in precision farming, particularly for rice crops in Asia and other regions where nitrogen management is critical. It complements more advanced tools like the SPAD meter by offering a low-tech, yet effective, solution for monitoring nitrogen levels in crops.

C.6. Steps for Using the LCC:

- **Select a Representative Plant:** Choose several healthy plants from different parts of the field.
- **Choose the Correct Leaf:** Use the LCC on the top, fully-grown leaf during the plant's active growth stages.
- **Match the Leaf Color:** Hold the chart next to the leaf and select the color that most closely matches it.
- **Take Action:** Based on the color match, decide if nitrogen fertilizer is needed. Darker green leaves suggest sufficient nitrogen, while lighter green to yellowish leaves indicate a deficiency.

In conclusion, the Leaf Color Chart is a practical, low-cost tool that helps farmers optimize nitrogen use and improve crop yields. It provides an effective way to monitor plant health, particularly in regions where high-tech solutions are not available, while promoting more sustainable and efficient agricultural practices.

A Leaf Color Chart (LCC) is a tool used primarily in agriculture to assess the nitrogen status of plants, especially in crops like rice. Here are some advantages of using a Leaf Color Chart:

- **Cost-Effective & Inexpensive Tool:** LCCs are relatively cheap compared to other methods of nitrogen assessment, making them accessible to farmers with limited resources and **No Special Equipment Needed:** Unlike some other testing methods, LCCs do not require expensive equipment or laboratory tests.
- **Ease of Use & Simple and User-Friendly:** LCCs are straightforward to use, even for farmers with minimal technical knowledge and **Quick Assessment:** The color comparison can be done in the field in real-time, providing immediate results.
- **Improved Nitrogen Management:** **Accurate Nitrogen Application:** LCCs help farmers apply the correct amount of nitrogen fertilizer, avoiding over- or under-fertilization, **Enhanced Crop Yield, and Quality:** Proper nitrogen management can lead to improved crop yields and better-quality produce.
- **Environmental Benefits:** **Reduced Nitrogen Runoff:** By optimizing nitrogen use, LCCs help minimize the runoff of excess nitrogen into waterways, reducing environmental pollution and **Sustainable Farming Practices:** LCCs promote more sustainable farming by encouraging the efficient use of fertilizers.
- **Versatility:** **Wide Applicability:** While commonly used for rice, LCCs can be adapted for use with other crops, making them versatile tools in various agricultural settings and **Different Growth Stages:** LCCs can be used at different stages of plant growth, providing ongoing monitoring and adjustments.
- **Improved Decision Making:** **Informed Fertilization Decisions:** Farmers can make more informed decisions about when and how much nitrogen to apply, based on real-time observations of leaf color and **Data-Driven Approach:** LCCs provide a data-driven approach to nitrogen management, reducing reliance on guesswork.
- **Support for Training and Extension Services:** **Educational Tool:** LCCs can be used in training programs to educate farmers about the importance of nitrogen management and how to use the tool effectively and **Extension Services:** Agricultural extension workers can use LCCs to provide on-site assistance and recommendations to farmers.
- **Enhanced Crop Monitoring:** **Ongoing Monitoring:** LCCs enable continuous monitoring of the crop's nitrogen status, allowing for timely interventions and **Adaptive Management:** Farmers can adjust their fertilization practices to align with the changing needs of the crop throughout the growing season.

4. Research Methods

Combining agronomic expertise with data analytics to make informed decisions on pest control, fertilizer, irrigation, and planting. **Pronouncement Support Systems (PSS)** are systems designed to aid in the generation, management, and dissemination of pronouncements, typically in the context of legal, medical, or organizational settings. These systems provide tools and frameworks to ensure that pronouncements are accurate, consistent, and effectively communicated (Ali & Farooqui, 2022).

A. Key Features of Pronouncement Support Systems

- **Data Integration:** PSS can integrate data from various sources, ensuring that the pronouncements are based on the most current and comprehensive information.
- **Decision Support:** They offer decision support tools that help users analyze data and make informed pronouncements. This is particularly useful in medical and legal contexts where decisions can have significant implications.
- **Automation:** Automation of routine tasks related to pronouncements, such as document generation, notifications, and updates, enhances efficiency.
- **Compliance and Standardization:** Ensuring that pronouncements comply with relevant laws, regulations, and standards is a critical function. PSS often includes templates and guidelines to help maintain compliance and consistency.

- **Communication:** Effective communication tools within PSS ensure that pronouncements are disseminated to the appropriate stakeholders in a timely manner. This might include email alerts, reports, or integration with other communication platforms.
- **Audit Trails:** Maintaining detailed records of pronouncements, including who made them, when, and under what circumstances, helps in accountability and transparency.

B. Data Analysis

Using sophisticated analytics and machine learning algorithms to process vast amounts of data and produce insights that may be used immediately. A lot of effort goes into cleaning data for analysis, but not much research has focused on making data cleaning easier and more effective (Pathan, 2023). This paper looks at an important part of data cleaning data cleansing. Tidy datasets, which have a specific structure where each variable is a column, each observation is a row, and each type of observational unit is a table, are easier to work with. This structure simplifies cleaning because only a few tools are needed to handle various messy datasets. It also helps in developing efficient tools for data analysis that both use and produce tidy datasets. A case study in the paper shows the advantages of having consistent data structure and matching tools, making the process free from common data manipulation tasks. (Bright, 2005b).

C. Precision Application

- The theory of precision application is rooted in the broader framework of precision agriculture, which seeks to optimize agricultural productivity by applying inputs such as water, fertilizers, pesticides, and seeds—more efficiently and sustainably. The main principle behind precision application is that different parts of a field have varying conditions and needs. Therefore, instead of treating the entire field uniformly, inputs are adjusted based on specific data-driven insights. Below is an exploration of the key theoretical principles behind precision application.
- The theory of precision application revolves around the notion that modern farming can be significantly improved by leveraging data, technology, and site-specific management practices. It rests on the pillars of field variability, input efficiency, sustainability, and the integration of cutting-edge technology. By aligning agricultural practices with real-time data and localized needs, precision application enhances crop productivity, reduces input waste, and supports more sustainable agricultural systems (Nguy-Robertson et al., 2015).

D. Timely Interventions

Use of treatments at certain phases of the crop growth cycle, maximizing the use of available resources, and raising total yield. Time-bound meticulous agriculture has several benefits, including increased output, lower costs, better supply chain management, and environmental sustainability. By using real-time data insights to link unindustrialized operations with specific times and complementing their decision-making processes, farmers may enhance outcomes across the completely agricultural value chain. Plant nitrogen (N) content must be evaluated to maintain the balance between crop N demands and N sourcing from the soil and supplemental fertilizer. Since leaf N status is linked to photosynthetic rate and biomass output, it is essential for optimizing plant improvement. More than half of the nitrogen (N) required globally for grain production comes from cereals, which utilize more N than any other type of fertilizer. The projected increase in the world's population would result in a considerable increase in the demand for cereals, requiring higher amounts of fertilizer N without commensurate advancements in N recovery and effective management. Crop N enhancement performance is often poor, ranging from thirty to fifty percent, and sometimes even lower, according to studies. Split N doses that are sprayed well exceed crop needs, leading to seepage and denitrification. Sustainable agriculture requires humanized, efficient N utilization. Nitrogen is very important for crop enhancement since it is employed in the production of photosynthetic pigments, which are necessary for photosynthesis and regular plant activity. Globally, the application of nitrogenous fertilizers has significantly increased agricultural production. Since chlorophyll absorbs most of the nitrogen in leaves, quantities of chlorophyll may be used to indirectly detect the nitrogen status of leaves. (Takebe & Yoneyama, 1989).

E. Digital Image Processing Technique for Image Enhancement

Digital image processing involves using a digital computer and relevant algorithms to process digital images. It is a subfield of digital signal processing with many advantages over analog image processing. Digital methods allow for more complex algorithms, enabling sophisticated performance and tasks that are impossible with analog techniques. This reduces problems like noise and distortion. Digital image processing operates in multidimensional systems and has advanced due to computer development, improvements in discrete mathematics, and growing application demands in fields like environmental science, agriculture, military, industry, and medicine.

Digital image processing involves manipulating digital images using a computer. It is a subfield of signals and systems with a focus on images. The process starts with a digital image as input, which is then processed using efficient algorithms to produce an output image and its corresponding description. (Zijlstra et al., 2011).

Gaussian Blur:

The Gaussian blur is a photo-blurring method that uses a Gaussian characteristic to decide the transformation for each pixel inside the photo. This function, which also represents the everyday distribution in information, is applied to achieve the blur impact. The only dimensional Gaussian characteristic is given with the aid of the system:

For Single / One Dimension:
$$g_{\sigma}(x) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{x^2}{2\sigma^2}\right) \quad (1)$$

For Double / Two Dimension:
$$G_{\sigma}(x, y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right) \quad (2)$$

Where x represents the distance from the origin along the horizontal axis, y represents the distance from the origin along the vertical axis, and σ is the standard deviation of the Gaussian distribution.

In two dimensions, this formula creates a surface with concentric circles centered on a Gaussian distribution (Zijlstra et al., 2011). The values from this distribution form a matrix used for convolution with the original image. Open CV offers efficient built-in functions to compute and apply these operations to image pixels."

Gaussian blur is an image-blurring filter that uses a Gaussian function to calculate the transformation applied to each pixel. In one dimension, the Gaussian function is expressed by a specific formula Eq.- 1, and in two dimensions, it becomes the product of two Gaussian functions one for each axis Eq.-2. When applied in two dimensions, this formula produces the desired blurring effect.

F. Gray Scale:

$$Y' = 0.299R' + 0.587G' + 0.114B' \quad (3)$$

For grayscale images, the output is a grid with rows and columns matching the image's pixel dimensions. Lower numbers represent darker shades, while higher numbers represent lighter shades. Typically, pixel values range from 0 to 255. To scale this, range from 0 to 1, we divide by 255.

Color images are stored as three-dimensional arrays, with each dimension representing a separate two-dimensional array for the red, green, and blue channels. Like grayscale images, each channel contains one value per pixel, and the value ranges are identical across all channels.

$$Y_{Linear} = 0.2126R_{Linear} + 0.7152G_{Linear} + 0.0722B_{Linear} \quad (4)$$

Contrast generally refers to the distinction in luminance or gray degree values in a photo and is an essential function. It may be described because of the ratio of the most intensity to the minimum depth over an image.

$$C = \frac{I(\max)}{I(\min)} \quad (5)$$

Contrast ratio has a strong bearing on the resolving electricity and stumble on capacity of a photo. Larger this ratio, easier it's miles to interpret the image.

G. Rice paddies require the following essential nutrients for proper growth and development

It is known that potassium, phosphate, and nitrogen are the three primary nutrients for plants; calcium, magnesium, and sulfur are the secondary nutrients; and iron, manganese, copper, zinc, boron, molybdenum, and chlorine are the minor elements or micronutrients. It is acknowledged that the primary and secondary nutritional components are the most important ones. This category is based on their extremely large quantity rather than their relative importance. Despite being the main nutrients for plants, micronutrients are only marginally essential (Radhamani et al., 2016).

Table 2: List of Primary Crop Nutrients and Secondary Crop Nutrients (Leghari et al., 2016)

S.No.	Primary Crop Nutrients	Secondary Crop Nutrients
1	Nitrogen (N)	Iron (Fe)
2	Phosphorous (P)	Manganese (Mn)
3	Potassium (K)	Copper (Cu)
4		Zinc (Zn)
5		Boron (B)
6		Molybdenum (Mo)
7		Chlorine (Cl)

H. Phosphorus (P)

Phosphorus is a fundamental element for life, influencing numerous biological processes and agricultural practices. Its unique properties and critical functions in energy transfer, genetic material, and cellular structure underscore its importance in both ecological and agricultural contexts. Proper management of phosphorus is essential for sustainable farming and environmental conservation.

G.1. Passphrase Deficiency Phosphorus Deficiency Symptoms When the rice plant's roots are still growing. If enough phosphorus is absorbed during early growth and the initial soil supply is insufficient, it can also be remobilized inside the plant during later stages of development, boosting resistance to disease. It strengthens the stems of cereal plants, reducing the chance that they may become stunted. It mitigates the harmful consequences of the plant's excess nitrogen. Additionally, if enough phosphorus was absorbed during early growth and the original soil supply was insufficient, phosphorus is remobilized inside the plant during later development stages, boosting disease resistance. By fortifying their stems, it reduces the possibility that cereal plants may become stunted. It mitigates the harmful effects of an excess of nitrogen in the plant.



Figure 4. Phosphorus Deficiencies



Figure 5. Phosphorus Deficiencies (IRRI Rice Knowledge Bank)



Figure 6. Rice leaf picture with Phosphorus Deficiencies



Figure 7. Slide of Fig. 6 for Analysis and Compare with Normal leaf



Figure 8. Rice leaf picture with normal Nutrient



Figure 9. Slide of Fig. 8 for Examine and Compare with Phosphorus Deficiencies Leaf

G.2. Solution Measures

Before floods, rock phosphates are sprayed on areas with low soil pH. You can use phosphor bacteria to coat seeds or to dip seedlings in the soil. Per acre, 15–30 kg of P fertilizer is applied.

G.3. Phosphorus sources

Biofertilizers (phosphate solubilizers), farmyard manure, Neemcake, Castor cake, Ammonium phosphate (Gromor), basic slag, messori, diammonium phosphate (SPIC), and super phosphate (single, double, and triple).

A. Potassium (P)

Potassium makes plants more resilient to diseases, pests, the cold, and other adverse conditions. Because it is essential to the synthesis and translocation of sugars as well as the creation of starch, it is especially important to crop heavy in carbs. In addition, it influences the activity of enzymes, helps photosynthesis form and migrate, makes it easier for other nutrients to be properly absorbed, and has an impact on grain size and weight as well as plant tillering or branching. Over 80% of the potassium absorbed by the plant is found in straw. Potassium is more likely to be needed in sand soil.

H.1. Potassium Deficiency and Potassium Deficiency Symptoms

In dark green plants with yellowish-brown leaf edges, brown necrotic markings on the tips of older leaves, and rusty brown stains on the panicles, slow grain production and a weak stem cause lodging.



Figure 10. Potassium Deficiencies



Figure 11. Potassium Deficiencies (IRRI Rice Knowledge Bank)



Figure 12. Rice leaf picture with Potassium Deficiencies



Figure 13. Slide of Fig. 12 for Analysis and Compare with Normal leaf



Figure 14. Rice leaf picture with normal Nutrient



Figure 15. Slide of Fig. 15 for Examine and Compare with Potassium Deficiencies leaf

H.2. Solution Measures

25% more K than is advised for the soil and 1% potassium chlorate KCL applied topically. Thoroughly scatter and mix the straw on the field prior to burning. Additionally, the field has to be covered with ashes from the burned straw mound.

H.3. Sources of potassium

Sources of potassium include farmyard manure, castor cake, neem cake, muriate of potash (KCl), and potassium sulfate.

5. Proposed Model

Therefore, in this paper we will review the use of digital image processing and machine learning and their significance to discover better techniques for crop nutrients and to improve the old techniques so that crop productivity can be increased at very low cost. To solve the above problem, two models are being prepared through this paper.

- Designing a new Model-1 of software engineering to find the best software and technology
- Designing a Model-2 to Identify Nitrogen Deficiency Using Techniques Derived from Model

Taking the above forward, we have designed a model, which is as follows

A. **Model-1:** Layer of Software Information System

B. **Model-2:** Crop Health Prediction System

A. **Model-1: Layer of Software Information System**

Several studies have investigated the link between designing metrics and finding defects in object-oriented software. Many have shown that models can accurately predict which parts of a software product are likely to have defects. However, these models are often built using data from one project and then applied to future projects. This raises the question: how accurate these models are when applied to different projects with varying characteristics (Wickham, 2014a).

Organizations evolve and learn over time. From a broader viewpoint, can we find evidence that these models are cost-effective tools for directing verification and validation efforts? This Model seeks to answer these questions by creating a general but adaptable cost-benefit model (Sharma et al., 2024). It uses defect and design data from two medium-sized Java systems developed in the same environment. Additionally, the paper introduces a new analysis method, MARS (Multivariate Adaptive Regression Splines), to build defect prediction models without prior knowledge of their functional form. The results show that models built on one system can effectively rank the likelihood of defects in another system (Briand et al., 2002) (Wickham, 2014a).

Outdated accuracy measures like MMRE are no longer useful. Instead, this new empirical validation framework gives us meaningful results. This approach will help with future meta-analyses and provide better recommendations for practitioners. Predicting outcomes is essential in any engineering field, including software engineering. For over 40 years, researchers have been developing prediction systems for things like cost, schedule, and defect-proneness. Despite the advanced methods used, the results of empirical evaluations have been inconsistent and hard to interpret. This is important because it makes it difficult to advise professionals who rely on software engineering research (Zijlstra et al., 2011). Software information system layer have contained four layers from bottom to top are:

A.1. **Layer of Software Information System Model**

This layer includes all types of computer software utilities, application packages, apps, computer games that are developed together or in one layer in the third layer system software and fourth layer application software. In this layer, we can select software utilities, application packages and other tools as per the requirement of the project. Examples of utility software: Various types of apps, SAP- ERP, MIS, DSS and others.

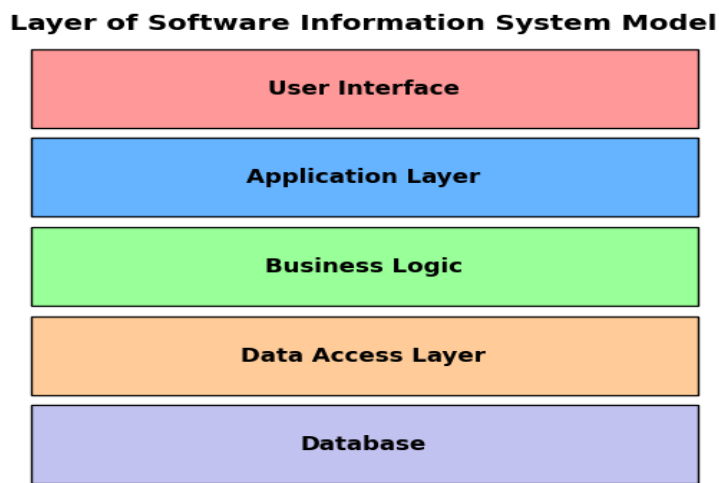


Figure 16. Layer of Software Information System Model

A.2. **Advantages of Layer of Software Information System Model**

1. It is easy to choose the appropriate software based on our needs.
2. Reduce hardware and software costs
3. Increase efficiency of hardware and software.

4. Increase hardware flexibility on the go.
5. Increase the execution speed of any software development framework.

A.3. Accuracy of the software & architecture

From the analysis of the above software layer, it is known that in this project, we are finding three computer languages in layer 2-system software, which are Java and C++, Python programming language respectively, and web technology tools in layer 3 for frontend. ML, SQL, JavaScript and RDBMS for databases and Android are the most popular languages for app development.

B. Model-2: Crop Health Prediction System Working of Crop Health Prediction System

The foreground is obtained for processing using this method. This is a prominent step to determine the crop in growing properly in the image taken. Hence, with the help of this technique about shortcomings of nutrients plants can be extracted from its image, as shown in Figure 15.

Several studies have investigated the link between designing metrics and finding defects in object-oriented software. Many have shown that models can accurately predict which parts of a software product are likely to have defects. However, these models are often built using data from one project and then applied to future projects. This raises the question: how accurate these models are when applied to different projects with varying characteristics (Bright, 2005a).

Organizations evolve and learn over time. From a broader viewpoint, can we find evidence that these models are cost-effective tools for directing verification and validation efforts (Byeon et al., 2024). This Model seeks to answer these questions by creating a general but adaptable cost-benefit model. It uses defect and design data from two medium-sized Java systems developed in the same environment. Additionally, the paper introduces a new analysis method, MARS (Multivariate Adaptive Regression Splines), to build defect prediction models without prior knowledge of their functional form. The results show that models built on one system can effectively rank the likelihood of defects in another system (Shepherd & MacDonell, 2012)

Outdated accuracy measures like MMRE are no longer useful. Instead, this new empirical validation framework gives us meaningful results. This approach will help with future meta-analyses and provide better recommendations for practitioners. Predicting outcomes is essential in any engineering field, including software engineering. For over 40 years, researchers have been developing prediction systems for things like cost, schedule, and defect-proneness (Sahu, 2023). Despite the advanced methods used, the results of empirical evaluations have been inconsistent and hard to interpret. This is important because it makes it difficult to advise professionals who rely on software engineering research (Wickham, 2014b).

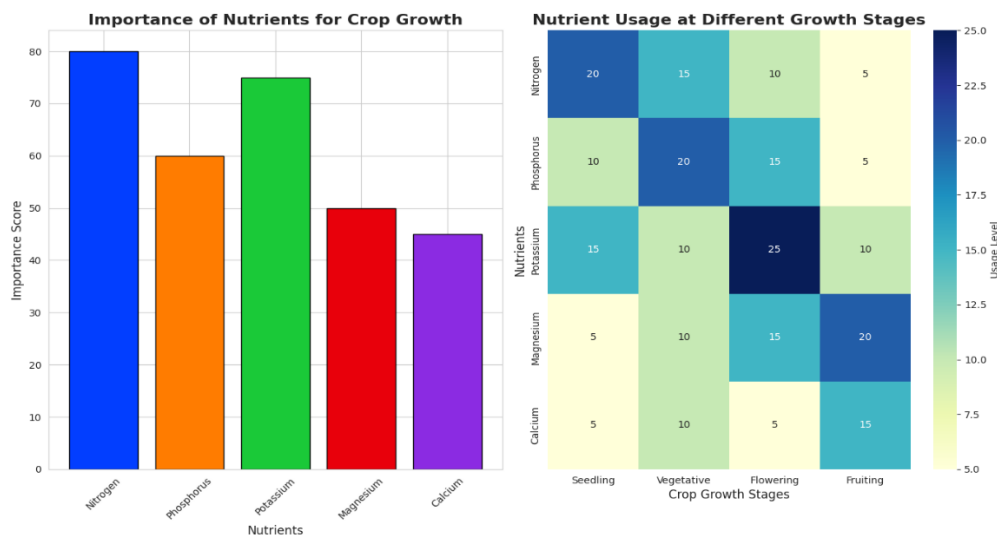


Figure 17. To Propose Model to develop a framework to Identify necessary crop Nutrients

Step 1: Input (Picture Collect of Paddy Leaf)

In agriculture, collecting images of paddy leaves is essential for monitoring plant health and identifying problems such as nutrient deficiencies, pests and diseases. High-resolution images are collected using a variety of methods, including manual photography or automated systems such as drones. These images provide visual data that can be analyzed to detect abnormalities such as discoloration or unusual leaf patterns that indicate stress or infection. With advances in technology, image-processing techniques are helping farmers make timely decisions, improving crop yields and sustainability by addressing problems at an early stage.

Step 2: Digital Image Processing (Remove Background and Image Enhancement)

Digital image processing plays a vital role in improving image quality and obtaining useful information. Removing the background from an image is a common technique used to isolate a subject and remove distractions, making the main subject stand out. This is done using algorithms that detect and distinguish the background from the foreground. Image enhancement, on the other hand, improves the visual appearance of an image by adjusting brightness, contrast, and sharpness or removing noise. Both techniques are widely used in fields such as photography and agriculture imaging to produce clearer and more informative images.

Step 3: Sampling (Make Slide of Leaf of the Crop)

Sampling in agriculture involves collecting plant material such as leaves to study crop health and condition. When making a slide from a crop leaf, the process usually involves selecting a representative leaf, preparing a thin section, and placing it on a microscope slide for observation. This enables analysis of cell structure, identification of signs of disease, pests or nutrient deficiency at a microscopic level. Studying these samples can help farmers and researchers detect problems early and allow early intervention to ensure crop health and productivity.

Step 4: Comparisons with Input Leaf's RGB code with as per Norms leaf color chart code by the KNN Approach

The K-nearest neighbors (KNN) approach is a widely used method in digital image analysis for classifying and comparing leaf colors based on RGB values. In this process, the RGB code of the given input sheet is first extracted from the image. This code is then compared to standard leaf colorist codes that serve as reference values for healthy or stressed plants. The KNN algorithm identifies the closest matching color based on the proximity of the input to known color codes. By comparing the RGB values of the input sheet with the norm using KNN, farmers and researchers can assess the health status of the crop, such as detecting nutrient deficiencies or stress, which helps make better crop management decisions.

Step 5: Achieve Result (Nutrients Deficiency of Phosphorus & Potassium as per leaf color chart norms of the Paddy Crop after using KNN Approach)

By applying the K-nearest neighbors (KNN) approach to rice crop leaf images, nutrient deficiencies such as phosphorus and potassium can be effectively identified. The process involves comparing the RGB values of the leaf to standard color chart standards that indicate healthy or deficient plants. Phosphorus deficiency usually causes leaves to appear darker, sometimes with purple tones, while potassium deficiency results in yellowing or browning along the edges of the leaves. After performing the KNN analysis, the closest matching color codes reveal these nutrient deficiencies, allowing farmers to diagnose the problem early and apply targeted fertilizers to restore rice health and productivity.

Step 6: Result: Provide Solutions Calculated Nutrients Phosphorus & Potassium as per Agriculture Norms

Based on the detected deficiencies of phosphorus and potassium nutrients using the color analysis of rice leaves, a solution can be provided by calculating the exact number of fertilizers required according to agricultural standards. Phosphorus deficiency can be corrected by applying phosphorus-rich fertilizers such as simple superphosphate (SSP), while potassium deficiency can be addressed with potassium sulfate or muriate of potash. The calculated dose is determined by the severity of the deficiency, the type of soil and the growth stage of the crop, which ensures the correct balance of nutrients. Guided by KNN analysis and agricultural standards, these targeted interventions help optimize crop health and effectively increase yields.

6. Output Result

Figure 18. Result provided by framework (Model B)

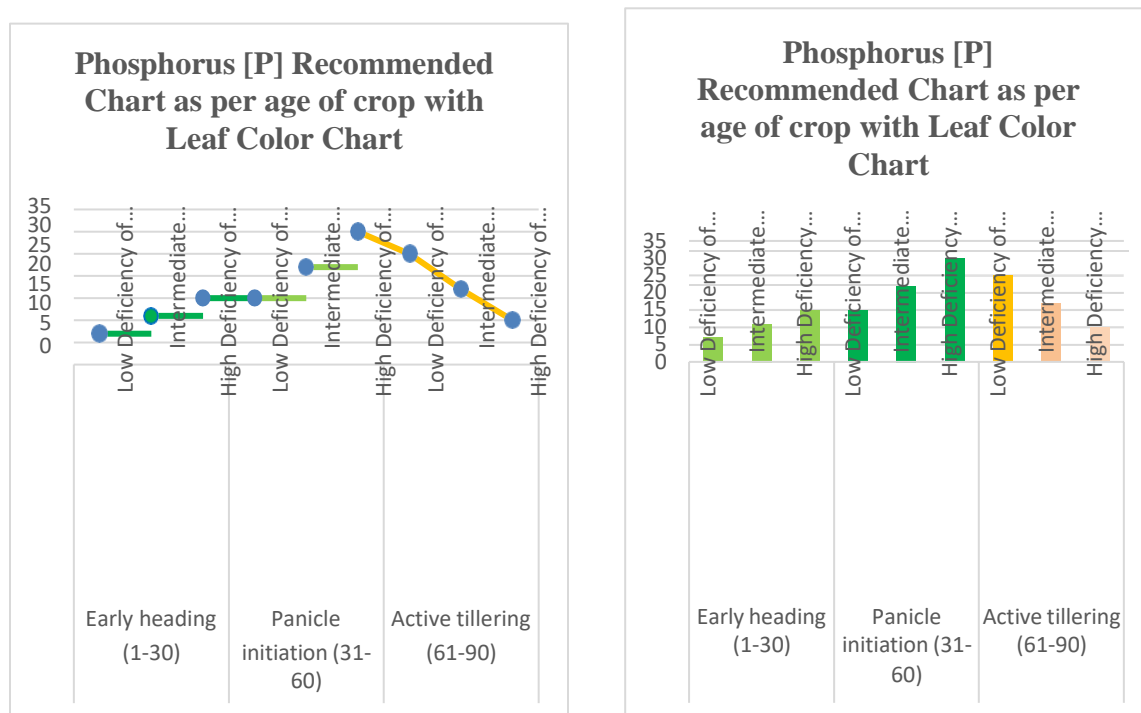


Figure 19. Phosphorus [P] Recommended Chart as per age of crop with Leaf Color Chart

Table 3: Result provided by framework (Model B)

Crop Age Stage	Deficiency Level	Leaf Color	RGB Code	Fertilizer P Rate (kg/ha)
Early heading (1-30)	Low Deficiency	Light Green	#8bc34a	5
Early heading (1-30)	Intermediate Deficiency	Yellow-Green	#cddc39	10
Early heading (1-30)	High Deficiency	Yellow	#ffeb3b	20
Panicle initiation (31-60)	Low Deficiency	Light Green	#8bc34a	30
Panicle initiation (31-60)	Intermediate Deficiency	Yellow-Green	#cddc39	35
Panicle initiation (31-60)	High Deficiency	Yellow	#ffeb3b	40
Active tillering (61-90)	Low Deficiency	Light Green	#8bc34a	35
Active tillering (61-90)	Intermediate Deficiency	Yellow-Green	#cddc39	25
Active tillering (61-90)	High Deficiency	Yellow	#ffeb3b	15

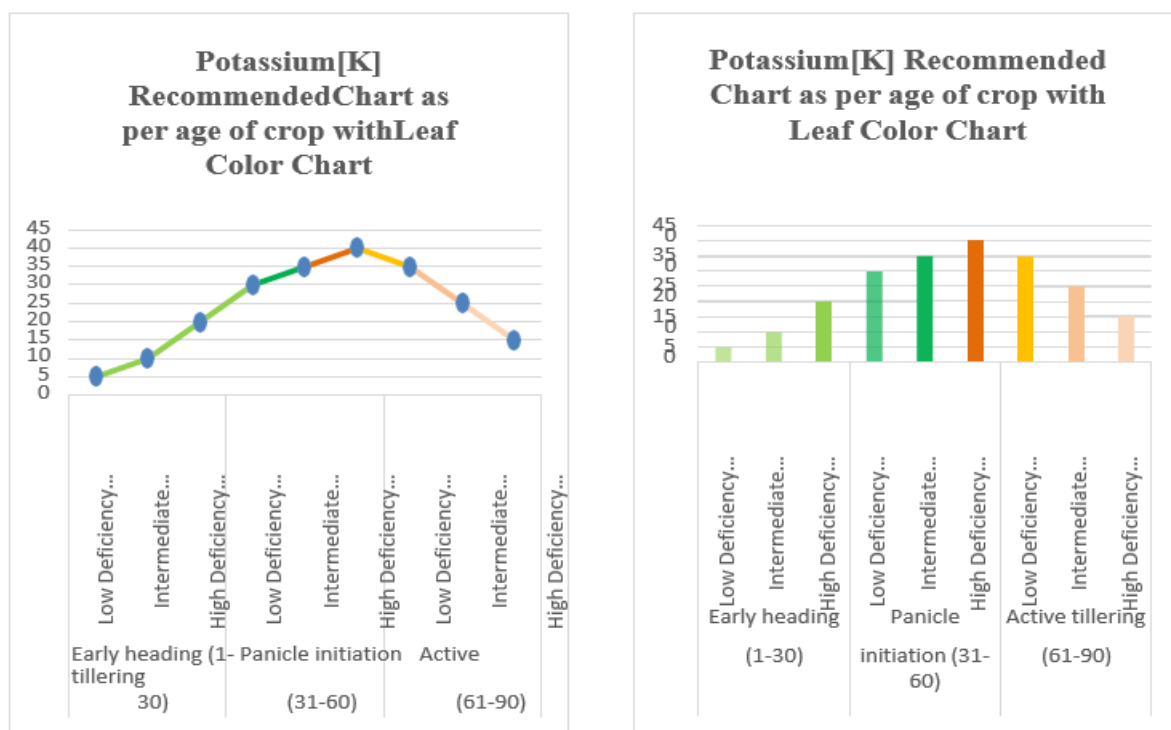


Figure 20. Potassium [K] Recommended Chart as per age of crops with Leaf Color Chart

7. Experimental Simulation, Result analysis, Comparison and Discussion

Our cutting-edge technology for soil testing solves the problems with both conventional and cutting-edge approaches, completely revolutionizing the way they are now done. Our method employs the Leaf Color Chart (LCC) method, which offers a less expensive alternative to labor-intensive and costly on-site soil sample collection for assessing plant nitrogen shortage. This manual, yet user-friendly, approach guarantees mobility and adaptability in many geographic regions, providing a free solution that yields precise results with high accuracy and efficiency in the shortest amount of time (Tiwari et al., 2019). Our method seeks to improve soil testing accessibility, practicality, and efficiency for farmers worldwide by addressing the shortcomings of current methods.

Above Model (Crop Health Prediction System) allows us to choose intelligent tools for task automation in the precision agriculture industry that use computer vision and artificial intelligence. As development moves forward, the gaps in their interaction with agricultural machinery must be addressed. Prospective directions for future research include extending the use of sophisticated artificial intelligence. For instance, a computer system designed to lower complexity and expense in the classification of gluten-containing grains from photographs might be advantageous for the cultivation of wheat, oats, and rice.

8. Key contribution of this research work:

- i. **Current limitations of soil testing:** Conventional methods of soil testing are time-consuming and expensive due to lengthy procedures and variable parameters. The cost of soil testing would range between Rs 3,000 to Rs 8,000 per kg, while the equipment is expected to cost between Rs 1.5 lakh to Rs 3 lakh. There is also the need to collect on-site samples from different parts of the farm, but the computer implementation of this model eliminates this difficulty, saving time and money.
- ii. **SPAD Chlorophyll Meter Analysis:** The current method of measuring nitrogen in crops is using the Soil Plant Analysis Development (SPAD) Chlorophyll Meter. This method costs between Rs 2 lakh to Rs 5 lakh and requires practical visits to the agricultural farms, whereas the computerized application of this model can be used by OT based drone camera, which can give more accurate results, saving time and money.

- iii. **Cost-Effective Alternative – LCC Method:** The Leaf Color Chart (LCC) method is a more cost-effective way to assess nitrogen deficiency in a plant. Although it is a manual process, the computerized application of this model provides a viable low-cost alternative.
- iv. **User-Friendly and Versatile System:** The proposed solution is easy to use, portable, and suitable for different locations around the world and provides accurate results with high accuracy and efficiency. Its operation requires minimal time and does not cause any costs.
- v. **Crop Plant Health Prediction System:** The proposed solution is easy to use, portable, and suitable for different locations around the world and provides accurate results with high accuracy and efficiency. Its operation requires minimal time and does not cause any costs. The proposed system includes an image processing method to determine crop health. This technique identifies nutrient deficiencies by analyzing the captured images of the plants, allowing relevant information on nutrient deficiencies to be obtained.
- vi. **Working of Crop Plants Health Prediction System:** The foreground is obtained for processing using this method. It is a prominent step in array to determine the crop in growing properly in the image taken. Hence, with the assistance of this technique, shortcomings of nutrients plants can be extracted from its image, as revealed in Fig. 17.

9. Conclusion

The results of this study demonstrated that the influence of environmental illumination on the accuracy of color detection could be minimized by including both the LCC and rice leaf sample in the same image taken under the same environmental condition. A model was developed in this study to determine rice leaf color levels using the leaf color chart (LCC) as a reference. This model will offer low-cost, low-complexity, high precision and simple ways to handle nitrogen fertilizer in rice production. The program's potential incompatibility with leaves that do not have consistent hues was the restriction; more research is needed in this area. The creation of an algorithm to calculate fertilizer application rates depending on the degree of leaf color will be the subject of future research. We can create a leaf coloration chart (Nitrom) for personal usage and optimal yield after evaluating this evaluation. It is imperative that we investigate new research zones to support the growth of agriculture, which is a pressing requirement. It appears that poor yield is frequently caused by improper nitrogen application. Farmers may now use labs to test soil and plant N deficiency. Thus, giving farmer's access to LCCs entails strengthening the agricultural sector and empowering them to manage nutrients on their own. They could discover the precise and appropriate fertilizer dosage, and they might see an increase in crop yield a benefit that will eventually benefit those who depend on agriculture. It was determined that there are still gaps in the development of intelligent gadgets that integrate with agricultural machinery and automate jobs in the field using computer vision and artificial intelligence. An alternative for the next work is to increase the application of sophisticated artificial intelligence. For example, cultivars of wheat, oats, and rice could profit from a computer system designed to make classifying gluten-containing grains from photos less complicated and expensive.

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References

- [1] L. C. Briand, W. L. Melo, and J. Wust, "Assessing the applicability of fault-proneness models across object-oriented software projects," *IEEE Trans. Softw. Eng.*, vol. 28, no. 7, pp. 706–720, 2002.
- [2] J. Bright, "Apple and pear nutrition," *NSW Department of Primary Industries. Primefact*, vol. 85, pp. 1–12, 2005.
- [3] M. N. Owaed, I. A. Abed, and S. S. S. Al-Saeedi, "Applicable properties of the bio-fertilizer spent mushroom substrate in organic systems as a byproduct from the cultivation of *Pleurotus* spp.," *Inf. Process. Agric.*, vol. 4, no. 1, pp. 78–82, 2017.
- [4] B. Elhami, M. Khanali, and A. Akram, "Combined application of Artificial Neural Networks and life cycle assessment in lentil farming in Iran," *Inf. Process. Agric.*, vol. 4, no. 1, pp. 18–32, 2017.

- [5] J. Gray, T. M. Banhazi, and A. A. Kist, "Wireless data management system for environmental monitoring in livestock buildings," *Inf. Process. Agric.*, vol. 4, no. 1, pp. 1–17, 2017.
- [6] Z. Islam, B. Bagchi, and M. Hossain, "Adoption of leaf color chart for nitrogen use efficiency in rice: Impact assessment of a farmer-participatory experiment in West Bengal, India," *Field Crops Res.*, vol. 103, no. 1, pp. 70–75, 2007.
- [7] K. Jha, A. Doshi, P. Patel, and M. Shah, "A comprehensive review on automation in agriculture using artificial intelligence," *Artif. Intell. Agric.*, vol. 2, pp. 1–12, 2019.
- [8] H. Sahu, "Fine_denseiganet: Automatic medical image classification in chest CT scan using Hybrid Deep Learning Framework," *Int. J. Image Graph.*, 2023. DOI: <https://doi.org/10.1142/s0219467825500044>.
- [9] S. J. Leghari et al., "Modern Leaf Colour Chart Successfully Prepared and Used in Crop Production of Sindh, Pakistan," *Eur. Acad. Res. J.*, vol. 4, no. 2, pp. 900–916, 2016.
- [10] Z. Li et al., "Recent advances in microfluidic sensors for nutrients detection in water," *TrAC Trends Anal. Chem.*, vol. 158, 116790, 2023.
- [11] X. Liu, M. Pedersen, and R. Wang, "Survey of natural image enhancement techniques: Classification, evaluation, challenges, and perspectives," *Digit. Signal Process*, vol. 127, 103547, 2022.
- [12] P. Moallem, A. Serajoddin, and H. Pourghassem, "Computer vision-based apple grading for golden delicious apples based on surface features," *Inf. Process. Agric.*, vol. 4, no. 1, pp. 33–40, 2017.
- [13] A. Nguy-Robertson et al., "Using a simple leaf color chart to estimate leaf and canopy chlorophyll a content in Maize (Zea Mays)," *Commun. Soil Sci. Plant Anal.*, vol. 46, no. 21, pp. 2734–2745, 2015.
- [14] S. Pathan, "Agricultural plant diseases identification: From traditional approach to deep learning," *Mater. Today: Proc.*, vol. 80, pp. 344–356, 2023. DOI: <https://doi.org/10.1016/j.matpr.2023.02.370>.
- [15] V. Patel and B. V. Singh, "Effect of need-based nitrogen management on yield and quality of kharif maize (Zea mays L.) Under central plain zone of UP," *Agricultural Res. J.*, vol. 10, pp. 45–53, 2022.
- [16] R. Radhamani, R. Kannan, and P. Rakkiyappan, "Leaf chlorophyll meter readings as an indicator for sugarcane yield under iron deficient typic haplustert," *Sugar Tech.*, vol. 18, no. 1, pp. 61–66, 2016.
- [17] S. Rathod and D. Singh, "Golden Leaf Publishers," Lucknow, India.
- [18] R. Sathyavani, K. JaganMohan, and B. Kalaavathi, "Classification of nutrient deficiencies in rice crop using denseNet-BC," *Mater. Today: Proc.*, vol. 56, pp. 1783–1789, 2022.
- [19] M. Shepperd and S. MacDonell, "Evaluating prediction systems in software project estimation," *Inf. Softw. Technol.*, vol. 54, no. 8, pp. 820–827, 2012.
- [20] A. Singh and H. Kaur, "Potato plant leaves disease detection and classification using machine learning methodologies," *IOP Conf. Ser.: Mater. Sci. Eng.*, vol. 1022, no. 1, pp. 1–6, 2021.
- [21] H. Byeon et al., "Enhancing medical image-based diagnostics through the application of convolutional neural networks techniques," in *Proc. 3rd Int. Conf. Distrib. Comput. Electr. Circuits Electron. (ICDCECE)*, Ballari, India, 2024, pp. 1–6.
- [22] A. Sharma et al., "Rose plant disease detection using image processing and machine learning," in *Int. Conf. Appl. Technol. (ICAT)*, Cham, Switzerland: Springer, 2024, pp. xx–xx. DOI: https://doi.org/10.1007/978-3-031-58953-9_6.
- [23] V. Singh and A. K. Misra, "Detection of plant leaf diseases using image segmentation and soft computing techniques," *Inf. Process. Agric.*, vol. 4, no. 1, pp. 41–49, 2017.
- [24] M. Takebe and T. Yoneyama, "Measurement of leaf color scores and its implication to nitrogen nutrition of rice plants," *Jpn. Agric. Res. Q.*, vol. 23, no. 1, pp. 86–93, 1989.
- [25] S. Tiwari, R. K. Gupta, and R. Kashyap, "To enhance web response time using agglomerative clustering technique for web navigation recommendation," in *Proc. Comput. Intell. Data Min. (Adv. Intell. Syst. Comput.)*, Singapore: Springer, 2019, pp. 1234–1245. DOI: https://doi.org/10.1007/978-981-10-8055-5_59.
- [26] H. Wickham, "Tidy data," *J. Stat. Softw.*, vol. 59, pp. 1–23, 2014.