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EXPLORING DEEP LEARNING APPROACHES FOR DETECTING NUTRITIONAL DEFICIENCIES IN CROP LEAVES: A COMPREHENSIVE OVERVIEW

[1*]Ms. Lalita Randive, [2]Dr. Shubhangi Sapkal and [3]Dr. Deepak Bornare

[1]Research Scholar Dr. BAM University, Chh. Sambhajinagar, Maharashtra, India, 431010.

[2]Asst. Prof., Department of Master Cosmputer Application, Government College of Engineering, Chh. Sambhajinagar, Maharashtra, India, 431010.

[3]Head & Asso. Prof. Department of Agriculture Engineering, Maharashtra Institute of Technology, Chh. Sambhajinagar, Maharashtra, India, 431010.

*Corresponding Author

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ABSTRACT

This research paper offers an extensive examination of diverse methodologies and computational approaches designed to identify deficiencies in critical plant nutrients, encompassing nitrogen, phosphorus, potassium, zinc, boron, sulfur, and iron. It systematically analyzes the diverse methodologies and strategies proposed by scholars, assessing their effectiveness, constraints, and precision. Plants demand 13 essential mineral nutrients for optimal growth, and any insufficiency or excess of these nutrients can critically disrupt growth or lead to plant mortality. Consequently, the establishment of a continuous monitoring system to oversee nutrient levels is imperative for the enhancement of crop yield and quality. Through diagnostic systems that utilize digital image processing, computer vision, machine learning, and deep learning frameworks (such as pre-trained Convolutional Neural Network models like InceptionV3, VGG16, VGG19, ResNet50, and ResNet152, along with Support Vector Machines), nutrient deficiencies can be detected significantly earlier than through manual methods, thereby allowing farmers to implement timely corrective actions. This article assesses the efficiency of these sophisticated methods in addressing the diagnosis of deficiencies in plant nutrients.

Keywords: Nutrition deficiency symptoms, Image processing, Machine learning, Deep Learning, YOLOs

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1. INTRODUCTION

The agricultural system is significantly dependent on a sufficient availability of water, sunlight, and the effective absorption of nutrients by plants. For plants to thrive, proper nutrition is essential. A balanced supply of all necessary nutrients in the correct proportions is crucial for healthy plant growth. For optimal growth and sustainability, vegetation requires a complete set of thirteen essential mineral nutrients. These plant nutrients are systematically organized into two essential classifications: macronutrients and micronutrients. Macro nutrients (calcium, nitrogen, potassium, magnesium, Sulphur and phosphorus) are those substances that are needed in relatively ample quantities. Micro nutrients (boron, manganese, iron, copper, zinc, chlorine) are required in minimal quantities.

Plant Indicators of Nutrient Deficiencies

Crop growth is influenced by various factors and represents the desired results for farmers. The process of growing crops reflects these influences and aligns with the grower's intended outcomes. Therefore, a careful study of a plant's growth can help identify specific nutrient deficiencies. When a plant is poor of a certain nutrient, distinctive symptoms may manifest. The lack of a nutrient does not directly cause symptoms. Instead, the normal physiological processes of the plant become disrupted, resulting in an accumulation of certain intermediate organic compounds while others become deficient. This imbalance leads to the unusual conditions recognized as symptoms. The visual diagnosis of nutrient deficiency should be utilized exclusively as a complementary strategy alongside alternative diagnostic approaches (e.g., soil and plant analysis). Nutrient deficiency symptoms can be categorized as follows:

1. Yield letdown during sprout growth or severely stunted plants.
2. Seasonal leaf symptoms and internal issues like clogged conductive tissues.
3. Delayed or abnormal plant maturity.
4. Visible or experimentally detected yield differences.
5. Poor crop quality, including protein, oil, starch, or storage issues.

Each symptom must be associated with a specific function of the nutrient within the plant. A particular nutrient may serve multiple functions, thereby complicating the elucidation of the physiological basis for a specific deficiency symptom. For instance, in instances of nitrogen deficiency, the foliage of the majority of plants exhibits a pale green or light-yellow coloration. When the availability of nitrogen is constrained, there is a diminution in chlorophyll synthesis, resulting in the prominence of yellow pigments, specifically carotene and xanthophyll, which manifest through various nutrient deficiencies, such as pale green or yellow leaves; furthermore, the deficiency must be correlated to a distinct leaf pattern or anatomical location on the plant. Nutrient deficiency symptoms are observed exclusively when the supply of vital nutrients has

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decreased to a point that hinders the physiological operations of the plants. In such scenarios, it would have been beneficial to have executed fertilization strategies well in advance of the onset of these symptoms. (Sudhakar & Swarna Priya, 2023) Table 1 describes nutrition deficiency symptoms and role of these nutrition in plant body.

Table 1: Macronutrients and Micronutrients Deficiency Symptoms and Role in Plants Body

Nutrients	Deficiency Symptoms				Role in plants body
	Type of leaves	**Color**	**Region**	**Texture**	
Calcium (Ca)	New	Yellow / brown	Spots	Death of leaf tips	Plays role in membranes structure and permeability
Nitrogen (N)	Old	Pale yellow	Whole	reduced height and smaller leaf area	Elements of proteins, coenzymes, chlorophyll, and nucleic acids.
Potassium (K)	Old	Brown	Edge/ segments	Curling of leaf tips	The essential function within modulating mechanisms involves the translocation of carbohydrates, the biosynthesis of proteins, and comparable processes.
Magnesium (Mg)	Old	Yellow	Between leaf veins	Leaf tips look burnt	Activator of enzyme and component of chlorophyll
Sulphur (S)	New	Yellow	Whole	stunted growth	Significant component of plant proteins.
Phosphorous (P)	Old	Reddish purple	Leaf tips & margins	Leaf tips look burnt	The key function in the regulation of processes such as carbohydrate translocation, protein biosynthesis, and other comparable mechanisms.
Zinc (Zn)	New	Yellow/Purplish	Between the leaf veins	Death of the younger leaves	Zinc plays a crucial role in regulating various metabolic processes within enzymatic systems

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Iron (Fe)	New	Yellow	Between the leaf veins	leaves may become smaller, deformed, or curled	Production of chlorophyll and enzymes involved in electron transport
Boron (B)	New	Yellow	Between the veins	leaves striped or mottled	vital in translocation of sugar and carbohydrate metabolism

Early detection of symptoms may allow for correction during the growing season. To address nutrient deficiencies promptly, foliar applications or side dressings can be employed in certain conditions for specific nutrients. However, crop yields typically remain lower than if adequate nutrients had been available from the start. Plant growth can be negatively impacted by deficiencies in any nutrient, especially macronutrients. Insufficient nutrients may lead to various issues such as stunted or slow growth, or chlorosis, which causes leaf yellowing. In severe cases of nutrient deficiency, leaves may exhibit signs of cellular death. (Sudhakar & Swarna Priya, 2023)

Agriculture faces challenges like groundwater scarcity, limited arable land, soil infertility, and inefficient production. Improper use of fertilizers and manures impacts crops, soil, and overall food quality. Techniques such as plant morphology and chemical analysis are used to diagnose deficiencies. Computer Vision algorithms show a critical role in monitoring crop health by analyzing images to identify deficiencies, enhancing productivity, and ensuring sustainable agricultural practices. These technologies are also applied in diverse fields like medicine, manufacturing, and phenotyping. (Sudhakar & Swarna Priya, 2023)

Part of Nutrients in Crop Development

Crop growth relies on the availability of essential minerals and nutrients, which are critical for completing their life cycles and achieving maximum sustainable yields. Deficiencies in these nutrients lead to symptoms such as stunted growth, reduced yield, and poor crop quality. Early identification and intervention are crucial for mitigating nutrient deficiencies and enhancing productivity. Macronutrients (NPK) are required in large quantities, while micronutrients (CaMgS) are essential in precise amounts depending on the plant species. Calcium provides structural support to plant cells, magnesium facilitates photosynthesis by activating growth enzymes, and sulfur aids in chlorophyll formation and protein synthesis. However, nutrient absorption is unfair by features such as soil moisture, temperature, pH, toxic elements, and salt levels, making it challenging to achieve optimal nutrition under experimental conditions. Effective diagnostic methods are necessary to identify abnormalities and implement corrective measures, ensuring improved crop health and productivity (Sudhakar & Swarna Priya, 2023). Figure 1 depicts various symptoms of nutrition deficiency in plant body.

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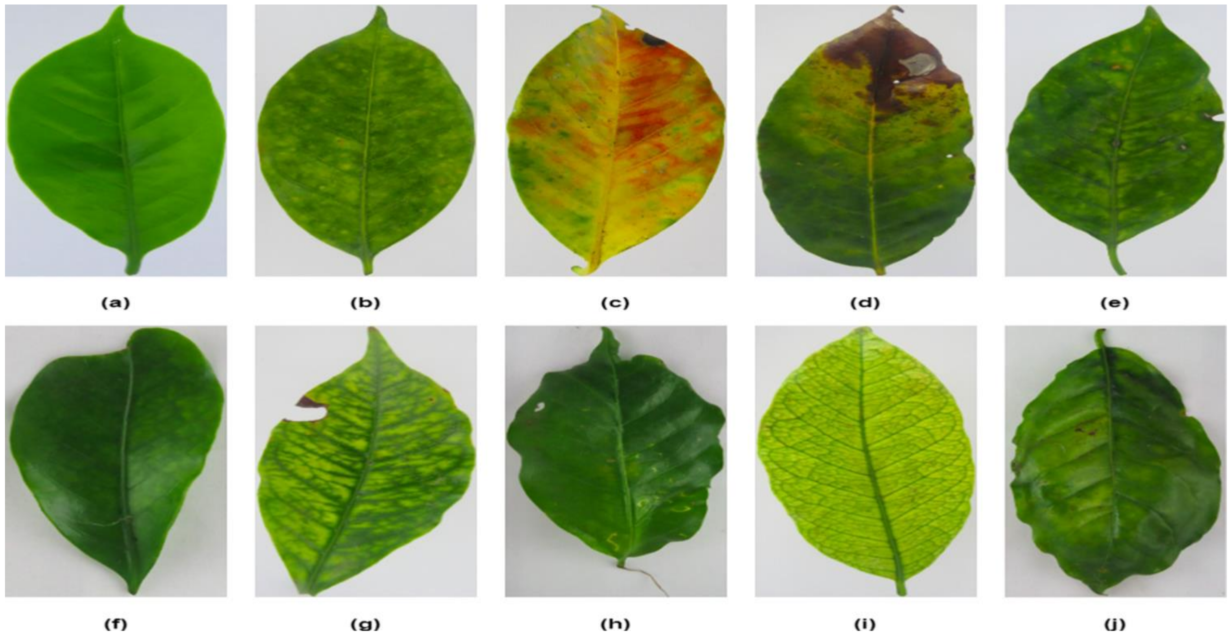

Figure 1: (a) Normal foliage, (b) Nitrogen-deficient leaves, (c) Phosphorus-deficient foliage, (d) Potassium-deficient leaves, (e) Magnesium-deficient foliage, (f) Boron-deficient leaves, (g) Manganese-deficient foliage, (h) Calcium-deficient leaves, (i) Iron-deficient foliage, (j) Leaves exhibiting multiple nutrient deficiencies (Tuesta-Monteza et al. – 2023)

Aspects of Crop Stress That Lead to Nutrient Deficiency

Nutrient deficiency is expressed through various distinct manifestations associated with crop health, which may encompass both observable and internal characteristics. For example, a deficiency in calcium results in aberrant leaf morphology. An insufficiency of nitrogen induces a chromatic transition in the foliage, manifesting as a pale green hue on the upper portion and a yellow tint at the lower extremity of the plant. Manganese deficiency is characterized by the emergence of perforations, whereas copper deficiency is evident through a light pink pigmentation situated between the leaf veins. Within the framework of precision agriculture, an array of robotic apparatuses has been developed to optimize crop productivity, including the renowned FarmBot and Agribots, which assess a multitude of crop-dependent variables such as soil salinity, depth for efficient seeding and soil organic carbon (SOC), among others. The principal factors contributing to crop stress encompass (1) Soil Quality and Nutrient Supply Discrepancies (Electric Conductivity and Nutrient Mobility), (2) Fertilizers, (3) climatic conditions, (4) pest infestations, (5) irrigation methodologies, and pH levels.

Unbalanced Soil Quality and Nutrient Availability

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Soil analysis is essential for measuring nutrient content and understanding factors influencing plant growth. Advanced tools like GIS, GPS, and VRT monitor soil conditions and recommend fertilizers. Research advancements include a Gaussian process classifier with SVM for detecting soil-moisture stress using remote imagery, an IoT-based NPK sensor system leveraging the colorimetric principle and fuzzy logic for nutrient monitoring, and the use of UAV and satellite imagery with machine learning models to predict nitrogen weight in wheat fields. These innovations enhance soil nutrient management and agricultural productivity.

Fertilizers

Fertilization strategies in crops are location-specific and depend on factors like soil nutrient concentration, crop size, and fertility rate. Over use of fertilizers can harm soil, crops, and also human health. An indicator of nitrogen status is the amount of nitrogen in leaves, aiding in precise fertilization measures in smart agriculture. However, factors like leaf area index and biomass are not always proportional to nitrogen content. Techniques like NDVI (Normalized Difference Vegetation Index) and the green color value (GCV) index are used to assess vegetative health and nitrogen levels. Studies, such as using NDVI for rice and GCV for spinach, demonstrate advancements in nutrient prediction and stress detection for optimizing fertilization.

Weather Conditions

Smart sensors in agriculture collect environmental data like humidity, temperature, moisture, and precipitation, which are analyzed using specific tools to enhance crop productivity and management. Research highlights include mapping climatic patterns for better crop selection, IoT-based frost prediction systems using machine learning, and decision-support systems for crop management that lower costs and increase yields. GPS coordinates from IoT devices aid in spatial analysis, field traversal, and weather monitoring. Additionally, smartphones with advanced communication protocols provide cost-effective and adaptable solutions for running high-end agricultural applications.

Pest Control in Crops

Pests and diseases significantly impact crop production, with pests often avoiding detection during the day. Advanced technologies have been developed to address this challenge, including sensor-based monitoring systems, drone-based pest identification systems using NVIDIA Tegra SoC, and deep learning (DL) models like YOLOv3 and YOLOv4. These innovations enable early pest detection and crop health monitoring, improving yields and quality. Key applications include identifying apple diseases, monitoring coconut farms, and controlling pests like *Tessaratoma papillosa*. Challenges like leaf occlusions, drone stabilization, and varying illumination conditions

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highlight areas for future study. Image pattern recognition offers a non-intrusive approach for enhancing pest management and crop yield.

Irrigation and pH

Smart irrigation systems leverage advanced technologies to address water scarcity and optimize crop health. These systems estimate water requirements based on crop type, soil, moisture, and climate conditions, using tools like wireless sensor networks, IoT-based frameworks, and machine learning (ML) algorithms. pH levels in soil are crucial for nutrient cycling and crop-environment interactions, with specific crops having varying pH tolerances. Innovations include dynamic models for alfalfa growth that regulate water and fertilizer, LSTM-based systems for environmental monitoring, and the AREThOU5A smart irrigation system with IoT sensors and 5G capabilities. These solutions enhance irrigation precision, balance soil pH, and improve yields.

2. RELATED WORK

1. Image Processing Methods

A variety of methodologies for detecting nutrient deficiencies in plants through leaf analysis have been offered within the domain of image processing. The various research projects and algorithms developed for determining healthy or unhealthy regions and classifying them according to the particular kind of nutrient disease or deficient indicators are analyzed in this study. The diagnostic system will consist of the subsequent components employing image processing methods: 1. Measurement of leaf area 2. The leaf's veins and edge segmentation 3. Identifying the Leaf's Shape 4. The classification of the mineral that is lacking 5. Evaluating the leaf's age 6. Obtaining the leaf's colour characteristics. (Jeyalakshmi & Radha, 2017)

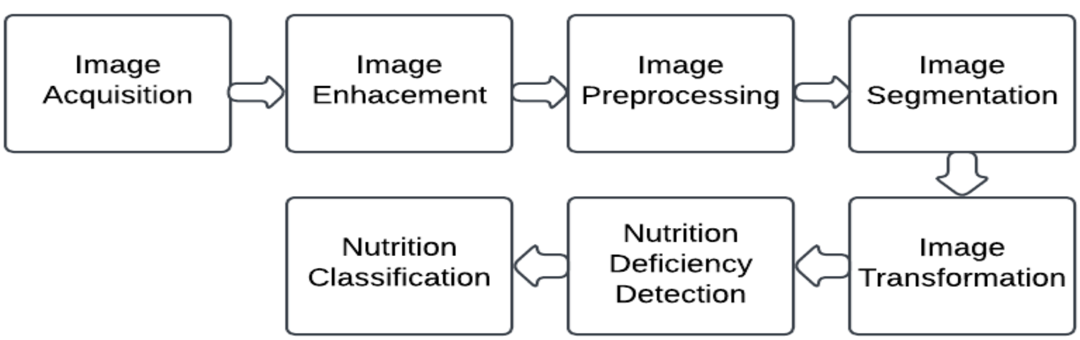

Figure 2: Work flow of Nutrition Deficiency Detection and Classification using Image processing

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Figure 2 illustrates the components necessary for detecting and classifying nutritional deficiencies via image processing. There are plenty of innovative methods for nutrient analysis and deficiency detection in crops using advanced technologies like hyperspectral imaging, image processing, and mobile applications. Cotton Nitrogen Estimation (Abulaiti, Y et al. 2020): Hyper-spectral data combined with fractional order derivatives (FOD) and optimized spectral indices achieved high predictive accuracy ($R^2 = 0.784$) for Total Nitrogen Content (TNC) estimation. FOD enhanced spectral resolution, with higher orders smoothing spectral curves. Sugarcane Nitrogen Analysis (Piti A Teerasit Ket.al. 2012): Portable camera-based analysis of leaf colors in RGB and IR spectrums revealed significant correlations between nitrogen levels and indices like G/B, G/R, and ((IR-R)/(IR+R)), highlighting the IR index's importance for model accuracy. Tomato Deficiency Diagnostics (Xu, G., Zhang, F., Shah 2011): A computer vision-based system identified nitrogen and potassium deficiencies in soilless tomato culture with over 82.5% accuracy, diagnosing issues 6-10 days earlier than traditional methods. Rice Nitrogen Management App (Tao, M., Ma, X., Huang 2020): A smartphone app utilizing a leaf color chart and CIELAB histograms achieved 96% accuracy in real-time nitrogen management, outperforming manual inspections. Maize Nitrogen Detection (Baresel, J. P., Rischbeck, P. et al. 2017): The 'Nitrate app' automates nitrogen estimation in maize leaves using RGB/HSV image analysis, ensuring efficient and accurate assessments critical for improving yields. Tomato Nutrient Deficiency Detection (Ghorai, A. K., Mukhopadhyay, et al. 2021): Image processing techniques, such as expectation-maximization segmentation, enabled precise detection of nutrient deficiencies in tomato leaves, aiding in early disease prevention and productivity enhancement. Advancements in Plant Diagnostics (Sivagami, S., & Mohanapriya, S. 2019): Studies underscore image processing advancements in diagnosing nutrient deficiencies and diseases, enabling rapid and precise field-level assessments for improved agricultural practices. Collectively, these studies demonstrate the potential of integrating modern imaging and computational tools into agriculture to enhance precision, efficiency, and sustainability.

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Table 2: Summary of Image processing models performance in crop nutrition analysis

Name of Publisher & Year	Nutrition Type	Image Type	Total Images	Image Processing method	Outcome Metrics	Image Processing Algorithm Performance
Elsevier 2020[1]	Nitrogen	hyper-spectral images range of wavelengths (from 325 nm to 1075 nm),	data was collected from 60 sampling plots (multiple data sets)	Spectral Data Processing and Fractional Order Derivative	R^2, RMSE and residual deviation of the prediction	0.5-NDSI - R^2 of 0.642, RMSE of 1.361, and RPD of 1.392 0-RSI model -R^2 of 0.784, RMSE of 1.333, and RPD of 1.800
ICAEBS 2012 [2]	Nitrogen	RGB and IR images	72 sugarcane leaves	Adaptive Thresholding+Edge Detection+Active Contour Model	R^2 value	R^2 value 2-month-old sugarcane - 91.39%. 4-month-old sugarcane- 72.11%
Elsevier 2011[3]	Nitrogen and Potassium	Color Images	80 images per class (normal, nitrogen potassium)	Fourier Transform Method +Color Feature Extraction+Fuzzy K Means classifier	Accuracy	85% -nitrogen-deficiency and 82.5% potassium-deficient
Elsevier 2017[5]	Nitrogen	24-bit RGB image	75 Images	Segmentation+Color Analysis+Thresholding+Batch Processing	Biomass, Color Indices	
IIR 2016	All Macronutrients	RGB Image	Work carried out on real data set	Image Segmentation+Feature Extraction+Texture Analysis+K-means Clustering	Accuracy	Indirectly specified through Hue Components

Name of Publisher & Year	Nutrition Type	Image Type	Total Images	Image Processing method	Outcome Metrics	Image Processing Algorithm Performance
Elsevier 2020	Nitrogen and Potassium	Color images captured by smart phone	multiple images were taken for each color panel under various conditions	Color Threshold Segmentation+Conversion from RGB to HSV+Color Feature Extraction+CIEDE 2000 Formula	Accuracy Rate, leaf color chart (LCC), Processing Time, User-Friendliness, Environmental Condition Adaptability	92%, 95%, and 95% for color levels 2, 3, and 4, PT- 248 ms,
IOP 2012	All Macro nutrients and sulfur	RGB Image	4049 images	resizing+ enhancing+ segmentation techniques such as thresholding and color co-occurrence	Accuracy, Receiver Operating Characteristic (ROC) Curve	Accuracy was 93%
Research Gate 2021	Nitrogen, Iron, Magnesium Zinc, Phosphorus, Potassium (NPK)	Hyperspectral Imaging, Digital Infrared Thermography, RGB, Multispectral and Thermal	Multiple images were used depending on type of deficiency detection	Image Pre-processing+Feature Extraction+Classification+Segmentation	Accuracy	Accuracy was 83.08% to 90.77%
Conference Proceeding 2014	Nitrogen	RGB image	Not exactly specified	GLCM for texture analysis, and color feature extraction using RGB and HSV models	Accuracy	Accuracy was high

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Blue Eyes Intelligence Engg & Sci. Pub. 2019	Mineral Nutrients	RGB and Black & White Image	Not exactly specified	Geometric Transformations+ GLCM+ANFIS classification	Accuracy	Accuracy was high

2. Deep learning methods

A computer model has the ability to perform classification tasks from images directly using a process called deep learning. Deep learning has occurred as a powerful tool for detecting plant nutrition deficiencies, offering significant improvements over traditional methods. By leveraging image-based analysis, deep learning models can identify nutrient deficiencies with high accuracy, providing timely and actionable insights for agricultural management. This approach utilizes countless deep learning architectures, including Convolutional Neural Networks (CNNs), Graph Convolutional Networks (GCNs), and Transformer-based models, to analyze visual symptoms in plant leaves.

The following sections explore the methodologies, datasets, and results from recent studies on this topic. To make the best decisions, it helps to gain a comprehensive understanding of all the main algorithms. Overall working of most of deep learning algorithm is as follows.

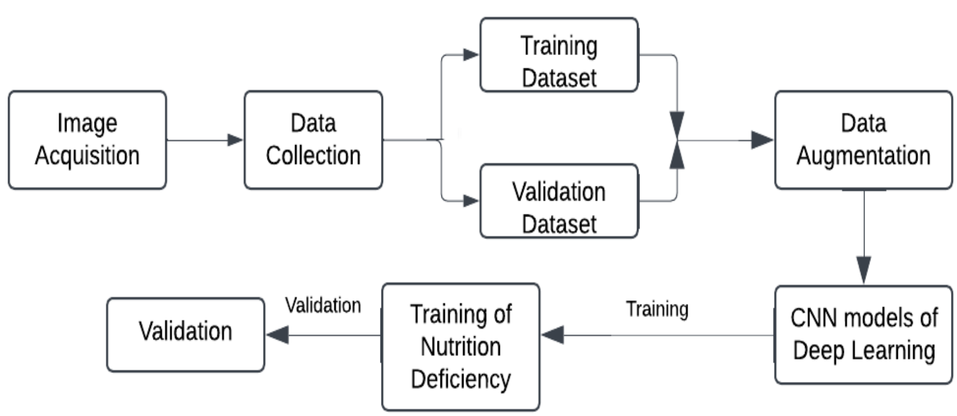

Figure 3: Deep Learning Approach in Predicting Nutrition Deficiency of Crop Leaves

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CNN-Based Approaches

Model Architectures: Several studies have employed architectures of CNN such as InceptionV3, InceptionResNetV2, and AlexNet to predict nutrient deficiencies in plants. These models have been fine-tuned using pre-trained weights and have demonstrated high accuracy in classifying deficiencies like copper, iron, magnesium, and others. For instance, the InceptionV3 model achieved an accuracy of 97.8% in predicting various nutrient deficiencies from leaf images (Shanthini et al., 2024). The use of large-scale datasets, such as the International Plant Nutrition Institute (IPNI) dataset, has been crucial in training these models. Image augmentation techniques have been applied to enhance the dataset, improving model accuracy and robustness (Sathyan & Palanisamy, 2024). RGB images have been effectively used to detect nutrient deficiencies in crops like barley, with CNN models achieving varying accuracies depending on the experimental setup. Soil-based experiments have shown higher prediction accuracies compared to hydroponic systems, highlighting the importance of the experimental environment in model performance (Deichmann et al., 2024). Figure 4 shows the common steps of CNN architecture.

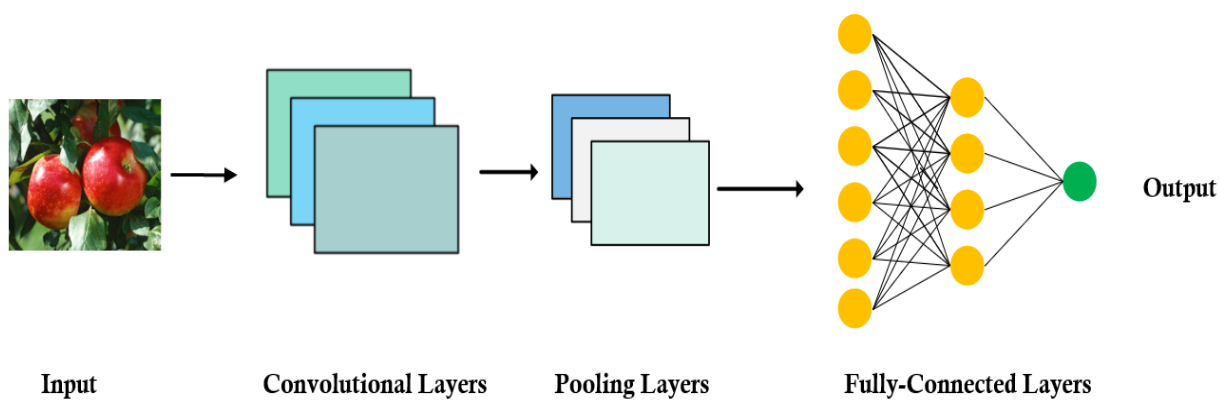

Figure 4: The General structure of a CNN

Advanced Deep Learning Techniques

The PND-Net model integrates GCNs with CNNs to improve the grouping of plant nutrition deficiencies and diseases. This approach focuses on regional feature learning, which enhances the model's ability to capture vital regions of diseased leaves, leading to improved classification accuracy (Bera et al., 2024). Transformer-based CNNs have been applied to detect nutrient deficiencies in coconut trees, achieving high accuracy across different environmental conditions. This method demonstrates the potential of transformer architectures in handling complex image data for nutrient deficiency detection (Ramesh et al., 2024).

Application in Specific Crops

Deep learning models have been specifically tailored for crops like rice and banana. In rice plants, models such as Xception and ResNet have been used to classify nitrogen, phosphorus, and potassium deficiencies with accuracies exceeding 92% (Kolhar et al., 2024) (Supreetha et al., 2024). For banana plants, a CNN with Skip Connections (CNNSC) has been developed to detect boron and iron deficiencies, reaching an accuracy of around 95% (Sunitha et al., 2024).

Dynamic and Time-Series Models

For aquaponically grown plants, a combination of Long Short-Term Memory (LSTM) networks and deep auto encoders has been used to classify nutrient status over time. This approach captures the dynamic nature of plant growth and nutrient uptake, providing a comprehensive assessment of nutrient status throughout the plant life cycle (Taha et al., 2024). While deep learning offers promising solutions for detecting plant nutrition deficiencies, trials remain in terms of model generalization across different plant species and environmental conditions. The integration of advanced architectures like GCNs and transformers shows potential for improving model robustness and accuracy. However, advance research is needed to improve these models and expand their applicability to a wider range of crops and nutrient deficiencies.

Discussion

Yi et al. (2020) introduced the Deep Nutrient Deficiency for Sugar Beet (DND-SB) dataset comprising 5,648 RGB images to detect deficiencies in nitrogen, phosphorus, and potassium in sugar beets. Five CNN architectures, including AlexNet, VGG, ResNet, DenseNet, and SqueezeNet, were evaluated, with pre-trained models outperforming those trained from scratch. Challenges in recognizing nutrient deficiencies across growth stages were noted. **Garcia & Barbedo (2019)** emphasize the progress in imaging for detecting subtle plant changes but stress the need for comprehensive datasets and improved data collection for practical adoption in agriculture. **Watchareeruetai et al. (2018)** demonstrate CNNs' effectiveness in identifying black gram deficiencies but note challenges in distinguishing multiple deficiencies due to within-class variations and suggest exploring time factors and nutrient mobility for improvement. **Azimi et al. (2020)** proposed a 23-layered CNN to classify nitrogen-induced stress in Sorghum shoots, outperforming traditional ML methods and established architectures like ResNet18, with an 8.25% accuracy improvement. Wulandhari et al. (2019) used the **Inception-ResNet-v2** architecture on okra plants, achieving **96% training accuracy** and **86% testing accuracy** through transfer learning and fine-tuning. They emphasized real-time detection via smartphone integration. **Kusanur & Chakravarth (2021)** focused on tomato plants, employing **Inception-V3**, **ResNet50**, and **VGG16** models. The **VGG16-SVM** combination achieved **99.14% accuracy**, while **Inception-V3** attained the best validation accuracy (**99.99%**). **Kumar et al. (2020)** employed CNNs combined with SVM classifiers to predict nitrogen deficiency in rice crops, using six

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architectures, including ResNet-50, and achieved a remarkable **99.84% accuracy** with ResNet-50+SVM on a dataset of **5790 nitrogen-deficient rice leaf images**. Meanwhile, **Sathyavani et al. (2021)** proposed an IoT-based system integrating CNNs for real-time nutrient deficiency detection in various plants, utilizing a 3000-image dataset and achieving improved classification accuracy through entropy-based feature weighting. Collectively, these studies highlight the transformative potential of advanced deep learning and IoT technologies in agricultural monitoring and crop management. **Tran et al. (2019)** utilized Inception-ResNet v2 and Autoencoder models to predict macronutrient and micronutrient deficiencies in tomato plants, achieving 91% accuracy through ensemble learning, emphasizing early detection for improved yields in greenhouse environments. **Sethy et al. (2020)** presented a CNN-based approach for nitrogen deficiency detection in rice, where ResNet-50 combined with SVM achieved a remarkable 99.84% accuracy, showcasing its superiority over other architectures.

In another study, **Kusanur and Chakravarthi (2021)** applied transfer learning on models like Inception-V3, ResNet50, and VGG16 for classifying nutrient deficiencies in tomato plants, achieving **99.14% accuracy** with VGG16+SVM and **99.99% validation accuracy** with Inception-V3. These studies underline the potential of deep learning and transfer learning in automating nutrient deficiency detection, offering significant advancements in agricultural monitoring and plant health management. Similarly, **Lavanya et al. (2022)** utilized CNNs and image segmentation to classify plant nutrient deficiencies by analyzing segmented leaf blocks and aggregating results through a winner-take-all approach and multi-layer perceptron, effectively diagnosing deficiencies using a diverse dataset of healthy and unhealthy plant images. **Tenaye & Bedaso (2022)** achieved 98.82% accuracy in detecting nutrient deficiencies in Coffee Arabica leaves using the Mobile Net model, outperforming VGG16 and Inception V3, with pronounced symptoms for boron and iron deficiencies aiding identification. **Taha & Abdalla (2022)** employed DCNNs to diagnose lettuce nutrient deficiencies in aquaponics, with Inceptionv3 reaching 96.5% classification accuracy, surpassing traditional methods and demonstrating potential for real-time monitoring.

Jayasiri et al. (2023) underscored the need for automated solutions to overcome the inefficiencies of manual inspections, advocating advanced technologies for crop disease detection and nutrient management. Hugar & Waheed (2023) employed a CNN framework with transfer learning to detect nitrogen, phosphorus, and potassium deficiencies in rice plants. Using a pre-trained model for feature extraction and achieving 96.67% accuracy, their study highlighted the potential of precision agriculture to optimize crop yields and promote sustainability. Tuesta-Monteza et al. (2023) developed the CoLeaf dataset, consisting of 1,006 images of coffee leaves exhibiting various nutritional deficiencies, including Boron, Iron, and Magnesium. Both deep learning and classical machine learning methods were applied, with a neural network achieving 87.75%

accuracy. Their research emphasized the importance of high-quality datasets and made the CoLeaf dataset publicly available to encourage further advancements in agricultural AI applications. **Swarna R M Priya (2024)** developed an ensemble-based model, **InceptionV3Dense169**, achieving **98.62% validation accuracy** in diagnosing micronutrient deficiencies in banana crops, with potential for further generalization to unseen data. Similarly, **Prakash & Srivenkatesh (2024)** combined **SRGANs** for image enhancement with CNNs for classification, demonstrating superior accuracy and image quality in detecting paddy crop deficiencies, validated using metrics like **PSNR** and **SSIM**. **Kolhar et al. (2024)** showcase the superior performance of the Xception model over other deep learning models in nutrient classification for rice, achieving **95.14% accuracy** with minimal trainable parameters, emphasizing its potential for optimizing fertilizer use. **Prakash & Srivenkatesh (2024)** provide a comprehensive review of remote sensing, IoT-based sensing, and computer vision technologies, advocating their integration with ML and DL to enhance crop health monitoring and sustainable agricultural practices.

YOLO in Agriculture

Bounding boxes are commonly used in computer vision tasks for object localization and detection. These boxes help in identifying specific regions of interest within images, aiding in nutrient deficiency detection and classification. Utilizing bounding boxes could enhance the model's ability to pinpoint areas in images corresponding to different nutrient deficiencies, thereby improving accuracy and performance.

YOLO Evolution

Al M., Alif R., & Hussain M. (2024) YOLOv1 introduced two sub-variants, achieving 63.4% mAP at 45 FPS, but faced challenges in recall and localization. YOLOv2 incorporated anchor boxes, skip connections, and combined datasets to improve small-object detection. YOLOv3 featured 53 convolutional layers and shifted evaluation to the MS COCO dataset for better performance. YOLOv4 optimized IoU calculations and improved small bounding box detection. YOLOv5 utilized multiple loss functions and achieved 50.7% mAP at 200 FPS on COCO. YOLOv6 introduced variants like YOLOv6nano for efficiency and performance. YOLOv7 employed novel training techniques for higher efficiency. YOLOv8 adopted anchor-free methods, enhancing accuracy through object center predictions. YOLOv10 eliminated NMS in training, reduced latency, and showcased applications like YOLO-WEED for weed identification with high precision.

Redmon and Farhadi present YOLOv3, a more rapid and precise version of the YOLO object detection framework. YOLOv3 reaches a mean Average Precision (mAP) of 28.2 at a resolution of 320 × 320, with a processing time of 22 ms, surpassing models such as RetinaNet in terms of speed. It enhances the detection of small objects through multi-scale predictions but encounters

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challenges in identifying medium and large objects. The model employs dimension clusters as anchor boxes and utilizes logistic regression for scoring objectness, thereby improving detection reliability. While it performs well against older detection metrics, it demonstrates comparatively weaker results on the COCO AP metric (.5 to .95 IoU). **Julie Ann, B. and Susa, W. C. (2022)** highlights the critical importance of early disease detection in cotton plants to prevent significant yield losses Utilizing the YOLOv3 model for classifying and detecting cotton plants, achieved a mean Average Precision (mAP) of 96.09% and detection accuracies between 74% and 99% in real-world situations. **Li et al. (2022)** present YOLO-JD, a dedicated deep learning model designed for the detection of diseases and pests in jute plants, catering to the increasing need for premium-quality fiber. **Goshika et al. (2023)** present a YOLOv5-based deep learning model for assessing soybean leaf damage, utilizing data augmentation and a dataset of 2,930 images**. Aldakheel et al. (2024)** integrate an image retrieval method with YOLOv4 to enhance the detection of plant leaf diseases, achieving 99.99% accuracy on the Plant Village dataset.

Table 3: Summary of Deep learning models performance in crop nutrition analysis

Author & Year	**Methodology**	**Crop Data set used**	**Detected Deficiencies**	**Result**
Shanthini, M., Ashwini et al. (2024)	InceptionV3, InceptionResNetV2 and AlexNet	Real Images	copper, iron, magnesium, molybdenum, nitrogen, phosphorus, and potassium	Accuracy of InceptionV3 was 97.8%, ResNetV2 was 97.7% and AlexNet was 92.22%.
Anish, Sathyan., Praveen, Palanisamy. (2024).	ANN CNN	Real Images	All type of Nutrition	Enhances effectiveness and efficiency than exiting models.
Marion, Deichmann., Jinhui, Yi., (2024)	CNN	RGB images were collected from hydroponic, pot, mini-plot, and long-term fertilizer field experiments.	NPK	Accuracy of 94.5% - long-term fertilizer field experiment (Diko) and the lowest of 38.52%- the hydroponic system (HyPo).
Asish, Bera., Debotosh, Bhattacharjee., Ondřej, Krejcar. (2024	PND-Net Built from CNN	Evalution on Public data set- Banana and Coffee plants Testing on Potato diseases and the PlantDoc dataset.	All type of Nutrition	Accuracy of 90.00% Banana plant and 90.54% for Coffee plant, and 96.18% - Potato diseases and 84.30%-PlantDoc

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				datasets using Xception model
Shrikrishna, Kolhar., Jayant, Jagtap., Rajveer, Shastri. (2024)	Xception model, vision transformer, and MLP mixer	rice plants	NPK	Accuracy of Xception model was 95.14%,
S, Supreetha., R, Premalathamma., S, H, Manjula. (2024)	pre-trained Convolutional Neural Network (CNN) models- InceptionV3, VGG16, VGG19, ResNet50, and ResNet152, Support Vector Machine (SVM)	rice plants	NPK	Accuracy of 97.40% on the dataset without augmentation and 99.05% on the dataset with augmentation
Chirag, Bavishi., Nagamma, Patil. (2024)	EfficientNetV2B0	OLID I (Open Leaf Image Dataset)	All type of Nutrition	Accuracy of 85.38% and an f1-score of 85.08.
Author & Year	**Methodology**	**Crop Data set used**	**Detected Deficiencies**	**Result**
M., Ramesh., K., Kodeeswari (2024)	Transformer Convolutional Neural Network (TCNN)	Coconut Trees (8990 images)	iron, nitrogen, and potassium	Training accuracy- 99.97% and a validation accuracy - 98.61%
Swarna R M Priya. (2024)	VGG-19, InceptionResNetV2, InceptionV3, Xception, DenseNet169 and DenseNet201	3450 Banana leaf images	Boron, Iron, Manganese	Accuracy was 98.62% and an F1 score of 93%
Mohamed, Farag, Taha et al. (2024)	long short-term memory (LSTM) and deep autoencoder (DAE)	Aquaponics Plant- Lettuse	All types of nurtition	Accuracy was 94%
(Prakash & Srivenkatesh, 2024)	Hybrid approach that combines Super-Resolution Generative	Paddy Crops Images	NPK	Accuracy was 93%

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	Adversarial Networks (SRGANs) and Convolutional Neural Networks (CNNs)			
Kolhar, S., Jagtap, J., & Shastri, R. (2024)	Xception model, vision transformer, and multi-layer perceptron-based (MLP) mixer model	1156 images of rice plants	NPK	Accuracy was 95.14%
Yi et al., (2020)	AlexNet, VGG, ResNet, DenseNet, and SqueezeNet	Sugar Beet (DND-SB) dataset-5648 RGB images	NPK	Overall Accuracy was 87% and 98.4 % for DenseNet-161
P., Sunitha., Uma, Bhandari.,et al. (2024).	Convolution Neural Network with Skip Connections (CNNSC)	Banana Plants	Boron and Iron	Accuracy was 95%
Hugar & Waheed (2023)	Transfer Learning methods, Inception-V3, ResNet50, and VGG16	Rice plants, total 1064 images, 448 images of healthy rice plants and 616 images had nutrient deficiencies	NPK	Accuracy was 96.67%
Tenaye, F., & Bedaso, M. (2022)	Mobile Net, VGG16, and Inception V3	422 images of Coffee Arabica plant	iron, potassium, calcium, and boron	Accuracy was 98.82%
Author & Year	**Methodology**	**Crop Data set used**	**Detected Deficiencies**	**Result**
Tuesta-Monteza et al. (2023)	A naive Bayes classifier and a neural network-based classifier	1006 images of coffee leaves	All Micro and Macro Nutrition Deficiency	Accuracy was 87.75%
Taha, M. F., Abdalla A (2022)	Inceptionv3 and ResNet18	3000 images of lettuce	NPK	Accuracy was 99.1% for segmentation and 96.5% for classification.

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(Kusanur & Chakravarth, 2021)	Inception-V3, ResNet50, VGG16 with Random Forest (RF) and SVM	880 images of Tomato Plants	Ca and Mg	Accuracy was 99.14%
(Sathyavani et al., 2021)	Convolutional Neural Network (CNN), IoT devices	3000 images of different plants including coriander, tomato, pepper, and chili	All type of Nutrition	Impoved Accuracy
(Sethy et al., 2020)	ResNet-18, ResNet-50, GoogleNet, AlexNet, VGG-16 and VGG-19 with SVM	5790 rice images	Nitrogen	Accuracy was 99.84%.
(Kumar et al., 2020)	ResNet-18, ResNet-50, GoogleNet, AlexNet, VGG-16, and VGG-19+ SVM classifier	5790 rice leaf images	Nitrogen	Accuracy of ResNet-50 with SVM was 99.84%
Azimi, S., Kaur, T., & Gandhi, T. K. (2020)	Classical Machine Learning (ML) and Deep Learning (DL)	96,867 images taken from the Donald Danforth Plant Science Center of Sorghum plants	Nitrogen	Average accuracy improvement was 8.25%
Tran, T.-T., Choi, J. et al. (2019)	Inception-ResNet v2 for supervised learning and Autoencoder for unsupervised learning	571 images of tomato plants	Calcium, Potassium, and Nitrogen	Accuracy was 91%
Wulandhari, L. A.Agung et al. (2019)	DCNN-Inception-ResNet-v2, transfer learning and fine-tuning	231 images of okra plants	NPK and Ca	Accuracy of Training -96 % and testing -86%

3. PERFORMANCE ANALYSIS METRICS

In general, a ML/DL model is evaluated for its performance using various parameters and metrics. The metrics is an indicator of the model's efficiency and thereby it helps to select the appropriate model for our task. Hence, the comparison of the models is realized using these mathematical

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operations. In Deep learning methods or machine learning methods, the evaluation of the model is done using the confusion matrices and by comparing metrics like accuracy, recall, precision and F1 score.

Table 4: Methods to Evaluate the Performance of a Deep Learning Models

<table>
<tr><th>Metric</th><th>Evaluation Formula</th><th>Description</th></tr>
<tr><td>Confusion Matrix</td><td><table><tr><td></td><td>Predicted Positive (1)</td><td>Predicted Negative (0)</td></tr><tr><td>Actual Positive (1)</td><td>True Positive (TP)</td><td>False Negative (FN)</td></tr><tr><td>Actual Negative (0)</td><td>False Positive (FP)</td><td>True Negative (TN)</td></tr></table></td><td>True positive (TP), true negative (TN), false positive (FP), and false negative (FN) prediction numbers are displayed in a matrix.</td></tr>
<tr><td>Accuracy</td><td>Accuracy = Correct Predictions / Total Predictions
Accuracy= TP + TN / TP + TN + FP + FN</td><td>Calculates the ratio of accurately predicted cases to determine the model's overall accuracy.</td></tr>
<tr><td>Precision</td><td>Precision = true positives / predicted positives
Precision = TP / TP + FP</td><td>The effectiveness of the model in predicting positive instances is indicated by the percentage of true positive predictions among all positive estimates.</td></tr>
<tr><td>Sensitivity aka Recall</td><td>Recall = (true positives / all actual positives)
Recall = TP / TP + FN</td><td>The model's ability to detect positive outcomes is shown by the percentage of accurate positive predictions among all real positives.</td></tr>
<tr><td>F1 Score</td><td>F1 Score = 2* Precision*Recall/Precision + Recall</td><td>The harmonic means of Precision and Recall</td></tr>
<tr><td>Specificity</td><td>Specificity = (true negatives / all actual negatives)
Specificity = TN / TN + FP</td><td>The model's ability to detect negative occurrences is demonstrated by the percentage of true negative predictions among all real negatives.</td></tr>
<tr><td>Mean Squared Error</td><td>$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$</td><td>Measures the average of the squares of the errors between predicted and actual values and used for regression tasks.</td></tr>
<tr><td>Root Mean Squared Error</td><td>$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$</td><td>The square root of MSE, providing the error in the same units as the output variable.</td></tr>
<tr><td>Mean Absolute Error</td><td>$MAE = \frac{1}{n}\sum_{i=1}^{n}\lvert y_i - \hat{y}_i\rvert$</td><td>The Mean Absolute Error gives average of the absolute differences between predicted values and actual values.</td></tr>
</table>

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R^2 (R-squared)	$R^2 = 1 - \frac{SS_{res}}{SS_{tot}}$	Regression tasks employ the percentage of the dependent variable's variance that can be predicted from the independent variables.

4. RESEARCH GAPS SHAPING THE SCOPE OF FUTURE RESEARCH

Current challenges involve satisfying food demand for a growing population while utilizing limited agricultural land, identifying specific factors such as restricted manpower, variations in environmental conditions, recognizing crop deficiencies across different light conditions and geographic locations causing total yield loss. The future scope with regard to the development of crop nutritional deficiency detection model is related to the above-mentioned research challenges and other specific factors such as the following:

1. Public standard crop leaf image dataset for nutrition analysis is not available, leading in difficulty of objective comparison among different studies.
2. Size of training dataset is small however for deep learning algorithms large numbers of images are required. In terms of the quantity of images used, there is a lot of variety.
3. Experts must classify the images used during the training process. The relationship between nutrition detection by the laboratory analyst and through a deep learning method has been studied in few researches.
4. Finding the nutritional deficiency in an early stage of crop growth is a difficult issue that necessitates the study of various feature selection, image segmentation, and thresholding techniques.
5. Selection of deep learning CNN architecture specific to agriculture application is challenging task with respect to accuracy of the model.
6. Nutrition imbalance quantification. Stress due to residues of pesticide application and pest damage or other external factors
7. Most research is based on Static Image Models and traditional image analysis methods

Proposed model integrates soil nutritional analysis with image-based crop health assessment to improve agricultural productivity. Utilizing soil health card data, this model identifies nutritional deficiencies in crops such as cotton, chili, and soybean. High-resolution images of crops are captured under controlled conditions, focusing on deficiencies of key nutrients like Nitrogen (N), Phosphorus (P), Potassium (K), and others. The labeled dataset, generated through soil test reports and expert agronomist insights, is validated using deep learning neural networks. The model will demonstrate superior performance on training datasets and generalizes effectively to real-world testing data, offering practical utility for precision agriculture. The agricultural industry would evolve as a highly progressive sector when these kinds of systems and tools or techniques are used for various management strategies, such as sowing to yield forecasting. The other advanced management strategies and approaches needed to be concentrated are the implementations of greenhouses, hydroponics, aquaponics, and vertical farming.

5. CONCLUSION

The study emphasizes the significant advancements made in the application of image processing and machine learning methodologies for identifying plant nutrient deficiencies, achieving accuracy rates between 82.5% and surpassing 99% in optimized conditions. Hyperspectral imaging is particularly noted for its accuracy, whereas RGB and smartphone-based techniques offer practical and user-friendly alternatives with moderate levels of precision. Deep learning architectures, especially Convolutional Neural Networks (CNNs), have shown exceptional effectiveness, reaching accuracy levels exceeding 99% in certain instances, particularly for specific crops and nutrients such as nitrogen, phosphorus, and potassium. Approaches like transfer learning and data augmentation have been crucial in improving these results. YOLOv3 is positioned as a strong and efficient tool for object detection tasks. Image preprocessing techniques can remove noise but may introduce artifacts, limiting adaptability to different growth stages or leaf locations. Traditional machine learning methods struggle with raw data processing and require extensive feature engineering, which can hinder efficiency. However, the variability in results linked to the quality of datasets, crop types, and experimental conditions accentuates the importance of formulating standardized datasets and methodologies to ensure uniform and trustworthy performance across various applications.

In order to increase the model's precision and effectiveness, future studies should look into the use of bounding boxes to precisely identify areas in plant imagery that are deficient in nutrients. The incorporation of soil nutrient assessments as a foundational step prior to the detection of plant deficiencies will guarantee a thorough comprehension of nutrient availability. Furthermore, the amalgamation of laboratory-based evaluations of foliar and soil nutrition with image-processing methodologies will yield a holistic and dependable system for detection.

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