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Review of Machine Learning Techniques for Identifying Nutrient Deficiencies in Okra Leaves: Progress and Future Prospects

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ABSTRACT

Nutrient deficiencies in plants often present as visual symptoms on leaves, but manual identification is imprecise and depends heavily on expert knowledge. Traditional diagnostic methods are time-consuming and labor-intensive. This study introduces an automated approach that applies machine learning and image processing to detect nutrient deficiencies in okra (Abelmoschus esculentus L.) leaves. By analyzing features such as color, texture, and shape, the model is trained to classify deficiencies using Convolutional Neural Networks (CNNs), known for their strong performance in image analysis. The system leverages a diverse dataset of leaf images to ensure reliability under real-world conditions. This approach offers a scalable and efficient tool for supporting farmers in nutrient management, contributing to improved crop yields, optimized fertilizer use, and more sustainable agricultural practices

Keywords: Micronutrient, Macronutrient, Okra, feature extraction, classification models.

INTRODUCTION

Global food security mostly relies on agriculture; hence, sustainable yields are significantly influenced by crop conditions [1], [2]. Okra (Abelmoschus esculentus) is one of the most cultivated horticulture crops in tropical and subtropical regions, primarily due to its nutritional and economic significance. Okra plants, similar to several other crops, are susceptible to nutrient deficiencies, which may significantly impact quality, growth, and yield [3]. Prompt intervention and effective crop management rely on the early and accurate diagnosis of micro and macro nutritional deficiencies in okra. Traditional methods for detecting nitrogen deficiencies in crops mostly rely on visual cues and laboratory analysis. These approaches are labor-intensive, time-consuming, and sometimes need professional expertise, despite yielding consistent results. The visual identification of symptoms is also susceptible to subjectivity and is complicated by the presence of pests, diseases, or environmental stressors. Recently, machine learning (ML) has emerged as a viable approach to automate and enhance the precision of nutrient deficiency detection in plants [4]. Employing images, spectral data, and physiological markers, among other extensive datasets, machine learning techniques develop predictive models capable of distinguishing various types of dietary deficiencies. Plant physiology is significantly affected by both macronutrients and micronutrients [5]. Essential for plant growth and metabolic functions, macronutrients such as nitrogen (N), phosphorus (P), and potassium (K) are required in substantial quantities. Deficiencies in these components result in stunted growth, chlorosis, necrosis, and reduced yield. Conversely, albeit in smaller quantities, micronutrients like as iron (Fe), zinc (Zn), manganese (Mn), and boron (B) are crucial for enzyme activity, photosynthesis, and reproductive development. A deficiency of micronutrients may result in leaf abnormalities, diminished flowering, and overall suboptimal plant health. Utilizing machine learning approaches to detect and differentiate these deficiencies may provide farmers real-time, precise, and cost-effective solutions.

Recent advancements in machine learning and computer vision have enabled the creation of models capable of analyzing leaf images to detect and classify nutritional deficiencies. Recognition of plant leaf patterns has shown

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significant accuracy in Convolutional Neural Networks (CNNs), support vector machines (SVMs), and deep learning frameworks [6]. These approaches train models to differentiate between healthy and defective leaves using databases of annotated images [7]. Moreover, prior to the manifestation of overt symptoms, hyperspectral and multispectral imaging, in conjunction with machine learning approaches, have shown potential in detecting subtle spectral variations associated with certain nutritional deficiencies. Despite the promising results, many challenges persist in the practical implementation of ML-based nutrient deficiency detection systems for okra [8]. A primary problem is the availability of high-quality, diverse, annotated information including various growing circumstances, cultivars, and environmental variables that reflect differences among these factors. Additionally, variations in lighting, background, and image quality affect model performance [9]. Moreover, the deployment of ML models in actual agricultural settings necessitates cost-effective and intuitive interfaces designed for farmers with little technical expertise [10].

This research examines the current status of machine learning algorithms for detecting macro and micronutrient deficiencies in okra plants, along with recent advancements, existing challenges, and future prospects. Addressing these issues would enable machine learning-driven solutions to enhance precision agriculture, therefore facilitating sustainable crop management and bolstering food security.

LITERATURE SURVEY

Machine learning techniques are becoming more popular in agriculture, especially for finding plants that aren't getting enough nutrients. Different methods, such as spectrum imaging, deep learning models, and regular machine learning, were used to check the okra plant's leaves for lack of macro and micronutrients [11], [12]. Each method has its own pros and cons that make it harder to use in real-life farming situations. Traditional machine learning methods, such as Support Vector Machines (SVM), Random Forest (RF), Decision Trees (DT), and k-Nearest Neighbors (k-NN), have made it much easier to keep an eye on plant health. A lot of the time, these algorithms use human feature extraction, which means picking out certain leaf picture characteristics like shape, color, and texture [13], [14]. These cost-effective computer methods work especially well in places with limited resources. When the numbers are smaller, the models are easier to understand and work more efficiently, which helps farming workers better understand the process of categorizing. The information and traits picked have a big effect on how well they do. Many of these models depend on human feature engineering, which means they might not work well in different temperatures, breeds, or leaf shapes [15], [16]. Visual signs that come together may make it harder to diagnose some illnesses. Convolutional neural networks (CNNs), which are a type of deep learning, are very good at finding nutrient deficits in plants [17], [18]. Convolutional Neural Networks are very good at getting hierarchical features from pictures that they are given, so humans don't have to pick out as many features [19], [20]. High-precision models like AlexNet, VGG16, ResNet, and EfficientNet can figure out complex patterns linked to leaf chlorosis, changes in texture, and flaws caused by not getting enough nutrients [21], [22]. One of the best things about deep learning is that it can handle huge amounts of data and find small differences that people might miss. These models are useful in real-life farming situations because they can adapt to changes in background, lighting, and obstacles [23], [24]. To train deep learning algorithms, you need a lot of labeled samples. This means that the results may not be perfect. A GPU or cloud computing are often needed when a lot of computer power is needed [25], [26]. The hard-to-understand features of deep learning models make it harder to make choices.

Combining machine learning techniques with hyperspectral and multispectral image systems has led to the creation of a new way to find nutritional deficiencies in okra plants [27], [28]. By collecting reflection data over a wide range of colors before they can be seen from the outside, these ways make it easier to find flaws early on. Spectral signature research makes it easier for machine learning systems to find food deficits with more accuracy [29], [30]. Hyperspectral imaging has a lot of benefits for accurate and thorough evaluations of plant health [31], [32]. Small-scale farmers are the only ones who can use these expensive methods, which depend on special sensors and image technology. Computers need to use complicated methods and a lot of store space to handle hyperspectral data [33], [34].

When machine learning and Internet of Things (IoT) devices work together, sensor-based tracking can find food shortages in real time. IoT devices, like cameras and band sensors, collect and send data so that machine learning

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methods can be used to analyze it in real time [35], [36]. This approach improves early identification and real-time tracking, but it needs reliable internet infrastructure and connection, which may not be available in rural places. There are pros and cons to each method. While many machine learning models are fast and easy to understand, they don't have a lot of generalization power [37], [38]. Even though they aren't very accurate, deep learning models need a lot of data and a lot of computing power. Even though it is very expensive and difficult to use, hyperspectral imaging helps with early spotting in IoT-connected systems, which improves real-time tracking even when infrastructure is limited [39], [40]. These problems could be solved by making machine learning methods for finding vitamin shortages in okra farming that work better and are more focused on the user.

MACHINE LEARNING TECHNIQUES FOR NUTRIENT DEFICIENCY DETECTION

The desired machine learning techniques are elaborated in the subsequent sections.

3.1 Nutrient Deficiency in Okra Plants

Identifying and correcting nutritional deficiencies is essential for the optimal production and quality of okra plants. Prompt diagnosis and correction can improve plant health and minimize production losses [41], [42]. Conventional methods for detecting vitamin deficiencies exhibit notable shortcomings; however, their widespread application persists, necessitating the adoption of modern, technologically advanced alternatives such as machine learning.

3.2 Traditional Methods of Nutrient Deficiency Detection

Previous studies employing traditional methods—visual symptom assessment, soil and plant tissue analysis, and expert consultation—have identified nutritional deficiencies in okra plants. The effectiveness of these tactics is limited; however, their inherent subjectivity makes them difficult to implement, often leading to considerable time and labor expenditure [43], [44].

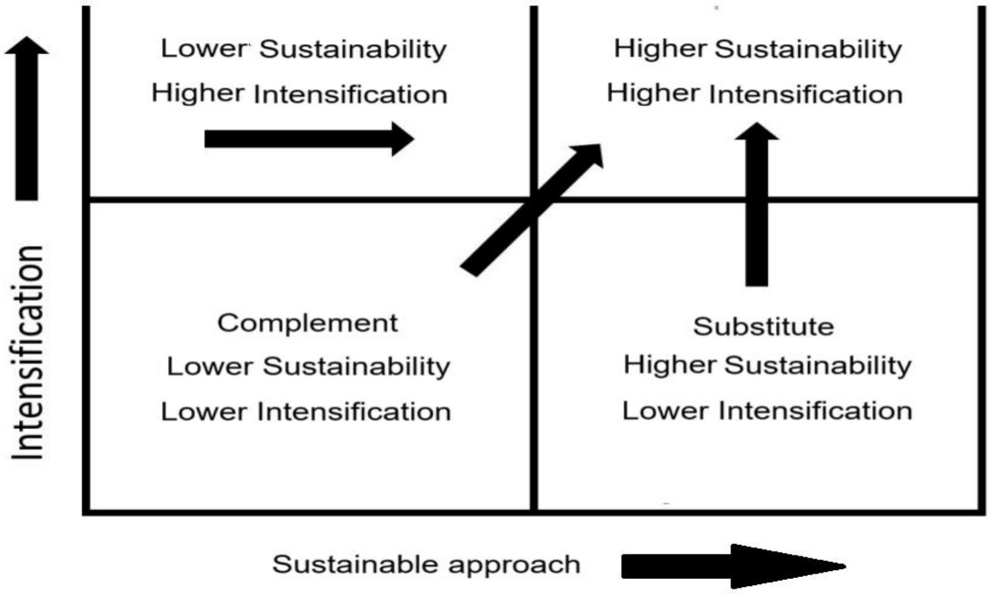

Fig. 1 Procedures for agricultural diversity and sustainability

Agriculturalists and agronomists primarily rely on visual indicators, such as variations in leaf pigmentation, texture, and morphology, to assess deficiencies. This technique exhibits challenges despite its seemingly rational nature. Multiple dietary deficiencies complicate their differentiation because of shared symptoms. Initial intervention may be constrained, as manifestations may only emerge in severe forms. Environmental factors such as drought stress or pest infestations can lead to symptoms that may cause misdiagnosis [45]. The evaluation of essential elements in soil and plant tissue clarifies nutritional differences with enhanced accuracy. Soil studies investigate nutrient availability within the substrate, while plant tissue research evaluates nitrogen absorption within the plant. While these methods

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yield precise results, they require laboratory space, specific instruments, and technical expertise. Small-scale farmers may consider these tasks impractical due to the time and financial resources required for sample collection, transportation, and analysis.

Identifying and rectifying dietary deficiencies requires specialized expertise. Agronomists and extension workers promote the importance of field observations and laboratory research. Identifying qualified professionals can be challenging, particularly in remote rural regions. Limited access to effective support for farmers can lead to delays and reduced agricultural productivity.

The demand for automated, data-driven systems that provide scalable, accurate, and swift solutions to fertilizer shortages in okra cultivation is rising. Machine learning has emerged as a viable solution to these challenges through image processing, spectrum analysis, and predictive modeling, facilitating high-precision real-time diagnosis.

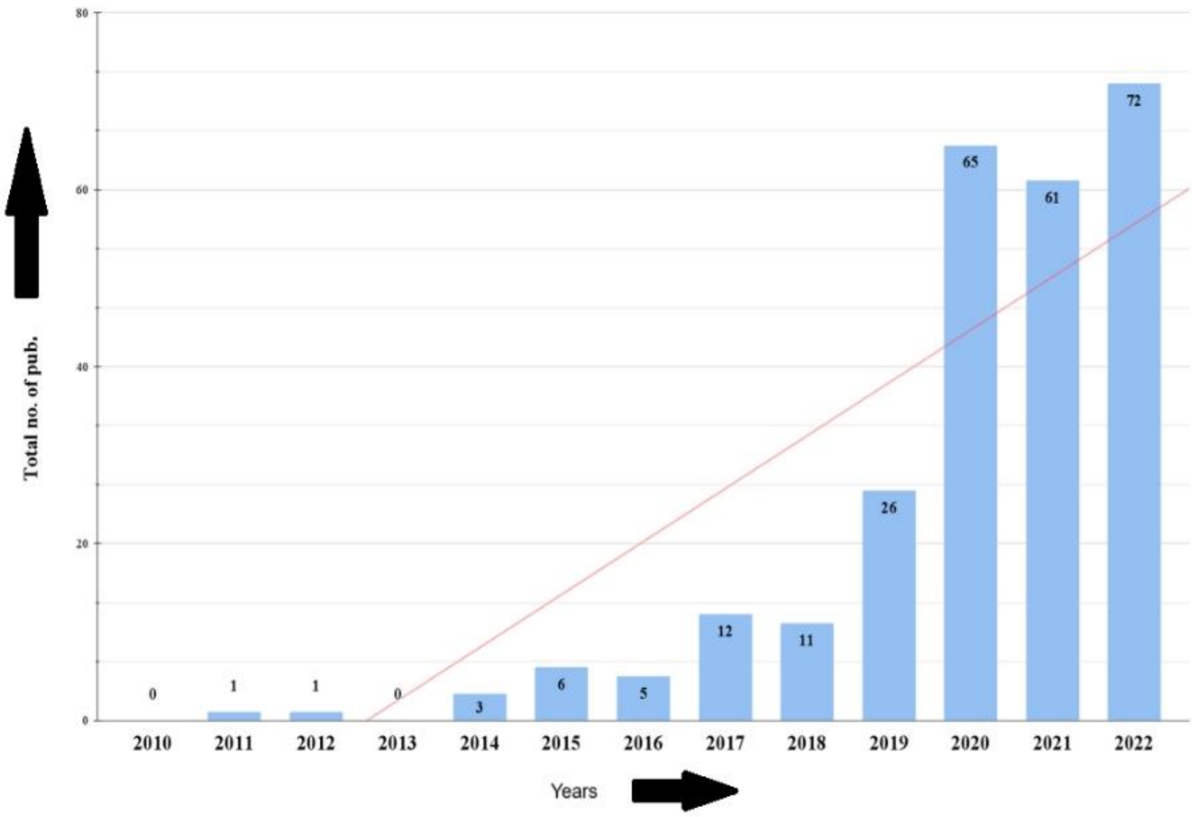

Fig. 2 Total number of publications using AI and sensor images for investigating stress for plants

3.3. Machine Learning Approaches for Nutrient Deficiency Detection

Machine learning (ML) has transformed agricultural diagnostics through the precise and automated detection of plant health problems, including nutrient deficiencies. Machine learning techniques utilize large datasets comprising environmental variables, spectral data, and leaf photographs to create effective predictive models for accurate defect diagnosis. The technologies can be classified into three main categories: traditional machine learning techniques, deep learning models, and machine learning applications utilizing hyperspectral imaging. Support Vector Machines (SVM), Random Forests (RF), Decision Trees (DT), and k-Nearest Neighbors (k-NN) are commonly employed in conventional machine learning approaches. These models deliberately select visual attributes such as shape, color, and texture for classification through manual feature extraction. These models demonstrate computational efficiency and interpretability, although their performance is contingent upon the quality of feature selection and the size of the dataset. Their complex limitations with overlapping symptoms may not consistently correspond with different developmental contexts [46], [47]. Convolutional neural networks (CNNs) are highly effective in detecting vitamin deficiencies within the realm of deep learning. Convolutional neural networks minimize the necessity for human

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feature engineering by independently learning and extracting features from images. By analyzing patterns of leaf discoloration and morphological changes, established architectures like AlexNet, VGG16, ResNet, and EfficientNet have demonstrated significant accuracy in detecting nutritional deficiencies. Deep learning models demonstrate advantages in agriculture due to their robustness against variations in background, lighting, and image quality. The significant computational requirements and large annotated datasets necessary for training these algorithms create a high demand for GPUs. The opacity of deep learning models complicates comprehension, thereby impacting farmers' and agronomists' understanding of the rationale underlying the model's predictions.

The combination of machine learning techniques with hyperspectral and multispectral imaging provides an effective method for detecting nutritional deficiencies [48]. These methods compile leaf reflectance data across a wide spectrum to enable the early detection of nutritional deficiencies before symptoms appear. Machine learning algorithms utilizing spectral fingerprint analysis enable precise fault identification. Hyperspectral imaging demonstrates minor physiological alterations that remain undetectable to unaided vision. These approaches are not readily accessible for widespread agricultural use due to their considerable cost and requirement for specialized sensors [49], [50]. The analysis of hyperspectral data necessitates complex analytical techniques and significant computational resources. Recent developments in sensor-based monitoring systems involve the integration of machine learning with Internet of Things (IoT) sensors for the real-time collection of data regarding plant conditions. IoT-enabled machine learning systems assess soil nutrient levels, leaf characteristics, and environmental factors to detect deficiencies and offer timely solutions. This method improves real-time monitoring and decision-making; however, it necessitates dependable infrastructure, technological expertise, and internet connectivity.

Machine learning technologies offer efficient, accurate, and scalable solutions for addressing nutritional deficiencies in okra plants, exceeding the capabilities of traditional methods. Challenges remain concerning practical implementation, data accessibility, and processing demands. Improving data collection, model development, and user-focused implementation strategies will help advance ML-driven precision agriculture by alleviating existing constraints.

CHALLENGES AND RESEARCH GAP

4.1 Accessibility and integrity of data

To attain consistent performance, machine learning (ML) models depend significantly on high-quality, diversified, and well labeled datasets. Nonetheless, in the domain of identifying nutritional deficiencies in okra plant foliage, several challenges and study limitations pertain to data availability and quality.

4.2 Limited Access to Annotated Data

The identification of nutritional deficiencies in okra plants mostly relies on the scarcity of publicly accessible, well-annotated data. Deep learning-based machine learning models particularly need a substantial quantity of tagged pictures of okra leaves exhibiting various macro and micro nutritional deficiencies. Regrettably, the paucity of study on okra, in contrast to crops such as rice, wheat, or maize, constrains researchers' ability to accumulate enough data for developing reliable models.

A significant research gap exists on the need for extensive, high-quality datasets including photos of okra leaves exhibiting diverse nutritional deficiencies, sourced from several settings and developmental stages.

Standardized, publicly accessible datasets may be generated via collaborative efforts among agricultural research institutions, universities, and artificial intelligence scholars.

4.3 Diverse Data Distribution

Numerous agricultural datasets exhibit class imbalances, with healthy plant samples often outnumbering those deficient in nutrients. Machine learning techniques may have a bias towards identifying healthy leaves while inadequately recognizing deficiencies, since they derive patterns from data distribution.

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Research on approaches to rectify class imbalances in nutrient deficiencies in okra plants—such as synthetic data creation (e.g., using GANs), data augmentation, and cost-sensitive learning—is particularly necessary.

Employing weighted loss functions, anomaly detection methodologies, or the Synthetic Minority Over-sampling Technique (SMOTE) may enhance model performance concerning minority-class data.

4.4 Inaccuracies in Imaging and Data Collection Techniques

Various study endeavors provide disparities in dataset quality due to the use of distinct imaging configurations, sensors, and data collection methodologies. Disparities in camera specs, lighting conditions, and image resolutions introduce biases that limit the generalizability of machine learning models.

A research gap exists due to the absence of standardized imaging and data collection procedures for documenting nutritional deficits in okra leaves. Tandardized imaging techniques, such as multispectral and hyperspectral imaging under controlled settings, may guarantee consistency among datasets.

4.5 Imperative for the Integration of Multimedia Data

Contemporary machine learning methodologies mostly use visual data—specifically leaf images—to identify nutritional deficiencies. Numerous variables affect plant health, including soil characteristics, climatic circumstances, and nutrient accessibility, among others. Images alone cannot provide a comprehensive understanding of dietary deficits.

There is a significant want for research on the detection of nutritional deficiencies in okra by the use of multimodal data, encompassing remote sensing, soil analysis, and plant physiological characteristics.

Employing sensor fusion methods may facilitate the development of resilient models including several affecting elements.

4.6 Diversity among okra plant cultivars

Okra is a highly diverse crop with several cultivars exhibiting unique physical, physiological, and genetic characteristics. This heterogeneity presents considerable hurdles for machine learning systems attempting to generalize across several okra cultivars.

4.7 Genetic and phenotypic variations among okra cultivars

Various okra varieties have distinct leaf forms, sizes, color variations, and growth patterns, hence complicating the ability of machine learning algorithms to generalize faulty patterns across all sorts. A model developed for one cultivar may have worse performance when assessed on another cultivar.

Research gap: Limited knowledge exists on transfer learning methodologies or cultivar-specific models for adapting models across several okra cultivars.

Domain adaptation strategies or meta-learning methodologies may assist models in accommodating various cultivars with little further training.

4.8 Symptoms of Differential Deficiency Across Varieties

Various okra cultivars may exhibit distinct signs of nutrient deficiency—such as chlorosis, necrosis, or stunted growth—thereby complicating the establishment of traditional diagnostic criteria. Some variants may exhibit delayed signs, whereas others may show accelerated yellowing under nitrogen deficit.

Research Gap: The majority of current research neglect the manifestation of nutritional deficits across various okra cultivars.

Proposed Solution: Adaptive learning frameworks or cultivar-specific machine learning models might be developed to accommodate such variations and enhance precision.

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4.9 Constrained Comparative Analysis of Varieties

The majority of machine learning models are trained and assessed using datasets derived from either a singular or restricted number of cultivars. The absence of benchmarking across several cultivars diminishes the relevance of models in practical agricultural settings.

Research Gap: A standardized framework for assessing ML-based deficiency detection models across various okra cultivars is lacking.

Comparative research might be enhanced by a benchmark dataset including many okra types from diverse locales.

4.10 Environmental Impacts

The absorption of nutrients and the manifestation of deficiencies in plants are significantly affected by environmental factors such as temperature, soil composition, and seasonal changes. These characteristics provide additional problems for machine learning-based identification of Okra nutritional deficiencies.

4.11 The Impact of Climate Conditions on Deficiency Symptoms

The nutritional absorption of the okra plant fluctuates with temperature, humidity, and precipitation levels. Excessive rainfall may lead to nutrient leakage, particularly nitrogen, while dry conditions may exacerbate symptoms of potassium insufficiency.

The research gap arises from the limited generalizability of most machine learning models, which are developed using information derived from distinct climatic conditions across various geographical locations.

Proposed Solution: Climate-conscious machine learning algorithms using meteorological data might enhance the reliability of nutrient insufficiency assessments.

4.12 Soil Heterogeneity and Its Impact on Nutrient Deficiency Identification

The solving of deficits in okra plants is influenced by area via soil variables such as pH, organic matter content, and nutrient availability. Differences in soil composition may result in a deficiency seen in one location manifesting differently in another.

The research gap is in the lack of interaction between machine learning-based visual recognition methods and soil nutrient analysis data.

Geospatial machine learning models that integrate satellite data, soil analysis, and plant phenotyping may provide a more comprehensive method for diagnosing shortfalls.

4.13 Seasonal and Developmental Phases: Variability

The plant's developmental stage and the seasonal cycle will influence the manifestation of nutrient deficiencies. A little deficiency at the outset may escalate in subsequent development stages, so jeopardizing production.

The research gap indicates that machine learning models developed using early-stage plant photos are incapable of identifying deficiency signs in later stages.

Proposed Solution: Time-series machine learning models or models tailored for certain growth stages may enhance problem diagnostics throughout the plant's lifespan.

CONCLUSION AND FUTURE WORK

Precision farming and early detection enabled by machine learning have showed great potential in identifying okra leaves that are deficient in micro and macronutrients. However, there are certain issues, such as a shortage of labeled datasets, an unpredictable environment, and the need for very precise models. Current systems depend heavily on image-based analysis, but combining data from many sensors and sophisticated deep learning algorithms might improve their accuracy and resilience. The primary aim of future research should be to generate big and diverse datasets, improve lightweight models for real-time applications, and integrate IoT-enabled smart tracking devices.

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Explainable AI and hyperspectral imaging may help physicians make more accurate diagnosis. Addressing these difficulties would result in repeatable and cost-effective solutions, encouraging alternative agricultural applications such as sustainable okra production. Machine learning advancements will alter how plant health monitoring and nutrient management are conducted.

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