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Deep Learning Approaches for Plant Nutrient Deficiency Detection and Classification: A Comprehensive Review

Jay Mane
Department of Artificial Intelligence & Data Science
Vidya Pratishthan's Kamalnayan Bajaj Institute of Engineering and Technology
Baramati, India

Pradip Shendage
Department of Artificial Intelligence & Data Science
Vidya Pratishthan's Kamalnayan Bajaj Institute of Engineering and Technology
Baramati, India

Harshal Patil
Department of Artificial Intelligence & Data Science
Vidya Pratishthan's Kamalnayan Bajaj Institute of Engineering and Technology
Baramati, India

Atharva Bhandvalkar
Department of Artificial Intelligence & Data Science
Vidya Pratishthan's Kamalnayan Bajaj Institute of Engineering and Technology
Baramati, India

Atharva Gole
Department of Artificial Intelligence & Data Science
Vidya Pratishthan's Kamalnayan Bajaj Institute of Engineering and Technology
Baramati, India

ABSTRACT
Nutrient deficiencies in plants significantly hinder agricultural productivity and sustainability. Early detection and classification of these deficiencies is vital for effective crop management, but traditional diagnostic methods are often subjective and labor-intensive. Recent advancements in the field of deep learning, notably Convolutional Neural Networks (CNNs) alongside other deep learning architectures, have brought about a revolution in this field by enabling automated and accurate detection and classification of nutrient deficiencies through leaf image analysis. Deep learning models excel in recognizing complex patterns in leaf morphology, making them effective in identifying and categorizing stress caused by nutrient imbalances. This comprehensive review examines various deep learning approaches for detecting and classifying leaf deficiencies, highlighting key methodologies, architectures, and datasets. It systematically categorizes the literature into crop-specific applications, preprocessing techniques, ensemble and hybrid models, and real-time systems. While these methods demonstrate high accuracy across various crops, challenges such as environmental variability, data imbalance, and model interpretability remain. Deep learning-based solutions are being integrated into precision agriculture systems which show promise for real-time monitoring and decision-making, contributing to sustainable farming practices. By addressing current shortcomings and inspecting future research directions, the development of scalable and precise solutions for nutrient deficiency detection and classification is aimed at, with the goal of enabling improved crop health management.
Keywords—Deep Learning, Plant Nutrient Deficiency, Image Classification, Convolutional Neural Networks (CNN), Transfer Learning, Precision Agriculture

I. INTRODUCTION

Ensuring agricultural productivity and sustainability is essential to meeting the increasing global food demand. Nutrient deficiencies in crops pose a significant challenge, impacting plant growth, yield, and quality. Detecting and managing such deficiencies early on is crucial in preventing severe losses. However, conventional diagnostic techniques, ranging from visual inspection to chemical analysis, are often labor-intensive, time-consuming and reliant on expert knowledge, highlighting the need for automated, scalable, and accurate solutions.

Recent advancements in the field of AI notably in deep learning, have transmuted agricultural diagnostics. Convolutional Neural Networks (CNNs) have proven to be highly effective in analyzing leaf images to detect nutrient deficiencies by learning complex patterns in leaf morphology. These models enable accurate classification of nutrient imbalances, offering actionable insights that support real-time monitoring and decision-making in precision agriculture.

This paper presents a comprehensive review of CNN-based methods for identifying nutrient deficiencies in plant leaves. It examines the methodologies, datasets, and architectures used across various crops, evaluating their advantages and limitations. Additionally, it discusses key challenges such as environmental variability, data imbalance, and model interpretability. By identifying these issues and outlining future research directions, this review contributes to the development of scalable and sustainable solutions for crop health monitoring.

II. RELATED WORKS

Several approaches have been developed for diagnosing nutrient deficiencies in plants, utilizing image processing along with deep learning to distinguish between healthy and affected leaf regions. The automation of this process has been significantly enhanced through the application of Convolutional Neural Networks (CNNs), which identify patterns associated with nutrient imbalances in leaf images. Methods involving ensemble learning, transfer learning, and hybrid models have further enhanced accuracy and efficiency compared to conventional methods. This section gives a synopsis of key algorithms and techniques, emphasizing advancements in nutrient deficiency detection while laying the groundwork for discussing challenges and future opportunities in the field.

Waheed et al. [1], [2] made significant contributions to ginger plant health monitoring through two complementary studies. Their initial work introduced a deep learning-based system utilizing CNNs and ANNs, achieving impressive accuracies of 99% for disease detection and 96% for nutritional deficiency identification. Building on this success, they developed a mobile-based system integrating it into an android app to provide real-time detection of ginger plant disorders, using a comprehensive dataset of 4,394 leaf images. The enhanced system employed VGG-16 for classification and YOLOv5 for object detection, achieving average mAP50 values of 80% for pest patterns and nutrient deficiencies, and 79% for soft rot disease. While these studies demonstrated the effectiveness of deep learning in plant health diagnostics, particularly through mobile applications, the lack of specific nutrient deficiency differentiation was identified as an area for future improvement

Muthusamy and Ramu [6] introduced an ensemble-based deep learning model, “IncepV3Dense” for detecting micronutrient deficiencies in banana leaves. The model combined multiple pre-trained deep learning architectures, including VGG19, InceptionV3, and DenseNet169, to enhance classification performance. The ensemble approach achieved a high validation accuracy of 98.62% and an F1-score of 93%, demonstrating its effectiveness in improving the accuracy of nutrient deficiency detection. This study highlights the potential of ensemble learning strategies and the success of InceptionV3 and DenseNet models in identifying specific micronutrient deficiencies, offering valuable insights for similar applications in detecting nutrient deficiencies in ginger leaves.

Paramanandham et al. [7] developed “LeafNet” a deep learning-based model for detecting groundnut leaf diseases, including nutrient deficiencies. Using a 10,361 groundnut leaf images dataset, the model achieved a test accuracy and F1- score of 97.225%. Its high performance was attributed to the integration of residual networks and weight initialization techniques, which enhanced efficiency. While the study focused on groundnut crops, the effectiveness of this approach in identifying nutrient deficiencies suggests its potential applicability for diagnosing deficiencies in other crops, such as ginger, offering valuable insights for plant health monitoring.

Deichmann et al. [5] developed a Convolutional Neural Network (CNN)-based model to detect nutrient deficiencies in barley plants. Using RGB images of barley leaves, the model effectively identified deficiencies in key nutrients, including nitrogen, phosphorus, and potassium, attaining an accuracy of 94.5%. This work highlights the ability of CNN-based approaches for nutrient deficiency detection in barley and suggests their applicability to other crops, such as ginger. The findings emphasize the role of deep learning in plant health monitoring and optimizing nutrient management in agriculture.

Sunitha et al. [24] proposed a novel deep learning approach, the Convolutional Neural Network with Skip Connections (CNNSC), for detecting micronutrient deficiencies, specifically boron and iron, in banana leaves. The CNNSC model, which features thirteen layers, outperformed noteworthy architectures such as VGG16, DenseNet, and Inception V3 in detecting nutrient deficiencies. This model attained an accuracy of close to 95% after having trained on a curated dataset of 11,000 images consisting nutrient-deficient banana leaves. The study demonstrated the effectiveness of the CNNSC model in identifying micronutrient deficiencies, which are crucial for optimizing banana plant growth and improving yield. This methodology offers valuable insights for similar applications in other crops, including nutrient deficiency detection in ginger leaves.

Alarfaj et al. [19] introduced a multi-step preprocessing method combined with UNet segmentation and transfer learning to detect diseases in pepper bell leaves. A stellar 99.48% accuracy was accomplished by the model, showcasing the power of advanced preprocessing and segmentation techniques in enhancing plant disease detection. While the study specifically focuses on pepper bell plants, the approach could be adapted for detecting nutrient deficiencies in ginger leaves. This work highlights the potential of leveraging sophisticated machine learning methods to improve plant health diagnostics and broaden the scope of their application in agriculture.

Samal et al. [16] reviewed the success of the Plantix app in detecting plant diseases and nutrient deficiencies. The app, powered by AI, is capable of identifying over 500 diseases and deficiencies across 30 crops. With a high level of accuracy, it serves as a valuable tool for farmers, offering real-time crop health management and solutions. The app’s extensive database, which includes scientifically verified solutions for a wide range of pests and diseases, has been downloaded by millions of users, particularly in India. This work highlights the power of AI in agriculture, and the app’s methodology could be extended to ginger crops for similar applications, aiding in nutrient deficiency detection and crop management.

Ali et al. [3] developed a deep learning-based system to detect nutrient deficiencies in grape leaves, focusing on deficiencies of potassium, magnesium, nitrogen, and phosphorus. The study utilized a Convolutional Neural Network (CNN) classifier, trained on a dataset of grape leaves affected by these nutrient deficiencies. The model achieved average accuracies of 77.97%, 77.74%, 81.81%, and 78.09% for potassium, magnesium, phosphorus, and nitrogen deficiencies, respectively, using conventional training-testing ratios. However, when applying n-fold cross-validation on the original dataset, the accuracies improved to 95.95%, 92.70%, 90.91%, and 94.76%. Augmenting the dataset further boosted performance. The study demonstrated the system’s potential for real-time application on mobile devices, offering a valuable tool for farmers to manage nutrient deficiencies in grape crops efficiently.

Ibrahim et al. [4] proposed a Convolutional Neural Network (CNN) approach for detecting nutrient deficiencies in palm leaves, specifically targeting deficiencies in nitrogen, potassium, magnesium, boron, zinc, and manganese. The study made use of a dataset featuring 350 images of healthy and deficient palm leaves. The CNN model achieved a promising detection accuracy of 94.29%, demonstrating the effectiveness of deep learning techniques for analyzing leaf images and identifying nutrient deficiencies. While the results were successful, the authors noted that increasing the dataset size could further enhance the detection performance. This approach offers a valuable tool for managing palm oil plantation health and improving crop quality in the commercial sector.

Abbas et al. [20] developed a deep learning-based method for detecting diseases in tomato plants, incorporating Conditional Generative Adversarial Networks (C-GAN) for synthetic image generation and the pre-trained DenseNet121 model for classification. By leveraging both real and synthetic images, the approach enhances training effectiveness, addressing the challenge of limited labeled data. Extensive testing on the PlantVillage dataset yielded high accuracy rates of 99.51% for 5 categories, 98.65% for 7 categories, and 97.11% for 10 categories respectively, for classifying tomato leaf images. The study demonstrated superior performance over existing techniques, emphasizing its potential for early disease detection in tomato crops and contributing to improved agricultural management.

Zermas et al. [17] proposed a novel methodology for detecting nitrogen (N) deficiency in corn fields using high-resolution RGB imagery captured by drones. The approach addresses key limitations of existing techniques, including lack of generality, difficulties in variable field conditions, and insufficient tool sophistication. The proposed system utilizes a low-complexity recommendation scheme to identify potential N-deficient plants and assists in the creation of a training dataset for deep neural network-based object detection. This methodology achieved a mean average precision of 82.3% for detecting N-deficient leaves in experimental field data. The results underscore the effectiveness of the approach, which offers significant potential for improving nutrient deficiency detection in large-scale agricultural practices, thereby benefiting both economic and environmental outcomes.

Talukder and Sarkar [8] introduced a Deep Ensemble Convolutional Neural Network (DECNN) model for detecting nutrient deficiencies in rice crops. The approach incorporates modified versions of pre-trained models, including InceptionV3, DenseNet169, InceptionResNetV2, DenseNet201, DenseNet121 enhanced with additional layers, data augmentation, and dropout techniques to improve accuracy. Among these, the revised DenseNet169 achieved the highest individual test accuracy of 96.66%. Weighted average ensemble method, further enhanced the performance resulting in an overall test accuracy of 98.33%. The efficacy of deep learning, especially ensemble learning, in accurately diagnosing nutrient deficiencies is underscored in the study, with notable improvements demonstrated across metrics such as precision, recall, and F1 score.

Majdalawieh, Khan, and Islam [14] explored deep learning-based approaches for detecting iron chlorosis, a plant condition resulting from iron deficiency. The study evaluated Single Shot Detector (SSD) MobileNet v2 and EfficientDet D0 as the two pre-trained models, for identifying nutrient deficiencies in plant leaves and assessing soil conditions. SSD MobileNet v2 demonstrated classification accuracies between 93% and 98% with faster processing times, whereas EfficientDet D0 achieved slightly higher accuracy (87% to 98.4%) but required more computational time. The findings suggest effectiveness of both of these models for real-time classification, however EfficientDet D0 offers superior accuracy despite increased processing demands.

Goyal et al. [25] developed an improved deep convolutional architecture for detecting and classifying wheat diseases, with a focus on the spike and leaves, which are the most affected parts of the plant. An impressive testing accuracy of 97.88% was achieved by the proposed model, surpassing popular deep learning models such as VGG16 and ResNet50 by 7.01% and 15.92%, respectively. The method also demonstrated superior performance in other metrics such as precision, recall, and F-score, making it a valuable tool for enhancing crop yield quality and disease management in wheat cultivation.

Amudha and Brindha [23] introduced a computer vision-based deep learning system, CAR-CapsNet, for classifying nutrient deficiencies in rice plants. The model uses a novel contextual attention routing (CAR) mechanism to enhance the interpretation of complex visual features, significantly improving classification accuracy. Trained on 1,155 images of rice leaves with deficiencies in nitrogen, phosphorus, and potassium, CAR-CapsNet achieved an impressive 97.1% accuracy, outperforming baseline models like CNN and the original CapsNet. It also demonstrated high recall (96.9%), Kappa score (95.4%), and F1-score (96.9%), surpassing prior methods like Random Forest Regression, SVM, and VGG19.

Nayak et al. [15] developed a smartphone-based system integrating image processing and transfer learning for detecting rice diseases and nutrient deficiencies. The study utilized 2,259 smartphone images along with 250 real-time validation images to classify 12 different symptoms related to rice health. Image segmentation techniques, including foreground extraction, were applied to enhance model performance, with optimizations enabling offline functionality on mobile devices. Among the deep learning models evaluated, DenseNet201, Xception, MobileNetV2, and ResNet50 demonstrated high validation accuracies of 98.03%, 97.78%, 97.56%, and 97.18%, respectively. MobileNetV2 emerged as the most suitable model for smartphone deployment, leading to the development of the "Rice Disease Detector" Android app, which was successfully tested for identifying multiple disease types in a single capture.

Srisook et al. [28] developed a deep learning-based approach for identifying nutrient deficiencies in oil palm leaves. The study utilized images of leaf fronds from 37 oil palm trees, focusing on essential nutrients such as Nitrogen (N), Phosphorus (P), Potassium (K), Magnesium (Mg), and Boron (B). Convolutional Neural Networks (CNNs) were employed to classify nutrient levels into three categories: deficiency, normal, and excess. Two CNN architectures, CSBio2020 and BettaNet, were evaluated, with BettaNet achieving the highest performance, attaining an average accuracy of 80.4%. The model also demonstrated strong precision, recall, and F1 scores, highlighting its potential as a practical solution for real-time nutrient deficiency detection in oil palm cultivation.

Bera et al. [11] introduced PND-Net, a novel method for classifying plant nutrient deficiencies and diseases using a Graph Convolutional Network (GNN) integrated with a Convolutional Neural Network (CNN). The method addresses the challenge of accurately detecting diseases and deficiencies by focusing on region-based feature learning and multiscale feature aggregation through spatial pyramidal pooling. PNDNet was evaluated on several public datasets, including those for banana, coffee, and potato diseases, achieving impressive classification accuracies of 90.00% and 90.54% for nutrition deficiency detection and 96.18% and 84.30% for disease classification. Moreover, the model demonstrated state-of-the art performance on additional datasets like the BreakHis and SIPaKMeD datasets, showing its robustness and potential for enhancing plant health monitoring in diverse agricultural settings.

Taha et al. [18] introduced a deep convolutional neural network (DCNN)-based method for identifying nutrient deficiencies in lettuce cultivated in aquaponic systems. Their approach combined color imaging with a multi-stage DCNN process, encompassing plant object detection and nutrient deficiency classification. Using a dataset of 3,000 images, the study categorized lettuce into four nutrient groups: full nutrition (FN), nitrogen deficiency (N), phosphorus deficiency (P), and potassium deficiency (K). The proposed DCNN model achieved 99.1% accuracy in segmentation and 96.5% in classification, surpassing traditional machine learning techniques such as SVM, decision trees and also KNN. These findings highlight the potential of DCNNs with color imaging for real-time nutrient monitoring, offering a reliable strategy to minimize production losses and enhance sustainability in aquaponic farming.

Ahmad et al. [13] presented a deep learning approach for cotton leaf disease detection using Vision Transformers (ViT). Cotton, an economically significant crop, is vulnerable to several diseases, and timely disease detection is crucial to prevent yield and quality loss. The study involved collecting and annotating a large dataset of healthy and disease-affected cotton leaves, which was used to develop an automated disease detection system. The research explored data collection, preprocessing, feature extraction, and potential applications. The Vision Transformer model achieved the highest accuracy in disease detection, with 96.72% for binary classification and 93.39% for multi-class classification, outperforming other pretrained deep learning techniques. The outcomes underline the ability of transformer-based models in advancing agricultural technology and supporting cotton crop protection and economic growth.

Venkatesh and Naik [9] developed a method for identifying nutrient deficiencies and predicting yield loss in groundnut crops using transfer learning. The study focused on the identification of deficiencies in key nutrients—nitrogen (N), phosphorus (P), and potassium (K)—which are crucial for plant growth and can severely impact crop productivity if deficient. The authors enhanced the VGG16 model by integrating it with a proposed nutrient severity identification module to classify leaf images and assess nutrient deficiencies. Using groundnut and rice plant image datasets, an accuracy of 98% for groundnut leaf classification was achieved by the model. Additionally, the model was able to estimate potential crop yield losses based on identified nutrient deficiencies. It was shown through comparisons with existing models that the proposed approach outperforms current state-of-the-art methods, positioning it as a promising tool for improving crop yield and nutrient management.

Sosa et al. [22] developed an algorithm to detect nitrogen (N), phosphorus (P), boron (B), and calcium (Ca) deficiencies in coffee leaves, addressing the subjectivity in traditional visual analysis that affects nutrient management plans. The method enhances image contrast through luminance adjustments, applies the Scale-Invariant Feature Transform (SIFT) algorithm for key point detection, and uses Hu and Fourier descriptors to train a neural network for classification. The algorithm achieved impressive accuracy rates of 96% for nitrogen and phosphorus, and 94% for boron, with Kappa coefficients of 0.96 for N and P, and 0.92 for boron. While the results were strong, the study suggested that calcium deficiency detection could be improved by expanding the dataset to include more diverse coffee-growing regions in Peru. This approach outperforms existing methods and provides a more objective, scalable solution for precision agriculture, facilitating better nutrient management in coffee cultivation.

Theerthagiri et al. [26] proposed a deep learning-based method leveraging SqueezeNet for the detection and prediction of maize leaf diseases. Their research focused on three primary diseases—common rust, blight, and grey leaf spot—using a dataset of 3,852 images from PlantVillage. To enhance model performance, they applied extensive pre-processing techniques such as sampling and labeling while utilizing the SMOTE algorithm to ensure class balance and mitigate overfitting. The study compared various deep learning architectures, including VGG16, ResNet34, ResNet50, and SqueezeNet. Among these, SqueezeNet outperformed the others, achieving a 97% accuracy in classifying four leaf classes, with an accuracy improvement of 2-5% and a 4-11% reduction in mean square error compared to competing models. The model's strong performance across metrics such as recall, precision, and F1-score highlights its effectiveness in automated maize disease diagnosis.

Nikitha et al. [12] introduced a Multi-Attention Convolutional Neural Network (MA-CNN) designed to enhance the analysis of plant nutrient deficiencies. This model incorporates channel attention, a customized spatial attention mechanism, and an improved self-attention approach, along with spatial pyramid pooling, to detect deficiencies in essential nutrients such as Nitrogen, Phosphorus, Potassium, Sulphur, and Iron. The lightweight architecture was rigorously evaluated across various crops using 5-fold cross-validation, highlighting its adaptability. When compared with conventional Multilayer Perceptrons and advanced pre-trained models, MA-CNN demonstrated superior performance, achieving accuracies of 93.27% for Mulberry, 97.19% for Rice, 96.11% for Maize, and 96.50% for Wheat datasets. Its ability to maintain high accuracy across multiple crops, along with its interpretability and efficiency, marks a significant step forward in automated nutrient deficiency detection systems.

Venkatesh and Naik [10] developed an ensemble transfer learning approach combining MobileNetV2 and shallow CNN for nutrient deficiency identification and yield-loss prediction. The study conducted two distinct experiments using comprehensive datasets: 4,399 rice leaf images and 4,550 groundnut leaf images, captured under real environmental conditions. The proposed ensemble method demonstrated exceptional performance, achieving 99% accuracy for groundnut and 94% for rice in nutrient deficiency classification. Additionally, yield losses of 28.34% for groundnut and 32.5% for rice crops due to nitrogen, phosphorus, and potassium deficiencies were successfully estimated using their deficiency-driven yield prediction method. The lightweight architecture outperformed existing algorithms while maintaining computational efficiency, making it particularly suitable for practical agricultural applications and potential deployment on edge devices.

Sharma et al. [29] proposed a cloud-based framework for detecting nutrient deficiencies in rice plants using ensemble deep learning models. Their work addresses the growing accessibility of computational resources through smartphones, enabling farmers to utilize high-end systems hosted in the cloud. The study implemented six transfer learning architectures: InceptionV3, ResNet152V2, Xception, DenseNet201, InceptionResNetV2, and VGG19, combining them in various ensemble configurations. Using two public datasets from Mendeley and Kaggle, their ensemble approach demonstrated significant improvements in classification accuracy. The model achieved perfect accuracy (100%) on the Mendeley dataset, improving from the single-model performance of 99.17%, while for the Kaggle dataset, accuracy increased to 92% from 90%. The framework's design prioritizes accessibility for farmers through cloud integration, making sophisticated deep learning models available for practical agricultural applications. Future developments aim to incorporate IoT-enabled systems for a comprehensive deficiency diagnosis support system, with particular focus on conditions affecting yield potential versus yield stress.

Razali et al. [30] developed CNN-based architectures for classifying nutrient deficiencies in oil palm leaves using standardized image acquisition protocols. The study evaluated four deep learning models—ResNet-50, VGG-16, DenseNet-201, and AlexNet—using a dataset of 180 leaf images equally distributed among healthy, nitrogen-deficient, and potassium deficient categories. The models demonstrated exceptional performance, with ResNet-50 achieving 96.7% accuracy, while both VGG-16 and AlexNet achieved perfect classification accuracy (100%), and DenseNet-201 reached 98.3%. Among the successful architectures, AlexNet emerged as the most computationally efficient due to its smaller number of convolutional layers compared to VGG-16. The research established a standardized image acquisition protocol and validated the samples through careful observation of characteristic features in healthy and nutrient-deficient leaves. The study's success points toward the potential development of smartphone-based intelligent applications for nutrient deficiency detection, which could reduce dependency on subjective human evaluation and enhance monitoring efficiency in oil palm cultivation.

Priyadharshini et al. [27] proposed a modified LeNet-based deep convolutional neural network architecture for maize leaf disease classification, addressing the critical challenge of rapid disease identification in agricultural settings. The study utilized the PlantVillage dataset to train the model for distinguishing between three disease classes and one healthy class. Their modified CNN architecture was designed to simultaneously learn both local and global features of leaf images. Through extensive parameter optimization, particularly focusing on kernel size variations, the research determined that a 3×3 kernel size was optimal for maize leaf disease classification. The model demonstrated impressive performance, achieving a classification accuracy of 97.89%. The study's findings not only established the effectiveness of their modified LeNet architecture for maize disease detection but also suggested its potential applicability for disease classification in other plant species, contributing to the broader field of automated agricultural disease diagnostics.

Oad et al. [21] proposed an innovative ensemble learning framework combining four deep learning models (VGG16, VGG19, ResNet101 V2, and Inception V3) for plant disease detection across 38 different classes. Their approach achieved 93% accuracy using a soft voting ensemble methodology and uniquely incorporated LIME (Local Interpretable Model Agnostic Explanations) for model interpretation. The decision making process of the model is being made transparent to users by LIME integration that generates visualizations highlighting influential image regions. The study stands out for its comprehensive coverage of disease classes and its novel combination of high-accuracy ensemble learning with explainable AI in agricultural applications. Future work proposes the implementation of bagging and boosting techniques, the integration of multiple XAI approaches, and the development of multilingual disease prediction explanations through generative AI, all of which are expected to make significant contributions to precision agriculture and sustainable farming practices.

Joseph et al. [31] developed datasets for rice, wheat, and maize diseases to address the challenge of limited real-time data in plant disease diagnosis. They evaluated eight refined deep learning models and introduced MRW-CNN, a novel CNN architecture. Their approach achieved high accuracy: Xception (95.80%) and MobileNet (94.64%) for maize, MobileNetV2 (96.32%) and MobileNet (96.28%) for wheat, and Xception (97.28%) and Inception V3 (96.20%) for rice. The MRW-CNN model outperformed others with 97.04% (maize), 97.06% (rice), and 98.08% (wheat). Using real-life images with varying disease severity and data augmentation, this study enhances early disease detection in agriculture.

The reviewed studies underlines the growing influence of deep learning in plant nutrient deficiency detection. CNN-based models dominate the field, with ensemble and transformer-based architectures improving classification performance. Mobile and IoT-enabled solutions have made real time deficiency detection more accessible, while dataset augmentation and explainable AI contribute to model robustness and interpretability. Future research should focus on lightweight models for edge computing, improved dataset diversity, and multi-modal data fusion for enhanced plant health diagnostics.

III. TABLES

TABLE I. SUMMARY OF SINGLE CNN-BASED ARCHITECTURES FOR PLANT DEFICIENCY AND DISEASE DETECTION

Ref.	Authors	Objective	Method	Key Findings
[26]	Theerthagiri et al. (2024)	Early detection and classification of maize leaf diseases (rust, blight, grey leaf spot)	VGG16, Resnet34, Resnet50, SqueezeNet comparison	SqueezeNet achieved 97% accuracy with enhanced computational efficiency
[12]	Nikitha et al. (2024)	MultiAttention CNN for plant nutritional deficiencies	MultiAttention CNN with spatial pyramid pooling	Accuracies: Mulberry (93.27%), Maize (96.11%), Rice (97.19%), Wheat (96.50%)
[7]	Paramanandham et al. (2024)	To develop LeafNet for groundnut disease and nutrient deficiency detection.	LeafNet with residual networks and weight initialization techniques	LeafNet achieved 97.23% accuracy with strong cross-dataset generalization for groundnut disease and deficiency detection

TABLE II. SUMMARY OF HYBRID AND ENSEMBLE CNN ARCHITECTURES FOR PLANT DEFICIENCY AND DISEASE DETECTION

Ref.	Authors	Objective	Method	Key Findings
[10]	Venkatesh & Naik (2023)	Ensemble transfer learning for deficiency and yield prediction	MobileNetV2 + Shallow CNN	Achieved 99% accuracy for groundnut, 94% for rice
[9]	Venkatesh & Naik (2023)	Enhanced VGG16 for groundnut nutrient deficiency	VGG16 + NSIM	98% accuracy with improved severity assessment
[24]	Sunitha et al. (2024)	CNNSC for banana micronutrient deficiencies	13-layer CNN with Skip Connections	95% accuracy with effective gradient handling
[17]	Zermas et al. (2020)	Nitrogen deficiency detection in corn	Faster RCNN + Color Space Segmentation	82.3% mAP at 50% IoU in field conditions
[19]	Alarfaj et al. (2023)	To develop automated pepper bell leaf disease detection system	UNET segmentation + InceptionV3 transfer learning	Achieved 99.48% accuracy with enhanced disease detection efficiency

IV. CONCLUSION

This review has explored the latest advancements in deep learning-based plant leaf nutrient deficiency detection, highlighting significant progress in automated identification and classification across various crop species. Convolutional Neural Networks (CNNs) and their variants have emerged as the leading methodologies, consistently achieving accuracy rates above 90%. Key developments include ensemble learning techniques, which have outperformed single-architecture models, and transfer learning approaches that enhance model generalization.

The transition from laboratory-based models to practical, field-ready solutions has been accelerated by innovations such as mobile applications and real-time detection systems. Advanced architectures like CAR-CapsNet and PND-Net have further improved detection accuracy while addressing computational limitations. Additionally, the integration of sophisticated preprocessing techniques and multi-modal data approaches has strengthened the reliability and robustness of these models.

Despite these advancements, challenges remain. The development and validation of models are hindered by the need for larger, more diverse datasets. Moreover, achieving high specificity in detecting multiple nutrient deficiencies simultaneously requires further research. Future efforts should prioritize improving real-time processing, enhancing model interpretability, and integrating these solutions into broader precision agriculture frameworks.

The field is poised for further growth with the adoption of upcoming technologies like edge computing, Internet of Things (IoT), alongside advanced sensor systems. These innovations will be instrumental in developing more comprehensive and efficient nutrient deficiency detection systems, supporting the demands of sustainable agriculture and precision farming.

REFERENCES

[1] Waheed, H., Zafar, N., Akram, W., Manzoor, A., Gani, A., Islam, S.: Deep learning based disease, pest pattern and nutritional deficiency detection system for ”zingiberaceae” crop. Agriculture 12(6), 742 (2022)

[2] Waheed, H., Akram, W., Islam, S.u., Hadi, A., Boudjadar, J., Zafar, N.: A mobile-based system for detecting ginger leaf disorders using deep learning. Future Internet 15(3), 86 (2023)

[3] Ali, A., Ali, S., Husnain, M., Missen, M.M.S., Samad, A., Khan, M.: Detection of deficiency of nutrients in grape leaves using deep network. Computational Intelligence and Neuroscience 2022, 3114525 (2022)

[4] Ibrahim, S., Hasan, N., Sabri, N., Abu Samah, K., Rahimi Rusland, M.: Palm leaf nutrient deficiency detection using convolutional neural network (CNN). International Journal of Nonlinear Analysis and Applications 13(1), 1949–1956 (2022)

[5] Deichmann, M., Yi, J.-h., Mihiret, Y.E., Zahra, S., Sauer, C., H¨uging, H., L´eon, J., Wissuwa, M., Gall, J., Schaaf, G.: RGB image-based detection of nutrient deficiencies in barley by deep learning methods. AgriRxiv 2024, 20240364935 (2024)

[6] Muthusamy, S., Ramu, S.P.: Incepv3dense: Deep ensemble based average learning strategy for

identification of micro-nutrient deficiency in banana crop. IEEE Access 12, 73779–73792 (2024).

[7] Paramanandham, N., Sundhar, S., Priya, P.: Enhancing disease detection with weight initialization and residual connections using leafnet for groundnut leaf diseases. IEEE Access 12, 91511–91526 (2024)

[8] Talukder, M.S.H., Sarkar, A.K.: Nutrients deficiency diagnosis of ricecrop by weighted average ensemble learning. Smart Agricultural Technology 4, 100155 (2023)

[9] Venkatesh, K., Naik, K.J.: Nutrient deficiency identification and yield-loss prediction in leaf images of groundnut crop using transfer learning. Signal, Image and Video Processing 18(5), 4553–4568 (2024)

[10] Venkatesh, K., Naik, K.J.: An ensemble transfer learning for nutrient deficiency identification and yield-loss prediction in crop. Multimedia Tools and Applications 83(32), 78535–78561 (2024)

[11] Bera, A., Bhattacharjee, D., Krejcar, O.: PND-net: plant nutrition de-ficiency and disease classification using graph convolutional network. Scientific Reports 14(1), 15537 (2024)

[12] Nikitha, S., Prabhanjan, S., Rupa, T.R., Dinesh, R.: Enhancing plant nutritional deficiency analysis: a multi-attention convolutional neural network approach. Multimedia Tools and Applications (2024)

[13] Ahmad, M.: Cotton leaf disease detection using vision transformers: A deep learning approach. African Journal of Biomedical Research 27(3S), 5760–5769 (2024)

[14] Majdalawieh, M., Khan, S., Islam, M.T.: Using deep learning model to identify iron chlorosis in plants. IEEE Access 11, 46949–46955 (2023)

[15] Nayak, A., Chakraborty, S., Swain, D.K.: Application of smartphone-image processing and transfer learning for rice disease and nutrient deficiency detection. Smart Agricultural Technology 4, 100195 (2023)

[16] Samal, I., Bhoi, T.K., Pradhan, A., Mahanta, D.k.: Plantix app: A success story of artificial intelligence in plant protection 10, 24–26 (2023)

[17] Zermas, D., Nelson, H.J., Stanitsas, P., Morellas, V., Mulla, D.J., Papanikolopoulos, N.: A methodology for the detection of nitrogen deficiency in corn fields using high-resolution rgb imagery. IEEE Transactions on Automation Science and Engineering 18(4), 1879–1891 (2021)

[18] Taha, M., Hassan, A., Elmasry, G., et al.: Using deep convolutional neural network for image-based diagnosis of nutrient deficiencies in plant grown in aquaponics. Chemosensors 10(2), 45 (2022)

[19] AlArfaj, A.A., Altamimi, A., Aljrees, T., et al.: Multi-step preprocessing with unet segmentation and transfer learning model for pepper bell leaf disease detection. IEEE Access 11, 132254–132267 (2023)

[20] Abbas, A., Jain, S., Gour, M., Vankudothu, S.: Tomato plant disease detection using transfer learning with c-gan synthetic images. Computers and Electronics in Agriculture 187, 106279 (2021)

[21] Oad, A., Abbas, S.S., Zafar, A., et al.: Plant leaf disease detection using ensemble learning and explainable ai. IEEE Access PP, 1–1 (2024)

[22] Sosa, J., Ram´ırez, J., Vives, L., Kemper, G.: An algorithm for detection of nutritional deficiencies from digital images of coffee leaves based on descriptors and neural networks. In: 2019 XXII Symposium on Image, Signal Processing and Artificial Vision (STSIVA), pp. 1–5 (2019)

[23] Amudha, M., Brindha, K.: Rice leaf nutrient deficiency classification system using car-capsule network. IEEE Access 12, 169518–169532 (2024)

[24] Sunitha, P., Uma, B., Kiran, A.G., et al.: A convolution neural network with skip connections (cnnsc) approach for detecting micronutrients boron and iron deficiency in banana leaves. Journal of Umm Al-Qura University for Engineering and Architecture 15(4), 467–485 (2024)

[25] Goyal, L., Sharma, C.M., Singh, A., Singh, P.K.: Leaf and spike wheat disease detection & classification using an improved deep convolutional architecture. Informatics in Medicine Unlocked 25, 100642 (2021)

[26] Theerthagiri, P., Ruby, A.U., Chandran, J.G.C., et al.: Deep squeezenet learning model for diagnosis and prediction of maize leaf diseases. Journal of Big Data 11(1), 112 (2024)

[27] Ahila Priyadharshini, R., Arivazhagan, S., Arun, M., Mirnalini, A.: Maize leaf disease classification using deep convolutional neural net-works. Neural Computing and Applications 31(12), 8887–8895 (2019)

[28] Srisook, N., Tuntoolavest, O., Danphitsanuparn, P., Pattana-Anake, V., Joseph, F.J.: Convolutional neural network based nutrient deficiency classification in leaves of elaeis guineensis jacq 14, 19–027 (2022)

[29] Sharma, M., Nath, K., Sharma, R.K., Kumar, C.J., Chaudhary, A.: Ensemble averaging of transfer learning models for identification of nutritional deficiency in rice plant. Electronics 11(1) (2022)

[30] Razali, M.I.H., Hairuddin, M.A., Jahidin, A.H., Som, M.H.M., Ali, M.S.A.M.: Classification of nutrient deficiency in oil palms from leaf images using convolutional neural network. IAES International Journal of Artificial Intelligence 11(4), 1314–1322 (2022)

[31] Joseph, D.S., Pawar, P.M., Chakradeo, K.: Real-time plant disease dataset development and detection of plant disease using deep learning. IEEE Access 12, 16310–16333 (2024)