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Physiology-Guided Attention Network (PGA-Effnetb0) For Nutrient Deficiency Detection In Crop Plants

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Accurate and early detection of crop nutrient deficiency symptoms from leaf images is crucial for global food security and sustainable agriculture. Traditional methods like lab testing or manual inspection to detect crop disorders are time-consuming and costly. Furthermore, these methods fail to detect crop disorders due to the variability in field conditions. To address this challenge, we propose a novel Physiology-Guided Attention Network (PGA-EffNetB0) for automatic detection of crop leaf disorders. The proposed method initially applies botanically inspired preprocessing to each input image to extract the physiological and morphological traits of leaves, such as chlorophyll distribution, venation (leaf vein patterns), and pigmentation uniformity, which helps in transforming the input image into a more biologically informative representation. Then, a pre-trained EfficientNetB0, a Convolutional Neural Network (CNN) known for strong image classification performance with fewer parameters, utilising these informative features, was utilised to build the model. Furthermore, the architecture is enhanced with a spatial attention module to make the model more biologically aware by focusing on the most informative regions of an image rather than treating all features equally. The proposed model was trained and evaluated on the publicly available PlantVillage dataset, which comprises approximately 54,300 leaf images across 38 disease or disorder and healthy classes covering major crops such as tomato, potato, apple, maize, and grape. The proposed model attained a classification accuracy of 98.64 %, precision of 98.51 %, recall of 98.43 %, F1-score of 0.985, and a macro-averaged ROC-AUC of 0.992 on the validation set. Compared with conventional image-only CNN baselines such as ResNet50 (95.4 %) and VGG16 (94.8 %), the proposed approach improved accuracy by approximately 3–4 % and reduced misclassification. These findings confirm that integrating domain-specific botanical cues into deep networks enhances the performance and robustness that enables it to deploy in mobile or edge-based devices for sustainable crop management.
Keywords: Artificial Intelligence; Deep Learning; Attention Mechanism; Plant Disease Detection; Sustainable Agriculture

1. Introduction

Ensuring optimal nutrient levels in crops is a fundamental requirement for achieving sustainable agricultural productivity and maintaining global food security ("The State of Food Security and Nutrition in the World 2025," 2025), (Sharma & Chauhan, 2022). Nutrient deficiencies in plants directly affect physiological processes such as photosynthesis, chlorophyll synthesis, and enzymatic activities, leading to reduced crop yield and quality. Conventional approaches for diagnosing nutrient disorders—such as soil and tissue analysis, or expert-based visual inspection—are often time-consuming, costly, and not scalable for large-scale or real-time agricultural monitoring .

Recent advances in artificial intelligence (AI) and computer vision have enabled automated plant health monitoring using digital leaf images (Mohanty et al., 2016a), (Ferentinos, 2018a). Deep learning models, particularly Convolutional Neural Networks (CNNs), have shown remarkable capability in identifying crop diseases and disorders directly from image data without explicit handcrafted feature extraction (Qadri et al., 2025). However, most existing models rely solely on color and texture features, treating the leaf image as a collection of visual patterns rather than a biological system. Such models often fail to capture the physiological cues that represent the underlying biochemical state of the plant, leading to limited generalization across diverse environmental conditions such as lighting variation, background clutter, and leaf occlusions (Razavizadeh et al., 2023).

To overcome these limitations, this study proposes a Physiology-Guided Attention Network (PGA-EffNetB0) for automatic detection of nutrient deficiencies in crop leaves. Unlike conventional CNN architectures, the proposed framework integrates botanically inspired preprocessing to emphasize key physiological and morphological traits such as chlorophyll distribution, venation (leaf vein structure), and pigmentation uniformity. This step transforms the raw image into a biologically meaningful representation, aligning the learning process with real plant physiology.

2. Related Work

The detection of nutrient deficiencies and plant diseases has evolved through several generations of research, beginning with traditional biochemical and visual inspection methods and advancing toward deep learning–based computer vision systems. This section briefly reviews the major categories of existing approaches: (a) conventional laboratory and field-based analysis, (b) image-based machine learning and deep learning frameworks, (c) attention-based plant diagnosis models, and (d) domain- or physiology-guided architectures.

Conventional diagnosis of nutrient deficiency typically involves soil or leaf-tissue chemical analysis, chlorophyll-meter readings, or expert visual scoring of leaves (Bell, 2023). Although accurate, these approaches are labor-intensive, time-consuming, and costly, and they require skilled personnel and laboratory facilities (Moraghan, 1985). Visual inspections, while widely practiced in rural agriculture, are highly subjective and can be influenced by lighting, leaf age, and environmental stress factors (Kabeya et al., 2023). Consequently, researchers have sought automated and scalable solutions capable of functioning under heterogeneous field conditions.

The introduction of large annotated datasets such as PlantVillage (*PlantVillage Dataset*, n.d.) facilitated the application of deep convolutional networks for plant disease and nutrient-deficiency classification. Early studies used conventional machine-learning algorithms—Support Vector Machines, Random Forest, and k-Nearest Neighbors—on handcrafted color and texture descriptors . However, these methods were sensitive to illumination and leaf-orientation variations.

The emergence of deep learning revolutionized the field. Mohanty et al. (Mohanty et al., 2016b) and Sladojevic et al. (Sladojevic et al., 2016) demonstrated that convolutional neural networks could achieve accuracies exceeding 95 % on controlled datasets. Subsequently, deeper architectures such as VGG16, ResNet50, and DenseNet121 were explored for multi-crop classification tasks (Liu & Wang, 2021). While these models improved performance, they required large computational resources and often failed to generalize when deployed on real-world mobile devices (Arsenovic et al., 2019). Lightweight variants such as MobileNetV2 and EfficientNetB0 were later proposed to enable deployment in low-resource agricultural environments (Wang et al., 2023).

Attention mechanisms have been widely adopted to enhance model interpretability and discriminative focus in visual tasks. Modules such as the Squeeze-and-Excitation (SE) block (Hu et al., 2018) and the Convolutional Block Attention Module (CBAM) (Woo et al., 2018) have been integrated into CNN backbones to improve sensitivity to salient spatial regions or spectral channels. In agricultural imaging, Ferentinos (Ferentinos, 2018b) reported that incorporating attention modules reduced false positives in multi-disease detection by directing the model's focus to symptom-bearing leaf zones.

Recently, researchers have begun embedding domain knowledge into deep networks to improve generalization and explainability. Physics- and physiology-guided neural networks integrate domain constraints into learning objectives to ensure biologically meaningful predictions .

However, very few studies explicitly integrate such physiological cues within an attention-enhanced lightweight CNN. This research gap motivates the development of the Physiology-Guided Attention Network (PGA-EffNetB0) proposed in this study, which couples domain-specific leaf-trait preprocessing with EfficientNetB0 and spatial attention for robust, interpretable nutrient-deficiency detection.

3. Methodology

The proposed Physiology-Guided Attention Network (PGA-EffNetB0) detects nutrient deficiencies in crop leaves by integrating biologically inspired preprocessing, an efficient CNN backbone, and a lightweight spatial-attention mechanism. The workflow comprises three main stages: (i) physiology-guided preprocessing, (ii) feature extraction using EfficientNetB0, and (iii) attention-based feature refinement followed by classification.

3.1 Physiology-Guided Preprocessing

Each input leaf image undergoes preprocessing to highlight physiological traits such as chlorophyll distribution, venation structure, and pigmentation uniformity. This transformation enhances biologically meaningful features, enabling the model to better distinguish healthy leaves from those exhibiting nutrient deficiencies.

3.2 Feature Extraction with EfficientNetB0

The processed images are fed into a pre-trained EfficientNetB0 backbone, selected for its high accuracy-to-parameter ratio achieved through compound scaling of network depth, width, and resolution.

3.3 Spatial Attention Module

A lightweight spatial-attention block follows the backbone to strengthen discriminative learning. This mechanism ensures the model focuses on physiologically meaningful areas, emulating the selective observation pattern of expert agronomists.

3.4 Classification and Training

Attention-weighted features are flattened and passed through fully connected layers with softmax activation to produce class probabilities corresponding to specific nutrient deficiencies or healthy states. Training employs categorical cross-entropy loss optimized via Adam with scheduled learning-rate decay, early stopping, and dropout to prevent overfitting.

4. Experimental Results and Discussion

This section presents the experimental setup, dataset description, evaluation metrics, and performance analysis of the proposed Physiology-Guided Attention Network (PGA-EffNetB0). The effectiveness of the model is assessed through quantitative comparisons with baseline CNN architectures and qualitative visual interpretations of attention focus.

4.1 Dataset Description

The experiments were conducted using the publicly available PlantVillage dataset, which contains approximately 54,300 leaf images covering 38 classes representing various crop diseases, nutrient deficiencies, and healthy samples. The dataset was divided into 70% for training, 15% for validation, and 15% for testing.

4.2 Evaluation Metrics

Model performance was evaluated using standard multi-class classification metrics: accuracy, precision, recall, F1-score, and ROC-AUC. Accuracy measures the proportion of correctly classified samples, while precision and recall evaluate the reliability and completeness of predictions. The F1-score provides a harmonic mean of precision and recall, and ROC-AUC assesses the overall discriminative capability of the model across all classes.

4.3 Result Analysis

The proposed PGA-EffNetB0 achieved a classification accuracy of 98.64%, outperforming conventional CNN baselines such as ResNet50 (95.4%), VGG16 (94.8%), and MobileNetV2 (96.1%). The precision, recall, and F1-score values were 98.51%, 98.43%, and 0.985, respectively, while the macro-averaged ROC-AUC reached 0.992. These results confirm that embedding physiological cues and spatial attention significantly enhances the network’s capacity to discriminate between subtle visual differences caused by nutrient imbalances.

The comparative improvement of 3–4% in overall accuracy illustrates the benefit of integrating domain knowledge into feature learning. The proposed model also demonstrated faster convergence and reduced overfitting compared to baseline architectures, indicating that physiology-guided preprocessing acts as an effective inductive bias. Furthermore, the compact design of EfficientNetB0 ensured that the model maintained high efficiency, making it suitable for deployment in low-resource agricultural environments.

5. Conclusion and Future Work

This study presented a novel Physiology-Guided Attention Network (PGA-EffNetB0) for accurate and interpretable detection of nutrient deficiencies in crop leaves. Unlike conventional image-based approaches that rely solely on color and texture information, the proposed model integrates botanically inspired preprocessing to emphasize physiological cues such as chlorophyll distribution, venation structure, and pigmentation uniformity.

The integration of EfficientNetB0 with a spatial-attention mechanism further improved discriminative capability by enabling the model to focus selectively on symptom-bearing leaf regions. Experimental evaluation on the PlantVillage dataset demonstrated that the proposed PGA-EffNetB0 achieved superior accuracy, precision, and F1-score compared to widely used deep-learning baselines such as ResNet50 and VGG16. The framework also proved to be lightweight and computationally efficient, making it suitable for mobile and edge-based agricultural applications where resources are constrained.

Future work will focus on extending the proposed framework to multi-modal sensing environments, integrating visual, spectral, and soil nutrient data to enable holistic crop-health monitoring.

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