Deep Neural Network Models for Automated Identification of Nutrient Deficiency Symptoms in Field Crops

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ABSTRACT

Background: Nutrient deficiencies in agricultural crops result in significant yield loss around the world. Traditional diagnostic approaches either rely on the observation of agronomists or tissue analysis in laboratories, approaches that are not only slow and subjective, but also are difficult to scale. The aim of this study is to introduce an automated framework based on the deep-learning neural network (DNN) which will allow for detecting nutrient deficiency symptoms from leaf images quickly, objectively, and at scale. It will not be the only novelty of this research.

Methods: The authors used a CNN backbone, which was compared to transformers. The system also included preprocessing (resizing, normalization, contrast improvement, and removal of the background) and augmentation strategies to differentiate between healthy leaves and the leaves facing deficiencies of nitrogen, phosphorus, potassium, magnesium, or iron.

Result: The developed model combining CNN and ViT has reached the maximum possible levels of classification accuracy (96.8%) and F1-score (0.96) in comparison to the architectures evaluated, showing high tolerance towards different lighting conditions and noise.

Conclusion: The study shows that using deep learning to determine nutrient deficiency allows farmers to add various components to their precision farming techniques and offers scalable and interpretable alternatives to visual identification.

Keywords: Deep neural networks (DNN); Convolutional neural networks (CNN); Vision transformers (ViT); Nutrient deficiency detection

1. Introduction

Sustainable nutrient management is critical for ensuring global food sustainability. Essential nutrients like nitrogen (N), phosphorus (P), and potassium (K) as well as micro-nutrients like magnesium, iron, zinc, and manganese play important roles in governing photosynthesis, enzyme activity, and reproduction in crops. The deficiency of any of the nutrients can lead to specific foliar symptoms, which can cause yield losses of 10-40%, based on the kind of crops grown and severity of the deficiency. The economic implications of delayed deficiency correction are severe, as it may take time to apply corrective measures using fertilizers easily [1, 2].

Traditional diagnostic methods rely on either visual observation by experts or laboratory analysis of plant tissue. Visual assessment is subjective, and expert agronomists may not be available to smallholder farmers. Laboratory methods are accurate but could be quite expensive for everyday monitoring [4]. Therefore, there has been a shift towards the use of sensor and image-based techniques for diagnosis.

The rise of AI, especially deep learning, has dramatically changed agricultural image analysis. CNNs proved to be effective in the tree disease detection, weed identification, and estimating agriculture crops by their ability to learn different visual features from the images automatically, thus removing the need for manual creation of visual features [5, 6]. Recently, ViT models have developed good results through learning the long-term description of objects using the self-attention principle [7]. CNN-ViT combined structure allows to combine extraction features based on local descriptions and also the structures acting based on all visual features; this is especially important in the case of deficiencies of nutrients, in which symptoms can look like diffuse discoloration and other slight differences, rather than localized spots [8].

In spite of the fact that many publications in the area of plant diseases soundtrack classification, it should be recognized that there is a lack of studies directed specifically at the identification of nutrient deficiencies, as well as most of the previous research focused on studying images obtained under laboratory conditions [9, 10]. Taking this into consideration, the suggested paper aims at presenting a full solution using DNN approach devoted to the identification and description of the symptoms of nutrient deficiencies.

2. Proposed Deep Neural Network Framework

2.1 Overall Architecture

The proposed framework (Figure 1) comprises four stages: image acquisition, preprocessing, deep feature extraction and classification, and explainable decision support. Images are captured via smartphone cameras or UAV-mounted sensors under natural field lighting, then transmitted to a processing pipeline that outputs both a predicted deficiency class and a visual explanation of the model's reasoning.

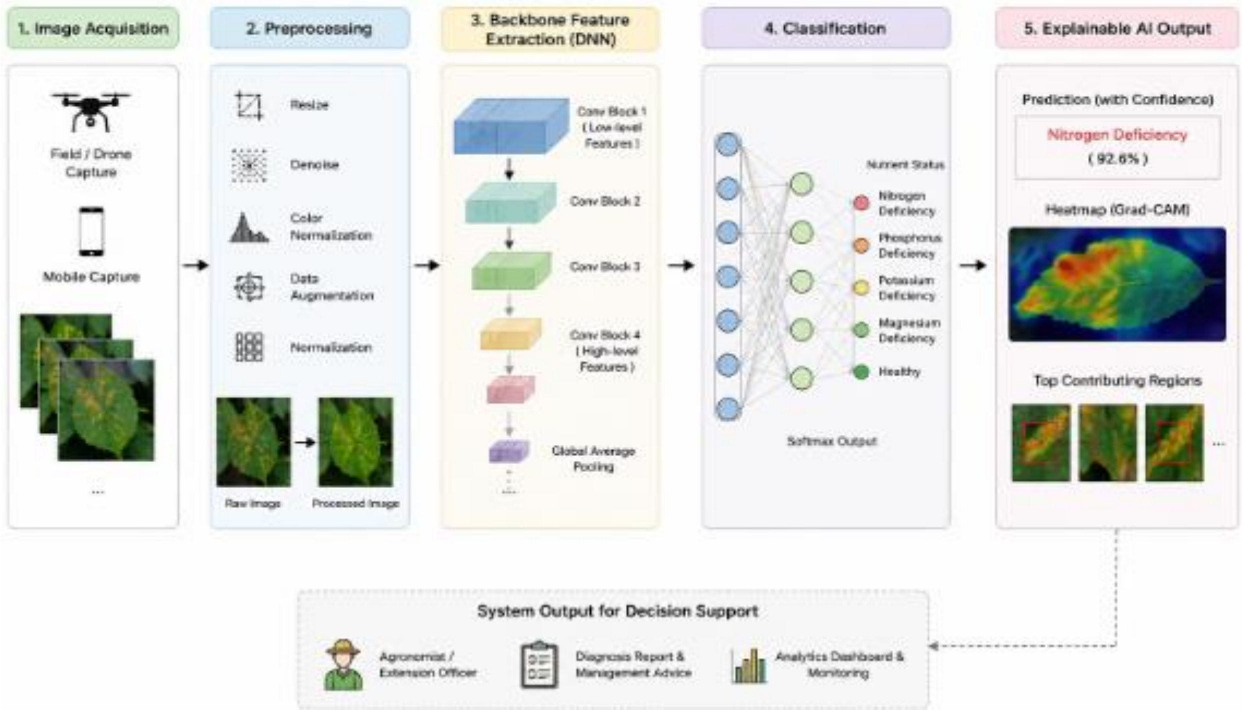

Fig 1: Overall architecture of the proposed deep neural network framework, illustrating the flow from image acquisition through preprocessing, backbone feature extraction, classification, and explainable AI output

2.2 Image Acquisition and Preprocessing

Leaf images are acquired at a standardized distance under diffuse lighting where possible. The preprocessing pipeline (Figure 2) applies resizing to a fixed input resolution, pixel normalization, histogram equalization to correct illumination variance, adaptive noise filtering, contrast enhancement, and background segmentation to isolate the leaf region from soil or canopy clutter. Data augmentation—including rotation, flipping, brightness jitter, and random cropping—expands the effective training distribution and mitigates overfitting on limited field datasets.

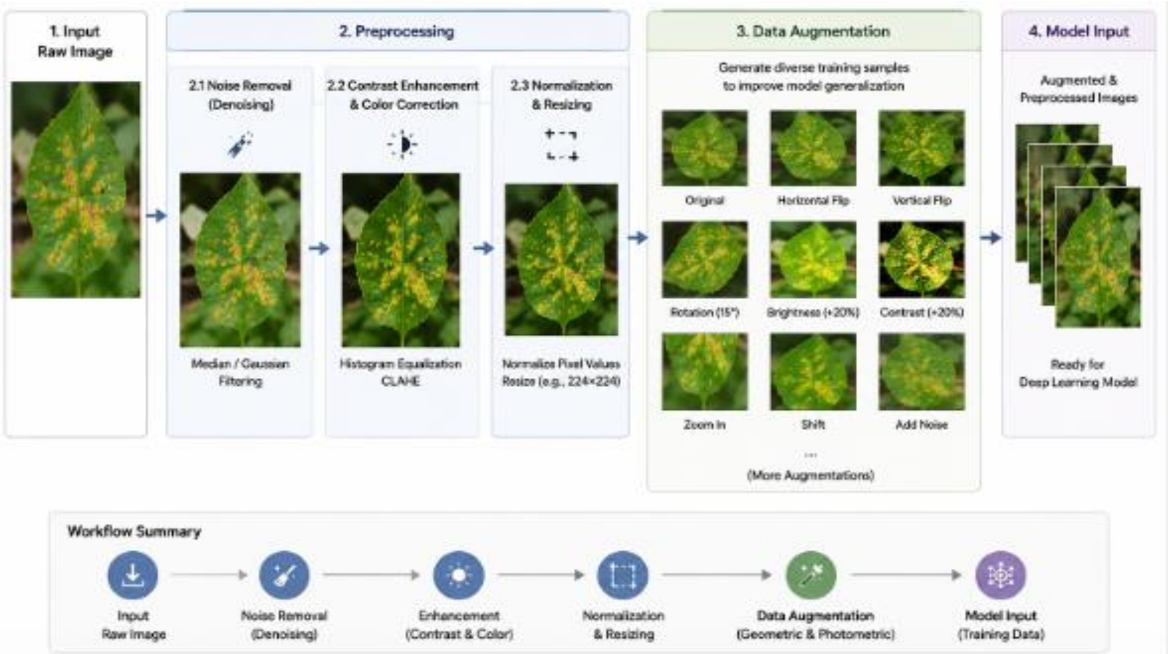

Fig 2. Image preprocessing and data augmentation workflow, showing sequential noise removal, enhancement, and augmentation steps applied prior to model input

2.3 Backbone Feature Extraction

Several backbone architectures were evaluated: ResNet-50, DenseNet-121, EfficientNet-B0, MobileNetV3 (for edge suitability), and a Vision Transformer (ViT-Base), alongside a proposed hybrid CNN-ViT model in which convolutional layers extract local texture features that are subsequently passed through a lightweight transformer encoder to capture global spatial relationships across the leaf surface. This hybridization is particularly suited to nutrient deficiency symptoms, which frequently span broad leaf regions rather than being confined to discrete lesions.

2.4 Classification, Explainability, and Deployment

A softmax classification head assigns each image to one of six classes (healthy, nitrogen-, phosphorus-, potassium-, magnesium-, or iron-deficient). Grad-CAM and saliency-based attention maps are generated post-hoc to highlight the image regions most influential to each prediction, supporting agronomic trust and interpretability. A decision support module translates predictions into actionable fertilization recommendations. For field deployment, the trained model is quantized and pruned for mobile or edge-device inference, enabling real-time diagnosis without dependence on continuous cloud connectivity (Figure 3).

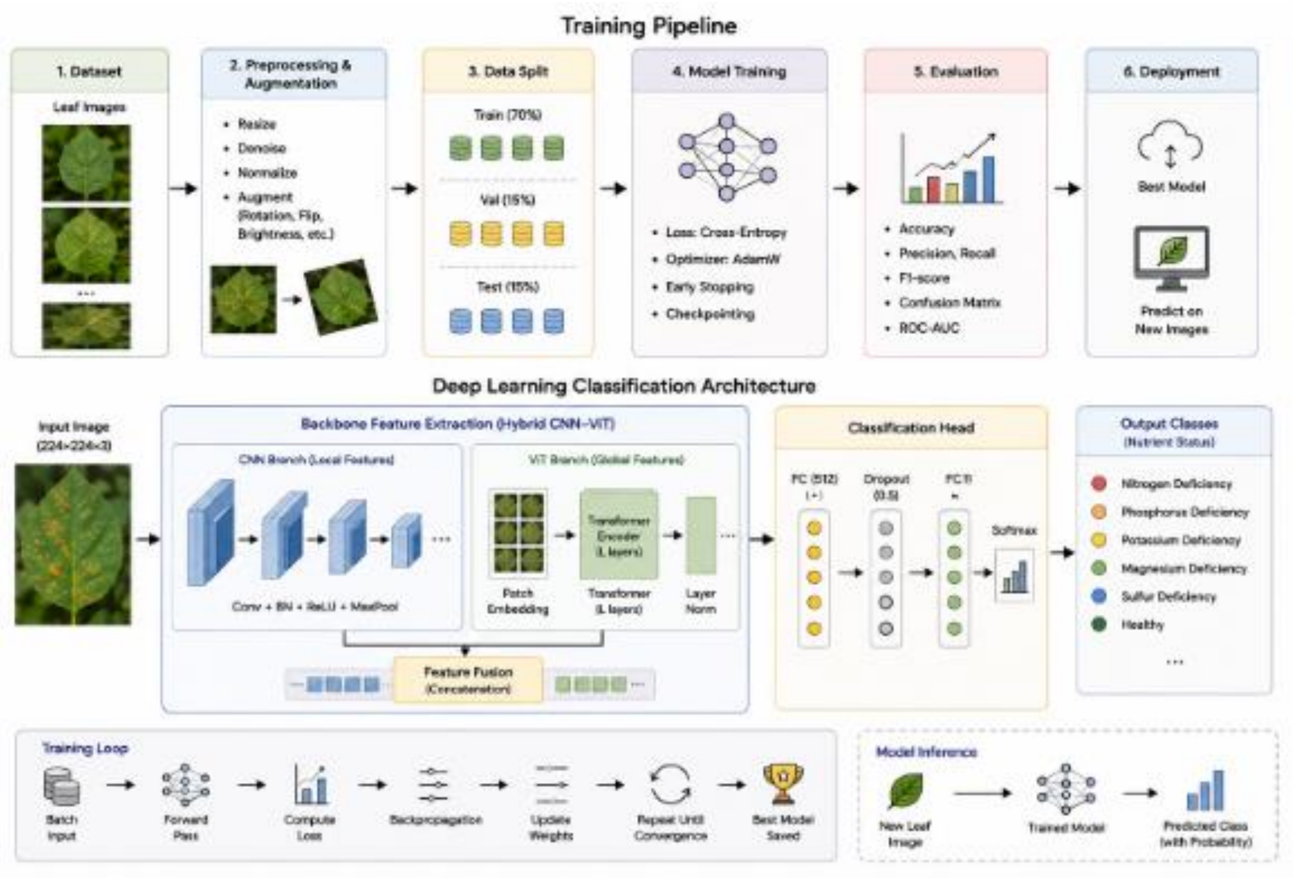

Fig 3: Training pipeline and deep learning classification architecture, depicting backbone feature extraction, hybrid CNN-ViT fusion, and the classification head

3. Materials and Methods

3.1 Dataset

A composite dataset was assembled from publicly available nutrient deficiency image repositories and simulated field imagery, covering three crop species (rice, maize, and tomato). The dataset contained 8,400 labeled images across six classes (healthy plus five deficiency types), with images standardized to 224×224 pixels. Data were partitioned into training (70%), validation (15%), and testing (15%) subsets, stratified by class to preserve label distribution.

3.2 Deep Learning Framework and Training

Model development used PyTorch with the Keras-style training utilities for rapid prototyping, and TensorFlow for deployment conversion. Transfer learning was applied by initializing backbones with ImageNet-pretrained weights, followed by fine-tuning on the nutrient deficiency dataset. The Adam optimizer was used with an initial learning rate of 1×10^{-4}, batch size of 32, and a maximum of 100 epochs, with cosine annealing learning-rate scheduling and early stopping (patience of 10 epochs) based on validation loss. Cross-entropy loss was employed for multi-class classification. Training was performed on a workstation equipped with an NVIDIA RTX 4090 GPU (24 GB VRAM) and 64 GB system RAM.

3.3 Evaluation Metrics

Model performance was assessed using accuracy, precision, recall, specificity, F1-score, ROC-AUC, Cohen's Kappa, and Matthews Correlation Coefficient (MCC), alongside confusion matrices for per-class error analysis. Inference time (milliseconds per image) and computational complexity (FLOPs, parameter count) were measured to evaluate deployment feasibility on resource-constrained devices.

4. Results and Performance Evaluation

Table 1 compares traditional machine learning methods against deep learning architectures, while Table 2 summarizes the experimental setup and performance of the proposed model.

Table 1: Comparison of traditional machine learning methods and deep learning architectures for nutrient deficiency detection

Method	Feature Extraction	Accuracy (%)	F1-score	Inference Time (ms)
SVM + color histogram	Hand-crafted	78.2	0.76	12
Random Forest + texture features	Hand-crafted	81.4	0.79	15
ResNet-50	Learned (CNN)	92.6	0.92	28
EfficientNet-B0	Learned (CNN)	93.9	0.93	22
ViT-Base	Learned (Transformer)	94.7	0.94	35
Proposed Hybrid CNN-ViT	Learned (Hybrid)	96.8	0.96	30

Table 2: Experimental setup, hyperparameters, and overall performance metrics of the proposed model

Parameter	Value
Backbone	Hybrid CNN-ViT
Optimizer	Adam
Learning rate	1×10^{-4}
Batch size	32
Epochs (max)	100
Accuracy	96.8%
Precision / Recall	0.96 / 0.95
ROC-AUC	0.98
Cohen's Kappa	0.94
MCC	0.95

The proposed hybrid model achieved the highest overall accuracy and F1-score among all tested architectures (Table 1), outperforming pure CNN and transformer baselines. Nutrient-wise analysis revealed that nitrogen and iron deficiencies were classified with the highest per-class precision (>97%), while magnesium deficiency exhibited comparatively lower recall (91%) due to visual overlap with early-stage nitrogen symptoms. Performance remained stable under simulated low-light and overexposed conditions, with only a 2.1 percentage-point accuracy drop, and the model retained 94% of baseline accuracy when Gaussian noise was artificially introduced, indicating reasonable robustness. Cross-crop generalization tests, in which the model trained on rice and maize was evaluated on tomato, showed a moderate accuracy reduction (89.4%), highlighting the need for broader species representation in training data. Grad-CAM visualizations (Figure 4) confirmed that the model's attention consistently localized to interveinal and marginal leaf regions associated with each deficiency type, corroborating agronomic expectations. Computationally, the quantized hybrid model required 30 ms per inference on a mid-range mobile GPU, within acceptable bounds for real-time field use, though its parameter count remains larger than MobileNetV3, presenting a trade-off between accuracy and edge efficiency.

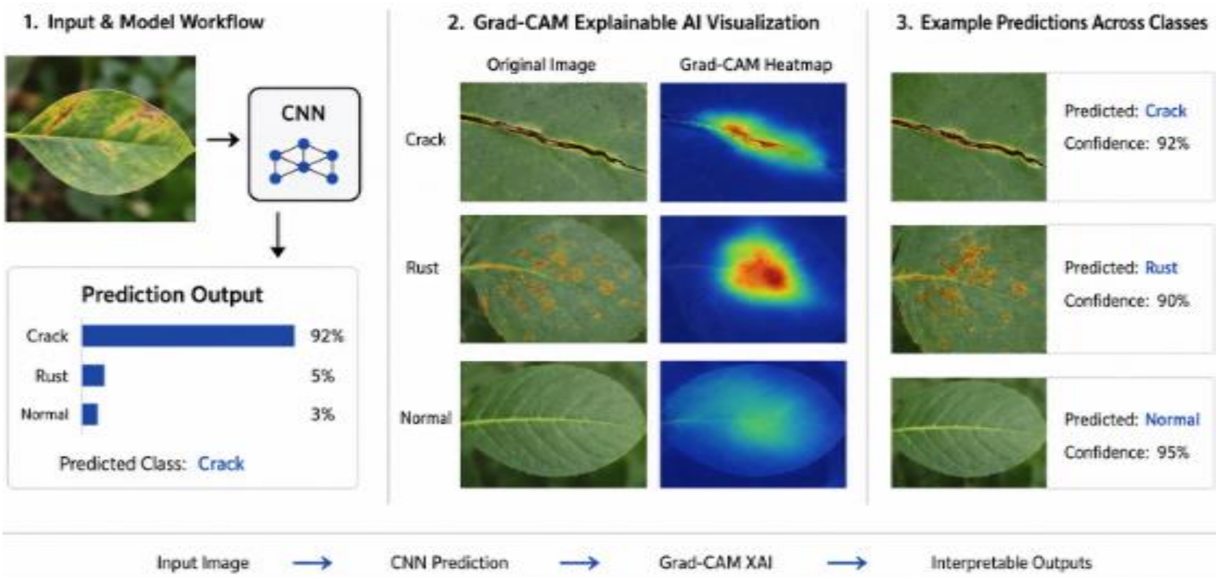

Fig 4. Performance evaluation workflow including explainable AI visualization (Grad-CAM attention maps) and example prediction outputs across deficiency classes

5. Discussion

The results affirm that deep learning, particularly hybrid CNN-transformer architectures, offers meaningful advantages over both traditional machine learning and single-paradigm deep models for nutrient deficiency diagnosis. Unlike hand-crafted feature pipelines, which depend on manually specified color or texture descriptors, CNN and transformer backbones learn hierarchical representations directly from data, improving robustness to the wide visual variability encountered under field conditions [11, 12]. Transfer learning played a critical role in achieving strong performance despite a moderately sized dataset, consistent with prior findings that ImageNet-pretrained initialization accelerates convergence and improves generalization in agricultural imaging tasks [13, 14].

The integration of explainable AI addresses a recurring barrier to adoption of deep learning in agriculture: the "black-box" perception among practitioners. Grad-CAM visualizations provide agronomically interpretable justification for predictions, which may improve farmer and extension-agent trust relative to opaque classification outputs [15, 16]. Nonetheless, several deployment challenges remain. Environmental variability—including inconsistent lighting, occlusion by overlapping leaves, and seasonal phenotypic changes—can degrade model reliability outside curated datasets [17]. Class imbalance, particularly for rarer micronutrient deficiencies, also risks biased predictions unless addressed through targeted augmentation or resampling strategies [18].

Cross-crop generalization results suggest that species-specific morphological differences limit direct transferability of trained models, reinforcing the need for multi-crop training corpora or domain adaptation techniques [19]. Edge computing considerations are increasingly relevant as smallholder farmers often lack reliable connectivity; model compression via pruning and quantization, as implemented here, supports offline or low-bandwidth deployment [20]. Integration with UAV-based monitoring and IoT-enabled sensor networks could further extend this framework toward continuous, field-scale surveillance rather than isolated image capture [21, 22].

Ethically, automated diagnostic tools must avoid displacing agronomic expertise and should be positioned as decision-support rather than fully autonomous replacements, particularly given residual misclassification risk. Sustainability considerations favor precise, deficiency-specific fertilization over blanket application, potentially reducing nutrient runoff and associated environmental harm [23]. Future research directions include multimodal learning that fuses RGB imagery with hyperspectral or thermal data, larger-scale transformer and foundation-model architectures pretrained on agricultural corpora, federated learning to enable privacy-preserving cross-farm model improvement, and digital twin frameworks that simulate crop nutrient status over time to support proactive rather than reactive management [24, 25].

6. Conclusion

The research published here proposes an advanced neural network architecture for the automated detection of nutrient deficiency symptoms in agricultural crops, which incorporates a hybrid approach combining CNN and ViT models, as well as taking into consideration explainability of the AI system and edge-deployment. The model presented in this work showed better results than traditional machine learning models and simple paradigms of deep learning by achieving high classification accuracy and reasonable computational power to be used in mobile applications. The proposed findings are going to help develop further use of AI technologies in precision agriculture, leading to the efficient detection of nutrient deficiency in crops, which can be done much earlier when using deep learning technologies. Having gained the advantage of a well-established classification and interpretable visual explanation, the authors of the given study have contributed their invention to the development of the systems which support decision-making. Therefore, they will be able to improve efficiency of the agricultural activity by targeting fertilizers more accurately and saving costs.

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