ML Models to Differentiate Nitrogen Deficiency from Other Nutrient Stress in Plants A Comprehensive Review

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***Abstract*—Differentiating nitrogen (N) deficiency from other nutrient stresses (e.g., phosphorus, potassium, sulfur, micronutrients) is a critical agricultural task: correct diagnosis leads to targeted fertilizer application, cost savings, and reduced environmental harm. Recent advances in machine learning (ML), remote sensing (hyperspectral/multispectral/UAV), and low-cost imaging have enabled non-destructive nutrient diagnosis, but most work has focused on detecting a single nutrient (often N) rather than distinguishing among multiple nutrient stresses. This review synthesizes literature (2018–2025+) on ML approaches for multi-class nutrient deficiency detection, surveys datasets and sensing modalities, compares methods (classical ML, deep learning, multimodal fusion), discusses evaluation practices, and identifies open challenges and research directions—particularly for reliable differentiation of N deficiency from other nutrient stresses in real-world conditions. Key recommendations include multimodal sensing, targeted data-collection protocols, domain adaptation/federated learning, and explainable models for agronomic adoption.**

***Index Terms*—nitrogen deficiency, nutrient stress, machine learning, hyperspectral, multispectral, UAV, multi-class classification, precision agriculture**

I. INTRODUCTION

Nitrogen is a primary macronutrient closely linked to chlorophyll content, photosynthetic capacity, and crop productivity. Deficiencies in N and other nutrients produce overlapping visual symptoms (chlorosis, stunting, necrosis), making field diagnosis error-prone. Laboratory assays (soil/leaf chemical analysis) are accurate but slow and costly; therefore, rapid, non-destructive, and field-deployable diagnostic tools are highly desirable. Machine learning models applied to spectral and image data can detect and quantify nutrient status; however, most studies focus on single-nutrient detection or regression of leaf nitrogen content rather than multi-class classification that discriminates N deficiency from other nutrient stresses and from biotic/abiotic disorders. This review examines the state of the art in ML methods addressing that discrimination problem, highlights available datasets and sensors, and lays out practical research pathways to build robust, generalizable systems for multi-nutrient diagnosis.

II. SCOPE AND METHODOLOGY OF THE REVIEW

Scope: peer-reviewed articles, datasets, preprints, and applied studies (≈2018–2025) that address (a) detection/estimation of nitrogen and other nutrient deficiencies using ML, (b) multi-class nutrient classification (N vs P vs K vs others), or (c) datasets and sensors useful for that task.
Method: targeted literature and dataset search (hyperspectral/multispectral/UAV + ML + nutrient deficiency), followed by synthesis across sensing modalities, feature-engineering practices, ML model families, evaluation protocols, and deployment considerations. Representative sources include hyperspectral leaf studies, UAV multispectral field mapping, and deep-learning classification frameworks for nutrient/disease discrimination.

III. WHY MULTI-CLASS NUTRIENT DIFFERENTIATION IS HARD (TECHNICAL CHALLENGES)

1.Symptom similarity: N, K, S and some micronutrient deficiencies produce overlapping leaf discoloration patterns; even agronomists can misidentify syndromes visually.

2.Confounders: Diseases, water stress, and nutrient deficiencies can co-occur, confounding spectral signatures.
3.Scale & geometry: Spectral signals differ between leaf-level (proximal) and canopy-level (remote) data; canopy structure, shadows, and soil background introduce noise.
4.Data scarcity: Few publicly available, well-labeled multi-nutrient datasets exist; many studies are crop- or region-specific, limiting generalization.
5.Temporal dynamics: Deficiency symptoms and spectra evolve with growth stage and treatment timing, so temporal data are often needed.

IV. SENSING MODALITIES & DATASETS — WHAT WORKS FOR DIFFERENTIATION

4.1 Hyperspectral (leaf and canopy)
•Strengths: Very high spectral resolution, capture subtle absorption features linked to chlorophyll, proteins, and leaf chemistry—effective for quantitative LNC (%N) estimation and for separating overlapping nutrient signals.
•Limitations: Cost, weight (for UAVs), large data volumes, and need for radiometric calibration. Leaf-level hyperspectral libraries (e.g., maize spectral libraries; crop-specific datasets) are valuable for training interpretable regressors/classifiers.

4.2 Multispectral & RGB (UAV / smartphone)
•Strengths: Cost-effective, scalable for field-scale mapping; vegetation indices (NDVI, GNDVI, red-edge indices) and texture features often provide discriminative signals when combined with ML. Smartphone RGB models democratize access.
•Limitations: Lower spectral fidelity can limit multi-class discrimination when nutrient signals are subtle; sensitive to illumination and soil background. Public UAV/SPAD datasets exist for SPAD/LNC mapping.
4.3 Proximal soil & in-situ sensors
•Strengths: Provide ground-truth or complementary inputs (soil nitrate sensors, ion-selective probes) that improve model robustness and mechanistic interpretation.
•Limitations: Requires deployment and maintenance on-farm.
4.4 Public datasets (examples)
•CoLeaf / CoLeaf-DB (coffee leaf nutrient deficiency images with multiple nutrient labels).
•Kaggle / community datasets for nutrient-deficient rice and other crops (useful starting points but often imbalanced).
•Spectral libraries / hyperspectral datasets (maize, wheat, fruit trees) that provide band-resolved signatures under controlled nutrient treatments.
Takeaway: For robust N-vs-other differentiation, multimodal datasets that combine hyperspectral (or multispectral) imaging with ground truth leaf/soil chemistry and temporal samples are ideal.

V. ML METHODS FOR MULTI-CLASS NUTRIENT DIFFERENTIATION

5.1 Classical ML & ensemble methods
•PLSR, SVM, Random Forest, XGBoost are widely used for regression (LNC/SPAD) and classification (deficiency vs healthy). They work well with engineered features (indices, selected bands) and modest dataset sizes and provide interpretable feature importance useful for agronomists.
5.2 Deep learning approaches
•CNNs & Transformers: Applied to RGB/UAV imagery for multi-class classification (N, P, K, disease). Transfer learning (pretrained ImageNet backbones) is common to mitigate data scarcity. Recent works (e.g., GNNs or region-aware CNNs) improve localization of symptomatic regions and multi-label classification.
5.3 Multimodal fusion & hybrid pipelines
•Feature-level fusion: combine spectral indices + texture + soil sensor readings → fed to RF/XGBoost or MLP.
•Decision-level fusion: independent predictors for spectral and soil inputs, fused by meta-classifier.
•Fusion is essential when differentiating subtle nutrient signals that manifest across modalities.
5.4 Recent algorithmic advances relevant to the task
•Attention and transformer-based backbones for richer context modelling in high-resolution images.
•Graph-based & region-aware networks (GNNs) that capture spatial relationships on a leaf (venation vs interveinal chlorosis differentiation).
•Generative models (GANs/diffusion) to synthesize scarce nutrient-deficiency images for data augmentation.
•Self-supervised / contrastive learning to leverage large unlabelled image collections and improve feature robustness.

VI. EVALUATION PRACTICES & BENCHMARKS

6.1 Targets and metrics

•Regression: leaf N% (chemical analysis), SPAD readings → RMSE, MAE, R^2, rRMSE.

•Classification: multi-class labels (N, P, K, S, micronutrient, disease, healthy) → accuracy, precision, recall, F1, per-class AUC; confusion matrices are crucial to inspect N vs P/K confusion.

6.2 Validation best practices

•Spatial / temporal holdout: to test generalization across fields and seasons.

•Stratified sampling by growth stage & cultivar to avoid confounding.

•Per-class balancing or cost-sensitive training because some nutrient classes are rarer.

•Explainability checks: feature importance, Grad-CAM or saliency maps to verify models rely on leaf regions/indices rather than spurious cues (pots, labels).

VII. REPRESENTATIVE STUDIES & FINDINGS (SELECT EXAMPLES)

•Hyperspectral leaf studies (Yamashita et al., 2020): dissection of hyperspectral reflectance enables robust estimation of leaf N and chlorophyll contents—useful baseline for regression tasks.

•ML frameworks for foliar nutrient prediction (Osco et al., 2020): demonstrated that ML regressors on hyperspectral measurements can predict multiple nutrient contents (e.g., N, Ca) in orange leaves.

•Deep multi-class classifiers (PND-Net and similar works): graph/region-aware models reported strong performance distinguishing nutrient deficiencies and disease classes in mixed datasets (2024 onward). These show promise for discriminative tasks but rely on curated datasets.

•UAV-based SPAD/LNC mapping (Raj et al., 2021; Khose et al., 2024): multispectral UAV data with ML achieved field-scale mapping of SPAD/LNC, supporting downstream VR-N prescriptions; however, many such studies focus on N only rather than multi-nutrient discrimination.

VIII. PRACTICAL CHALLENGES & FAILURE MODES

1.Class confusion: Models often confuse N deficiency with other causes of chlorosis (S deficiency, some diseases). Confusion matrices often show N ↔ K/P overlap.

2.Dataset bias and covariates: Non-standard image backgrounds, pot labels, or experimental setups can cause models to learn spurious correlations.

3.Scale mismatch: Models trained on leaf-level controlled conditions may fail on canopy-level field images.

4.Environmental variability: Illumination, soil background, and seasonality change spectral responses—robust preprocessing and temporal models are needed.

5.Operational deployment: Translating model output into actionable fertilizer recommendations requires agronomic mappings (how much N to apply given predicted class/level) and economic validation.

IX. PROMISING RESEARCH DIRECTIONS (RECOMMENDATIONS)

9.1 Dataset & Benchmarking

•Build large, multi-crop, multi-nutrient, multi-stage datasets with lab-measured leaf/soil chemistry as ground truth (include N, P, K, S, common micronutrients, plus diseases and abiotic stresses). Use standardized acquisition protocols (illumination, distance, metadata). Public release is high-impact. (Examples: expand CoLeaf / CoLeaf-DB.)

9.2 Multimodal & Temporal Fusion

•Combine hyperspectral/multispectral/RGB + soil sensors + weather time series; temporal models (LSTM/transformer) can capture symptom evolution for earlier discrimination.

9.3 Domain Adaptation & Federated Learning

•Use domain adaptation (unsupervised/supervised) and federated learning so models trained across farms generalize while preserving data privacy. This addresses cross-region generalization problems.

9.4 Explainability & Agronomic Integration

•Integrate XAI (saliency maps, feature importance) and agronomic rules (crop-specific thresholds) so outputs are interpretable and actionable by extension agents and farmers.

9.5 Synthetic & Self-supervised Data Strategies

•Use generative models to augment rare nutrient classes and self-supervised pretraining on large unlabeled imagery to improve learned representations before fine-tuning for multi-class tasks.

9.6 Field Trials & Economic Assessment

•Conduct multi-season VR-N/VR-NPK trials where ML-derived prescriptions are compared against farmer practice to measure yield, profit, and environmental outcomes. This closes the loop from detection to management.

X. PROPOSED RESEARCH ROADMAP (PRACTICAL PLAN — CONCISE)

1.Data collection: controlled greenhouse + field plots; induced single-nutrient deficiencies (N, P, K, S) across growth stages; collect hyperspectral leaf scans, UAV multispectral imagery, RGB close-ups, soil/leaf lab chemistry, and metadata.

2.Baseline models: PLSR / RF / XGBoost on engineered indices; evaluate regression (leaf N%) and classification (multi-class).

3.Deep learning pipeline: fine-tune CNNs (MobileNet/EfficientNet) and transformer backbones on RGB/UAV images; use Grad-CAM to validate saliency.

4.Fusion: combine spectral features + soil sensor inputs in RF / MLP fusion model.

5.Generalization: test spatial/temporal holdout; attempt domain adaptation and self-supervised pretraining.

6.Field trial: generate prescription maps and run small VR-N/VR-NPK trials; evaluate agronomic & economic metrics.

XI. CONCLUSION

Differentiating nitrogen deficiency from other nutrient stresses using machine learning is an active and emerging research area with high practical value. Advances in hyperspectral sensing, UAV mapping, multimodal fusion, and deep learning architectures make multi-class nutrient discrimination increasingly feasible. Key bottlenecks are high-quality multi-nutrient datasets, cross-domain generalization, and the final translation of model outputs into agronomic decisions. Addressing these through standardized datasets, multimodal time-series approaches, explainable models, and on-farm trials will be critical to bring robust diagnostic systems into routine agricultural use.

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REFERENCES

[1] 1.Yamashita, H., et al., Dissection of hyperspectral reflectance to estimate nitrogen and chlorophyll contents, Scientific Reports, 2020.

[2] 2.Osco, L. P., et al., A Machine Learning Framework to Predict Nutrient Content in Leaf Hyperspectral Measurements, Remote Sensing, 2020.

[3] 3.Khose, S. B., et al., UAV-based multispectral image analytics and machine learning for predicting crop nitrogen (SPAD) values, 2024.

[4] 4.Bera, A., et al., PND-Net: plant nutrition deficiency and disease classification using GNN, Scientific Reports, 2024.