Artificial Intelligence: Transforming Nutrient Deficiency Detection in Precision Agriculture

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Introduction

Nutrient deficiency remains one of the most common yet most preventable causes of yield loss in Indian agriculture. Nitrogen, phosphorus and potassium (NPK) deficiencies alone are estimated to depress crop productivity across large tracts of intensively cultivated land, often because farmers detect the problem only after visible symptoms such as yellowing, stunted growth or leaf curling appear by which time considerable yield potential is already lost. Traditional diagnosis relies on visual scouting by trained agronomists or on laboratory soil and plant analysis, both of which are slow, subjective and impractical to scale across millions of small landholdings. Artificial intelligence (AI) and deep learning (DL) in particular, is now changing this picture. By combining low-cost sensors, digital imagery and spectral data with trained neural networks, researchers are building systems that can flag a nutrient deficiency within seconds, well before the human eye would notice it. This article reviews four such approaches that illustrate where the field currently stands and where it is headed.

Why Early, Automated Detection Matters

Fertilizer use in India is frequently blanket and calendar-based rather than need-based, leading to both under- and over-application. Under-application caps yield; over-application wastes money, pollutes water bodies and in the case of nitrogen, contributes to greenhouse gas emissions. Site-specific, timely nutrient diagnosis is therefore central to the twin goals of raising farm income and reducing the environmental footprint of agriculture. AI-based detection systems aim to close the gap between when a deficiency begins and when it is corrected, converting a reactive management style into a proactive, data-driven one.

Four AI Approaches to Nutrient Diagnosis

1. IoT-Based Colorimetric Sensing

One practical approach couples the century-old colorimetric soil test with modern electronics. A soil sample is mixed with a reagent and the resulting colour change is read by an optical or LDR (Light Dependent Resistor) sensor rather than by the human eye. The digitised reading is transmitted via an IoT (Internet of Things) module (commonly an Arduino-ESP8266 pairing) to a cloud dashboard, giving farmers or extension workers an NPK estimate without sending samples to a laboratory (Madhumathi *et al.*, 2022). This approach is inexpensive and field-deployable, making it attractive for smallholder contexts, though it still requires basic sample preparation and reagents.

2. Image-Based Deep Learning (YOLOv8s)

A second, rapidly growing approach skips wet chemistry altogether and reads deficiency symptoms directly from leaf images. In one notable study, a You Only Look Once Version 8 (YOLOv8), small variant (YOLOv8s) object-detection model was trained on over six thousand RGB images of soybean leaves grown under long-term, controlled nutrient-deficient conditions. The model learned to localise and classify nitrogen, phosphorus and potassium deficiency symptoms with a mean average precision (mAP) of 99.18 per cent during training and 98.51 per cent on validation data, processing each image in only a few milliseconds - fast enough for real-time use on a smartphone or drone feed (Jeong *et al.*, 2025). This demonstrates how camera-based diagnosis, once symptoms are visible, can already rival laboratory-grade discrimination.

3. Deep Learning on ICP-AES Spectral Data

For applications demanding laboratory-grade accuracy across a wider range of elements, deep learning models are increasingly being paired with Inductively Coupled Plasma - Atomic Emission Spectroscopy (ICP-AES) data. Rather than manually interpreting the emission spectra produced when a digested plant or soil sample is excited in a plasma torch, a neural network learns the complex, overlapping spectral patterns associated with each nutrient, improving both throughput and consistency compared with manual calibration (Nakamura *et al.*, 2025). This route remains destructive and lab-bound, but it offers a route to multi-nutrient profiling including micronutrients that image-based methods cannot yet match.

4. Hyperspectral and Reflectance Spectroscopy

The fourth approach senses nutrient status without ever touching the plant. Hyperspectral or multispectral reflectance instruments capture how a leaf or canopy reflects light across hundreds of narrow bands spanning the visible to near-infrared range; deep learning models then link subtle reflectance signatures to nitrogen and other nutrient concentrations (Wan *et al.*, 2024; Rivadeneira-Bolanos *et al.*, 2024). Because it is fully non-contact, this method is well suited to scaling up from a single leaf to Unmanned Aerial Vehicle (UAV)-based canopy surveys, though sensor cost and the complexity of high-dimensional spectral data remain barriers to on-farm adoption.

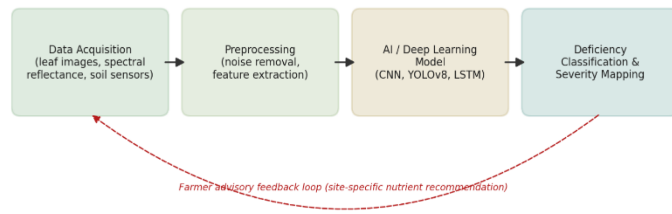

Fig. 1: General workflow of an AI-based nutrient deficiency detection system

Comparing the Approaches

Table 1 summarises the data source, target nutrients and reported performance of the four approaches discussed above, while Table 2 sets out their principal trade-offs.

Table 1. Comparison of representative AI-based nutrient deficiency detection approaches

AI Approach	Data / Sensor Type	Target Nutrient(s)	Reported Performance	Reference
IoT-based colorimetric sensing	Reagent colour change via colour/optical sensors, cloud-linked	N, P, K (soil)	~90–93% classification accuracy	Madhumathi *et al.*, 2022
YOLOv8s object detection	RGB leaf images (field/glasshouse)	N, P, K (soybean leaf)	mAP@0.5 = 99.18% (training), 98.51% (validation)	Jeong *et al.*, 2025
Deep learning on ICP-AES spectral data	Elemental emission spectra from plant/soil digests	Multi-nutrient (macro and micro)	High correlation with lab reference values	Nakamura *et al.*, 2025
Hyperspectral/reflectance spectroscopy + DL	Canopy or leaf reflectance (400-2500 nm)	N primarily; extendable to P, K	~93–96% estimation accuracy	Wan *et al.*, 2024; Rivadeneira-Bolanos *et al.*, 2024

Table 2. Advantages and limitations of each approach

Approach	Key Advantage	Key Limitation
IoT colorimetric sensing	Low-cost, field-deployable, real-time cloud logging	Needs sample preparation/reagents; limited to macronutrients
Image-based [YOLOv8s, Convolutional Neural Network (CNN)]	Non-destructive, fast (millisecond-scale) inference from a photo	Sensitive to lighting, background clutter and training-data diversity
ICP-AES + deep learning	Very high analytical accuracy across many elements	Destructive, lab-bound, high cost per sample
Hyperspectral/reflectance + DL	Non-contact, scalable to canopy/UAV level	Expensive sensors; large, high-dimensional data need careful modelling

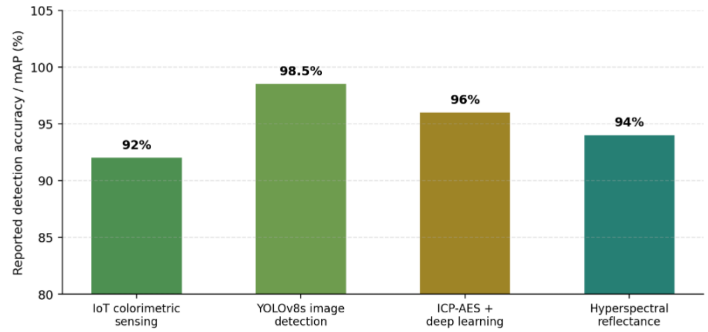

Fig. 2: Bar chart of reported detection accuracy/mAP

Challenges on the Path to Field Adoption

Despite encouraging results, none of these systems is yet a plug-and-play solution for the average Indian farm. Image-based models need large, diverse, locally-collected training datasets to generalise across crop varieties, growth stages and lighting conditions; sensor-based systems need ruggedisation and calibration for field use; and spectral methods remain capital-intensive. Data connectivity in rural areas, the cost of hardware and the need for regional-language advisory interfaces are equally important, non-technical barriers. Integrating outputs from multiple sensing modalities for example, combining a low-cost image classifier for rapid screening with periodic ICP-AES confirmation may offer the most realistic near-term pathway to field-ready systems.

The Road Ahead

The direction of travel is nonetheless clear. As camera-equipped smartphones, low-cost sensors and cloud computing become more accessible in rural India, AI-based nutrient diagnosis is well placed to move from research laboratories to extension services and eventually, into the hands of farmers themselves. Coupling such diagnostic tools with site-specific fertilizer recommendation engines could meaningfully reduce both input costs and the environmental burden of Indian agriculture, while helping close the yield gap that nutrient deficiencies continue to create.

Conclusion

Artificial intelligence is transforming nutrient deficiency diagnosis from a slow, reactive process into a rapid, precise and data-driven decision support system for precision agriculture. The approaches reviewed in this article including IoT-based colorimetric sensing, image-based deep learning using CNN and YOLOv8s, deep learning integrated with ICP-AES spectral analysis and hyperspectral reflectance spectroscopy demonstrate the potential of AI to detect nutrient deficiencies with high accuracy while reducing dependence on conventional laboratory analyses. Although challenges related to sensor cost, data availability, field variability, connectivity and model generalization remain, continued advances in machine learning, affordable sensing technologies and digital agriculture are expected to accelerate their adoption. As these technologies become more accessible, AI-enabled nutrient diagnosis can support site-specific fertilizer management, improve nutrient use efficiency, enhance crop productivity, reduce environmental impacts and contribute to the development of more sustainable and climate-resilient agricultural systems.

References

Jeong M., Park S., Kwon S. M., Lim K., Jung D. R., Lee H. S., Kim H. J. and Shin J. H. (2025). Rapid detection of soybean nutrient deficiencies with YOLOv8s for precision agriculture advancement. Scientific Reports, 15(1), 13810.

Madhumathi R., Arumuganathan T. and Shruthi R. (2022). Soil nutrient detection and recommendation using IoT and fuzzy logic. Computer Systems Science & Engineering, 43(2), 455-469.

Nakamura S., Imaya A. and Ikazaki K. (2025). Deep learning using inductively coupled plasma spectroscopy spectra accurately predicts various soil physicochemical properties for soil diagnosis. Scientific Reports, 15(1), 37753.

Rivadeneira-Bolanos F. E., Nope-Rodriguez S. E., Paez-Melo M. I. and Pinedo-Jaramillo C. R. (2024). Automated prediction of phosphorus concentration in soils using reflectance spectroscopy and machine learning algorithms. MethodsX, 13, 102996.

Wan S., Hou J., Zhao J., Clarke N., Kempenaar C. and Chen X. (2024). Predicting soil organic matter, available nitrogen, available phosphorus and available potassium in a black soil using a nearby hyperspectral sensor system. Sensors, 24(9), 2784.

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