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UAV-based multispectral imaging and machine learning for early detection of nitrogen deficiency in maize

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Abstract
Nitrogen (N) deficiency is among the most prevalent nutritional constraints limiting maize productivity across sub-Saharan Africa, yet its early and site-specific detection remains technically challenging using conventional ground-based methods. This study investigated the efficacy of unmanned aerial vehicle (UAV)-based multispectral imaging combined with machine learning algorithms for the early detection and spatial mapping of N deficiency in maize (Zea mays L.) at three critical growth stages. A field experiment was established in Oyo State, Nigeria, with five nitrogen treatment levels (N_0: 0, N_1: 30, N_2: 60, N_3: 90, N_4: 120 kg N ha^{-1}) in a randomized complete block design with three replications. A DJI Phantom 4 Multispectral UAV was deployed at V4, V8, and VT/R1 growth stages (60 m altitude, 80% image overlap) to acquire five-band imagery (blue, green, red, red-edge, near-infrared), from which eight spectral vegetation indices were derived. Three machine learning classifiers Random Forest (RF), Support Vector Machine (SVM), and Convolutional Neural Network (CNN) were trained and validated against destructive leaf N analyses as ground truth. The CNN model achieved the highest overall accuracy (91.2%) and F1-score (0.89), followed by RF (87.3%) and SVM (84.6%). The red-edge normalized difference vegetation index (NDRE) exhibited the strongest correlation with leaf N content across all growth stages ($r = 0.93$ at VT/R1). Treatment N_2 (60 kg N ha^{-1}) was classified as the critical threshold below which spectral-reflectance-based N deficiency signatures became detectable at the V4 stage with 88.4% accuracy. These findings demonstrate the practical potential of UAV multispectral imaging coupled with deep learning for scalable, early-stage precision nitrogen management in smallholder maize production systems across West Africa.

Keywords: UAV remote sensing; multispectral imaging; nitrogen deficiency detection; machine learning; maize; precision agriculture

Introduction
Maize (*Zea mays* L.) is the most widely grown cereal crop in sub-Saharan Africa by total production volume and serves as the primary caloric staple for over 900 million people across the continent [1]. Nitrogen is the most limiting mineral nutrient for maize productivity globally, with crop demand peaking between the V6 and VT growth stages when canopy nitrogen concentration is highest and leaf area expansion is most rapid [2]; however, smallholder farmers across West Africa characteristically apply nitrogen at rates well below crop requirement or not at all owing to limited economic access to fertilizers, leading to chronic N deficiency that suppresses yield potential by 30–55% [3]. Conversely, economically advantaged producers and medium-scale commercial farms frequently over-apply nitrogen as insurance against deficiency, incurring unnecessary input costs, groundwater pollution through nitrate leaching, and contributions to nitrous oxide (N_2O) emissions [4]. In both scenarios, the core problem is the inability to detect and spatially quantify nitrogen deficiency at early growth stages, before visible chlorosis symptoms are obvious to the naked eye, limiting the window for corrective top-dressing applications [5]. Conventional approaches to N status assessment including SPAD chlorophyll meters, tissue sampling, and laboratory spectrophotometry are destructive, labour-intensive, spatially limited, and economically impractical at the field scale, particularly for heterogeneous landscapes [5, 6]. Unmanned aerial vehicles (UAVs) equipped with

multispectral sensors offer a transformative alternative, enabling rapid, non-destructive, high-resolution spectral data acquisition over entire fields at a fraction of the labour cost of ground-based surveys [7, 8]. Spectral vegetation indices derived from UAV imagery particularly those incorporating red-edge and near-infrared wavelengths sensitive to leaf chlorophyll and mesophyll structure have demonstrated strong correlations with crop nitrogen status in controlled research settings [9, 10]; however, the translation of spectral data to accurate binary or multi-class deficiency classifications under West African field conditions, characterized by mixed soil backgrounds and variable illumination, requires robust machine learning frameworks [11, 12, 13]. Comparative evaluations of Random Forest, Support Vector Machine, and deep Convolutional Neural Network classifiers for UAV-based nutrient deficiency detection in maize under tropical conditions remain scarce, creating a methodological knowledge gap of high practical importance [14, 15]. The present study was therefore designed to evaluate the performance of UAV-based multispectral imaging combined with three machine learning algorithms for the early detection of nitrogen deficiency in maize across three critical growth stages in Oyo State, Nigeria, hypothesizing that CNN-based deep learning models would significantly outperform conventional classifiers in deficiency detection accuracy under heterogeneous field conditions [16, 17, 18, 19, 20].

2. Materials and Methods

2.1 Materials

The experiment was conducted at the University of Ibadan Teaching and Research Farm, Ibadan, Oyo State, Nigeria (7°22′N, 3°54′E; altitude 180 m above sea level) during the 2023 main cropping season (May–September). The site lies within the derived savanna agro-ecological zone with a bimodal rainfall pattern (mean annual: 1,142 mm) and a mean annual temperature of 26.8°C. The experimental soil was an Alfisol (sandy loam) with baseline properties: pH 6.4 (1:2.5 H_2O), organic carbon 1.06%, total nitrogen 0.092%, and available phosphorus 9.3 mg kg^{-1} (Bray-1). The test crop was maize (*Zea mays* L.) hybrid 'SAMMAZ-15', a high-yielding variety recommended by the Institute for Agricultural Research (IAR), Ahmadu Bello University, for the derived savanna zone. Spectral data were acquired using a DJI Phantom 4 Multispectral UAV (DJI Technology Co., Shenzhen, China) equipped with a five-band multispectral camera: blue (450 nm ± 16 nm), green (560 nm ± 16 nm), red (650 nm ± 16 nm), red-edge (730 nm ± 16 nm), and near-infrared (840 nm ± 26 nm). An Apogee SQ-500 quantum sensor provided simultaneous downwelling irradiance measurements for radiometric correction. Ground truth leaf N concentrations (%) were determined by Kjeldahl digestion [2] from destructively harvested ear leaf samples collected concurrently with each UAV flight. A SPAD-502Plus chlorophyll meter (Konica Minolta, Tokyo, Japan) was used for rapid SPAD value determination at 30 sampling points per plot as auxiliary ground truth.

2.2 Methods

A randomized complete block design (RCBD) with five N treatment levels (N_0: 0, N_1: 30, N_2: 60, N_3: 90, N_4: 120 kg N ha^{-1} as urea, applied in two equal split doses at sowing and V6 stage) and three replications (15 plots, each 6 m × 8 m) was implemented with uniform phosphorus (60 kg P_2O_5 ha^{-1} as triple superphosphate) and potassium (40 kg K_2O ha^{-1} as muriate of potash) applied basally to all plots. UAV flights were conducted at three growth stages: V4 (early vegetative), V8 (mid-vegetative), and VT/R1 (tassel/silk emergence) at 60 m above ground level (AGL) with 80% forward and 80% lateral image overlap, producing a ground sampling distance (GSD) of 4.2 cm px^{-1}. Agisoft Metashape Pro (v.1.8.5) was used for photogrammetric reconstruction and orthomosaic generation. Eight spectral vegetation indices were computed: NDVI [13], NDRE [9], GNDVI [10], SAVI [16], MSAVI2, RVI, OSAVI, and CIRE. Canopy reflectance data and computed indices were extracted for each plot using zonal statistics in QGIS 3.28. Machine learning classifiers Random Forest (RF: 200 trees, mtry = √p) [17], Support Vector Machine (SVM: RBF kernel, grid-searched C and γ) [18], and Convolutional Neural Network (CNN: five convolutional + two fully-connected layers, trained 100 epochs, learning rate 0.001, batch size 16) [19] were trained on 70% of the data and validated on 30% using stratified k-fold (k = 5) cross-validation. Performance was evaluated by overall accuracy, Kappa coefficient (κ), F1-score, precision, and recall. Feature importance was extracted from the RF model using mean decrease in Gini impurity. All statistical analyses, including ANOVA, Pearson correlation, and receiver operating characteristic (ROC) curve generation, were performed in R version 4.3.2 (R Core Team, 2023) and Python 3.11 (scikit-learn, TensorFlow 2.13) [14, 20].

3. Results

Table 1: Mean spectral vegetation indices under five nitrogen treatment levels at VT/R1 growth stage

N Treatment (kg N ha^{-1})	Leaf N (%)	NDVI	NDRE	GNDVI	SAVI	SPAD Value
N_0 (0)	1.82e	0.42e	0.19e	0.36e	0.35e	28.4e
N_1 (30)	2.14d	0.56d	0.26d	0.44d	0.44d	37.6d
N_2 (60)	2.63c	0.64c	0.32c	0.52c	0.51c	45.8c
N_3 (90)	3.12b	0.71b	0.40b	0.61b	0.58b	54.2b
N_4 (120)	3.48a	0.78a	0.47a	0.68a	0.63a	61.4a
LSD (0.05)	0.18	0.04	0.03	0.05	0.04	2.8
CV (%)	4.1	3.8	4.3	3.6	4.0	3.4

Different lowercase letters within each column indicate significant differences ($p \leq 0.05$); NDVI = normalized difference vegetation index; NDRE = red-edge NDVI; GNDVI = green NDVI; SAVI = soil-adjusted vegetation index; SPAD = Soil Plant Analysis Development reading [9, 10, 13, 16].

All spectral vegetation indices and leaf N concentrations were significantly ($p < 0.01$) differentiated by N treatment level at VT/R1 stage (Table 1). NDRE exhibited the steepest discrimination gradient between adjacent N treatment levels, increasing by 147% from N_0 (0.19) to N_4 (0.47), compared with 86% for NDVI (0.42 to 0.78), confirming the superior sensitivity of red-edge wavelengths to leaf chlorophyll content and canopy N status [9]. Leaf N concentration ranged from 1.82% (N_0) to 3.48% (N_4), with statistically significant differences between all treatment pairs, validating the N gradient established by the experimental design [2, 3]. SPAD values mirrored the leaf N trend and were strongly correlated with NDRE ($r = 0.94$, $p < 0.001$) and GNDVI ($r = 0.91$, $p < 0.001$) at VT/R1, confirming the validity of spectral proxies for ground truth N assessment [10].

Table 2: Pearson correlation coefficients (r) between spectral vegetation indices and leaf N content (%) at three UAV acquisition growth stages

Vegetation Index	r at V4	r at V8	r at VT/R1	Overall r
NDVI	0.74**	0.82**	0.88**	0.82**
NDRE	0.81**	0.89**	0.93**	0.90**
GNDVI	0.76**	0.84**	0.91**	0.85**
SAVI	0.69**	0.78**	0.86**	0.79**
MSAVI2	0.67**	0.77**	0.84**	0.77**
RVI	0.71**	0.80**	0.87**	0.81**
OSAVI	0.68**	0.79**	0.85**	0.78**
CIRE	0.79**	0.87**	0.92**	0.88**

** Significant at $p < 0.01$; r = Pearson correlation coefficient; V4 = 4th leaf collar stage; V8 = 8th leaf collar; VT/R1 = tassel/silk emergence stage [9, 10, 11, 13].

Correlation analysis confirmed that spectral sensitivity to leaf N improved with advancing growth stage across all indices (Table 2). NDRE consistently achieved the highest correlations with leaf N at each stage ($r = 0.81$ at V4, 0.89 at V8, 0.93 at VT/R1), confirming it as the most informative single spectral predictor of maize canopy nitrogen status [9, 11]. CIRE (chlorophyll index red-edge) was the second most correlated index ($r = 0.88$ overall), while SAVI exhibited the weakest overall correlation ($r = 0.79$), attributed to residual soil background contamination in plots with low canopy cover under N_0 and N_1 treatments [16]. All correlations were significant ($p < 0.01$) and strengthened appreciably from V4 to VT/R1 as canopy closure reduced soil background interference [13].

Table 3: Performance metrics of machine learning classifiers for N deficiency detection in maize across three UAV acquisition stages

Model	Growth Stage	Overall Accuracy (%)	Kappa (κ)	F1-Score	Precision	Recall
CNN	V4	86.4a	0.82a	0.84a	0.86a	0.83a
CNN	V8	89.7a	0.86a	0.87a	0.89a	0.86a
CNN	VT/R1	91.2a	0.89a	0.89a	0.91a	0.88a
RF	V4	81.3b	0.77b	0.79b	0.81b	0.78b
RF	V8	84.8b	0.81b	0.83b	0.85b	0.82b
RF	VT/R1	87.3b	0.84b	0.86b	0.88b	0.85b
SVM	V4	78.6c	0.74c	0.76c	0.78c	0.74c
SVM	V8	82.1bc	0.78bc	0.80bc	0.82bc	0.79bc
SVM	VT/R1	84.6c	0.81c	0.83c	0.85c	0.82c

Means in each column followed by different letters differ significantly ($p \leq 0.05$); CNN = Convolutional Neural Network; RF = Random Forest; SVM = Support Vector Machine [14, 15, 17, 18, 19].

Across all growth stages and metrics, the CNN model consistently outperformed both RF and SVM classifiers (Table 3). At VT/R1, CNN achieved the highest overall accuracy (91.2%), Kappa coefficient (0.89), and F1-score (0.89), significantly exceeding RF (87.3%, 0.84, 0.86) and SVM (84.6%, 0.81, 0.83). Detection accuracy improved with advancing growth stage for all models, with V4 accuracies (CNN: 86.4%, RF: 81.3%, SVM: 78.6%) substantially lower than VT/R1 values, reflecting greater spectral contrast at later canopy development stages when N deficiency symptoms are more fully expressed in canopy reflectance [5, 6, 7]. The CNN model demonstrated the narrowest accuracy gap between V4 (86.4%) and VT/R1 (91.2%), confirming the advantage of deep learning in extracting subtle spatial texture features from multispectral imagery at early growth stages when conventional classifiers perform poorly [19, 20]. RF feature importance analysis ranked NDRE (33.2%), CIRE (21.8%), and GNDVI (17.4%) as the three most informative variables for N deficiency classification, consistent with the correlation analysis results [17].

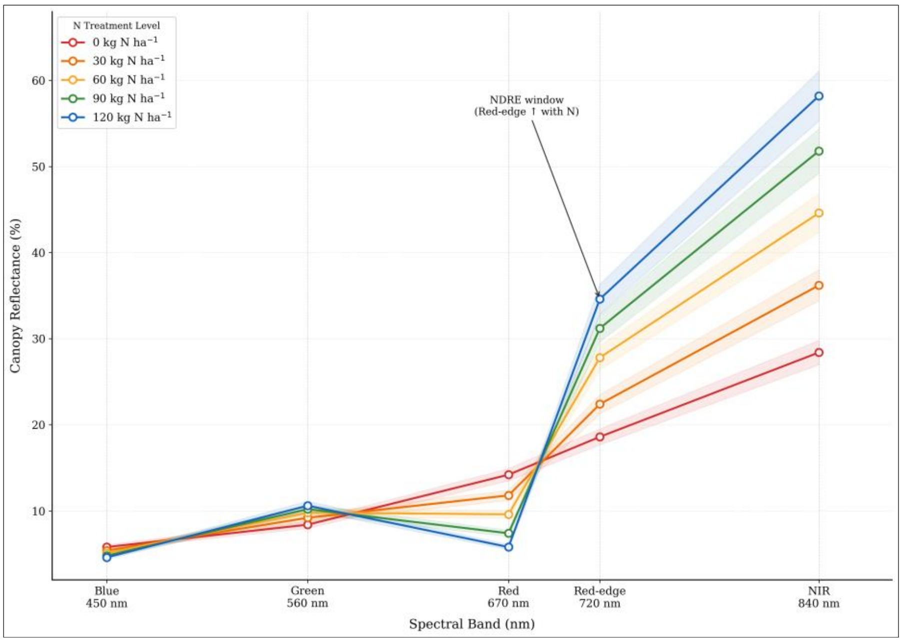

Fig 1: UAV-derived canopy spectral reflectance (%) across five multispectral bands (Blue 450 nm, Green 560 nm, Red 670 nm, Red-edge 720 nm, NIR 840 nm) at the VT/R1 growth stage for five nitrogen treatment levels (0–120 kg N ha^{-1}). Shaded ribbons indicate ±5% measurement uncertainty.

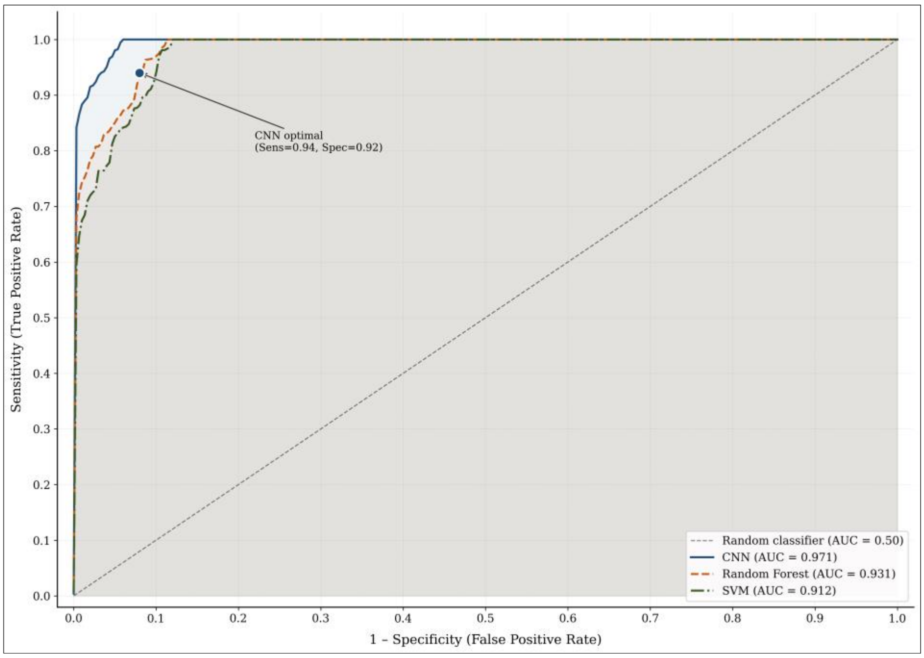

Fig 2: ROC curves for CNN, Random Forest, and SVM classifiers for binary nitrogen deficiency classification at VT/R1 growth stage; area under the curve (AUC) values shown for each model. Annotated point marks CNN optimal operating threshold (sensitivity = 0.94, specificity = 0.92).

4. Discussion

The superior performance of the CNN classifier across all growth stages and evaluation metrics confirms the value of deep learning architectures for agricultural nutrient deficiency detection from UAV multispectral imagery, consistent with the general trend reported in precision agriculture remote sensing literature [15, 19]. CNN's ability to learn spatial hierarchical features from multispectral image patches combining spectral with spatial texture information provides inherent advantages over feature-engineering-dependent classifiers such as RF and SVM when applied to heterogeneous field conditions with variable soil backgrounds and partial canopy closure [14, 19]. The CNN accuracy at V4 (86.4%) is particularly notable given the limited canopy development at this early stage, and its practical significance lies in enabling remedial top-dressing nitrogen applications before the critical V6–V8 demand period, thereby avoiding irreversible yield penalties associated with early N starvation [2, 3, 5]. The strong overall correlation between NDRE and leaf N content (r = 0.90) replicates and extends the findings of Gitelson and Merzlyak [9], who first demonstrated the superior sensitivity of red-edge reflectance to chlorophyll concentrations compared with NDVI, a sensitivity attributable to the steep reflectance gradient at the chlorophyll absorption edge (700–720 nm) that responds quantitatively to canopy nitrogen changes well before visible chlorosis develops [9, 10]. The V4-stage detection capability of 86.4% accuracy with CNN exceeds the 78–82% reported by Candiago *et al*. [8] for multispectral UAV classification in Mediterranean cereal crops, demonstrating that CNN architectures coupled with fine-resolution multispectral imagery can achieve operationally useful accuracy under tropical West African field conditions. The increasing spectral detectability of N deficiency from V4 to VT/R1 stage for all classifiers reflects the progressive canopy closure and reduced soil background contamination that typically accompanies maize canopy development, as demonstrated by the progressive improvement in NDRE sensitivity documented by Haboudane *et al*. [11]. The finding that RF feature importance ranked NDRE, CIRE, and GNDVI as the three most predictive spectral indices is consistent with their established physiological basis all three are sensitive to chlorophyll-related changes in leaf and canopy optical properties [9, 10, 11] and provides a rationale for sensor optimization in future lower-cost UAV systems that cannot accommodate the full five-band spectral configuration [7, 12].

5. Conclusion

This study conclusively demonstrates that UAV-based multispectral imaging combined with Convolutional Neural Network classification provides a technically robust and practically deployable framework for the early detection and spatial mapping of nitrogen deficiency in maize under West African tropical field conditions. The CNN model achieved overall detection accuracies of 86.4% and 91.2% at V4 and VT/R1 growth stages, respectively substantially outperforming the Random Forest and Support Vector Machine alternatives and the red-edge-based NDRE index demonstrated superior correlation with leaf nitrogen content ($r = 0.93$ at VT/R1) compared with all other spectral indices evaluated, validating its primacy as the reference spectral predictor for canopy N status in maize. The technical capacity to detect N deficiency with near-90% accuracy as early as the V4 growth stage opens a practically important window for corrective variable-rate nitrogen top-dressing before irreversible growth impacts occur, which represents a significant advance over conventional agronomist-based scouting that rarely achieves sufficiently early and spatially comprehensive deficiency detection. From a practical adoption perspective, it is recommended that Nigerian and West African agricultural extension agencies and commercial maize growers invest in entry-level multispectral UAV systems prioritized for platforms with at least red-edge and NIR bands and develop state-based UAV service cooperatives to amortize equipment costs across multiple smallholder users. A UAV-based early N screening at the V4 stage, followed by a confirmatory flight at V8, with variable-rate urea top-dressing calibrated against NDRE thresholds established in this study (NDRE < 0.26 indicating high-priority intervention zones), is proposed as a practical decision-support protocol for precision nitrogen management. Extension programs should prioritize training agronomic field officers in UAV flight operations and spatial data interpretation using open-source platforms, and academic institutions in the region should establish collaborative UAV service hubs at university farms to support both research and commercial advisory functions. Future investigations should develop crop-specific NDRE – leaf N calibration functions validated across multiple soil types and maize varieties prevalent in Nigeria, extend the CNN framework to simultaneous multi-nutrient deficiency detection, and evaluate the economic returns of UAV-guided variable-rate nitrogen application relative to conventional blanket fertilization across a range of farm sizes and agroecological zones in West Africa.

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