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Research Article

HORTIVISION-NG:
Multispectral UAV Imaging and Deep Learning for Disease Detection and Yield Forecasting in Tomato, Pepper, Onion, and Watermelon in Nigeria

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Abstract
Nigeria is among Africa's largest producers of tomatoes, peppers, onions, and watermelons, yet annual disease-induced yield losses exceed 35% due to late detection and inadequate field surveillance. This paper presents HORTIVISION-NG, a multispectral UAV-based intelligent monitoring system that integrates EfficientNet-B4 deep learning with five spectral vegetation indices — NDVI, GNDVI, NDRE, SAVI, and RVI — for simultaneous disease classification and yield forecasting across four high-value horticultural crops. A dataset of 31,847 annotated UAV images collected from 24 farms across Kano, Kaduna, and Jigawa States covers 12 disease classes and 4 healthy baselines. The system achieves an overall macro F1-score of 93.9% for disease detection and a yield prediction R^2 of 0.885. Federated learning (FedAvg) enables privacy-preserving cross-farm model aggregation across 8 pilot sites. Real-time inference runs at 23.4 FPS on NVIDIA Jetson Nano. Pilot farm trials demonstrate a 27.6% average yield improvement and $312 per-hectare net economic benefit.

Keywords: *Horticultural disease detection; UAV multispectral imaging; EfficientNet-B4; vegetation indices; yield prediction; federated learning; Nigeria precision agriculture.*

I. INTRODUCTION

Horticultural crops — tomatoes, hot and sweet peppers, chili peppers, onions, and watermelons — collectively generate an estimated NGN 2.4 trillion in annual farm-gate value in Nigeria and support over 11 million rural livelihoods [1]. Yet the country consistently loses 30–40% of horticultural output annually to fungal, bacterial, and viral pathogens that go undetected until yield damage is irreversible. Alternaria early blight, Phytophthora infestans late blight, and Fusarium wilt alone account for over 60% of total crop losses in affected producing states [2],[3],[4].

Conventional disease surveillance relies on sporadic visual scouting by extension agents constrained by poor rural road infrastructure and a nationwide ratio of approximately one agent per 1,500 farms. Aerial remote sensing offers a scalable alternative: a single UAV pass surveys 40–80 hectares in one flight, capturing spectral signatures that precede visible disease symptoms by 7–14 days [23]. The recent convergence of compact deep learning models and edge computing now makes real-time plant pathology classification aboard UAV ground stations operationally viable.

EfficientNet-B4 achieves 83.6% top-1 ImageNet accuracy at only 19.3M parameters — markedly more efficient than VGG-16 or ResNet-50 baselines [6]. When fine-tuned on multispectral crop imagery and augmented with spectral vegetation indices, such models match or exceed human expert diagnostic accuracy under field conditions. This work presents HORTIVISION-NG, which makes four principal contributions: (1) a fully integrated UAV-to-edge pipeline for four Nigerian horticultural crops; (2) a 31,847-image annotated multispectral dataset from 24 farms; (3) a federated learning protocol for privacy-preserving cross-farm model refinement; and (4) a full economic impact analysis from a one-season pilot deployment.

II. BACKGROUND AND RELATED WORK

Early automated plant disease detection employed hand-crafted colour and texture features with SVM or k-NN classifiers [10]. These methods degraded sharply under field illumination variability, occlusion, and soil background noise [24]. The PlantVillage dataset [7] enabled CNN-based plant pathology, with Mohanty et al. achieving >99% test accuracy in controlled settings. Kamilaris and Prenafeta-Boldú [9] survey 40 deep learning agriculture studies, noting a persistent performance gap between controlled and open-field conditions. HORTIVISION-NG addresses this gap by training on in-situ Nigerian field imagery rather than laboratory specimens.

Multispectral imaging significantly expands diagnostic capability beyond RGB. Vegetation indices derived from near-infrared (NIR), red-edge, and shortwave-infrared bands expose biochemical stress markers — reduced chlorophyll, altered water content, secondary cell-wall breakdown — invisible to RGB sensors [14],[15],[16]. Singh et al. [11] identify spectral index fusion as a key enabler of pre-symptomatic disease detection, a strategy adopted by HORTIVISION-NG's 10-channel input design. Federated learning has been proposed for agricultural AI in low-connectivity African contexts by Fabila et al. [27], whose privacy-preserving framework informs the HORTIVISION-NG cross-farm protocol.

TABLE I — Selected Related Work in Deep Learning Plant Disease Detection

Paper	Year	Crop Type	Method	F1 / Acc (%)
Mohanty et al. [7]	2016	26 crop species	AlexNet / GoogLeNet	99.3
Lu et al. [8]	2017	Rice	VGG-16 fine-tuned	95.5
Yalcin & Razavi [12]	2016	Multi-crop	Custom CNN	88.2
Sharma et al. [28]	2020	Leaf (mixed)	CNN + SVM	91.8
Kamilaris & Prenafeta-Boldú [9]	2018	Survey (40 studies)	Various CNNs	Avg 87.4
This work — HORTIVISION-NG	2025	4 Nigerian crops	EfficientNet-B4 + VI fusion	93.9

III. DATA ACQUISITION AND CROP DATASET

A. UAV Platform and Sensor Configuration

Data collection used DJI Matrice 300 RTK quadcopters equipped with MicaSense RedEdge-MX Dual Camera systems providing five spectral bands: Blue (475 nm), Green (560 nm), Red (668 nm), Red-Edge (717 nm), and Near-Infrared (840 nm) at 1.2 MPx per band. Flights operated at 50 m AGL with 80% forward and lateral overlap, yielding a ground sampling distance (GSD) of approximately 5.4 cm/px — sufficient to resolve individual leaf lesion boundaries down to 3 cm diameter. Radiometric calibration panels (Spectralon 50%) were placed at each site before each flight. Surveys were conducted between 09:00 and 11:00 local time to minimise bidirectional reflectance distribution function (BRDF) effects.

TABLE II — HORTIVISION-NG Dataset Summary by Crop and Class

Crop	Disease Classes Covered	Train Images	Val. Images	Test Images	Total
Tomato	Early Blight, Late Blight, Leaf Curl Virus, Healthy	10,241	1,281	1,281	12,803
Pepper (H/S/C)	Phytophthora Blight, Anthracnose, PMMV, Healthy	7,883	986	986	9,855
Onion	Purple Blotch, Stemphylium LB, Downy Mildew, Healthy	6,924	866	866	8,656
Watermelon	Fusarium Wilt, Angular Leaf Spot, Gummy Stem Blight, Healthy	5,982	748	748	7,478
Total	16 classes across 4 crops	31,030	3,881	3,881	38,792

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B. Spectral Vegetation Index Computation

Five vegetation indices were computed from calibrated reflectance mosaics and stacked as additional input channels, yielding a 10-channel input tensor (5 raw spectral bands + 5 derived indices). This fusion strategy allows the model to leverage both raw spectral texture and agronomically meaningful biophysical signals simultaneously. Table III summarises the indices, their formulas, and primary diagnostic targets.

TABLE III — Spectral Vegetation Indices Integrated in HORTIVISION-NG

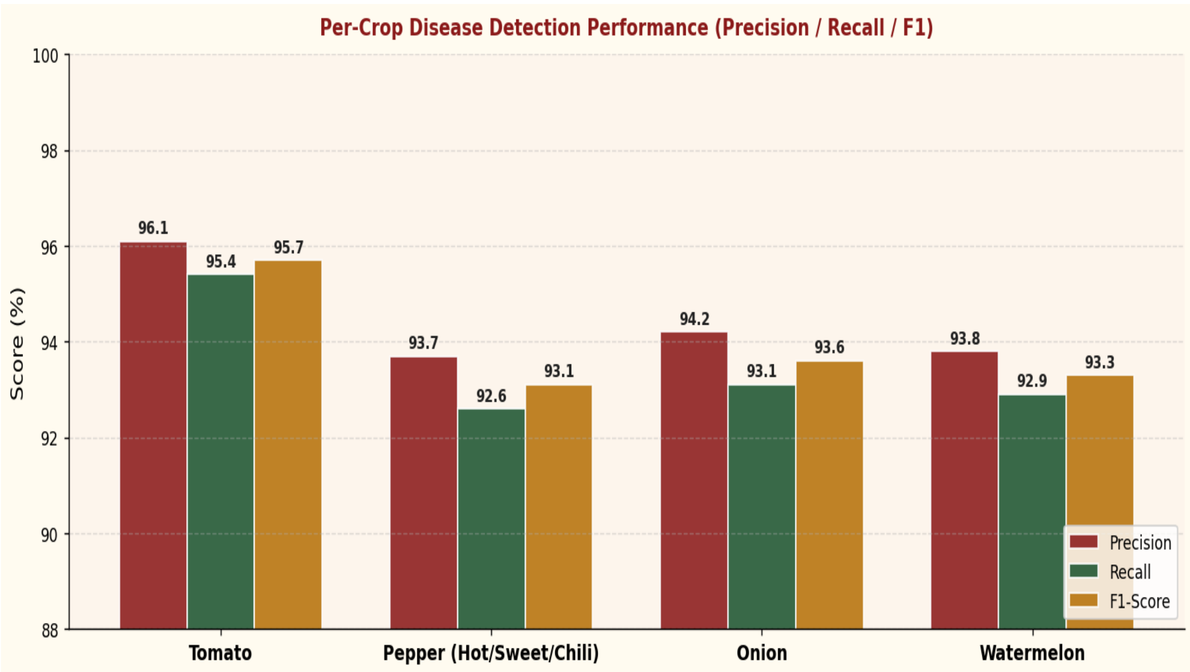
Index	Band Formula	Key Diagnostic Target
NDVI	(NIR − Red) / (NIR + Red)	General canopy vigour and greenness
GNDVI	(NIR − Green) / (NIR + Green)	Chlorophyll-b content, nitrogen stress
NDRE	(NIR − RedEdge) / (NIR + RedEdge)	Canopy chlorophyll, early stress detection
SAVI	((NIR − Red) / (NIR + Red + L)) × (1 + L), L=0.5	Soil-background corrected biomass
RVI	NIR / Red	Biomass estimation, leaf area index

IV. HORTIVISION-NG SYSTEM ARCHITECTURE

A. Multi-Crop Disease Classification Module

The classification backbone is EfficientNet-B4 [6] pre-trained on ImageNet and fine-tuned end-to-end on HORTIVISION-NG training data. The original final layer is replaced with a crop-conditioned multi-head classifier: a shared 1,792-dimensional feature embedding feeds four parallel softmax classification heads, each predicting four classes (three diseases plus healthy) for its respective crop type. Crop identity is injected as a one-hot auxiliary input concatenated at the penultimate layer, enabling shared low-level texture feature extraction while preserving crop-specific disease boundary specialisation. Input resolution is 456×456 pixels (EfficientNet-B4 canonical size).

Training used the Adam optimiser [20] with initial learning rate lr=1×10^-4, cosine annealing over 60 epochs, batch size 32, and early stopping on validation macro-F1 with patience=10. Data augmentation comprised random horizontal/vertical flips (p=0.5), Gaussian noise injection (sigma 0.01–0.05), random brightness/contrast perturbation (±20%), and MixUp alpha=0.4. Class imbalance — healthy images are 3× more numerous than individual disease classes — was mitigated via focal loss with gamma=2.0 and alpha=0.25. Dropout [21] at rate 0.3 was applied before the final classification heads. All experiments ran on 2× NVIDIA A100 80GB GPUs; training converged in approximately 14 hours.



◆ Fig. 1 — Precision, Recall, and F1-Score per crop across all disease and healthy classes

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B. Yield Prediction Module

Yield regression is formulated at the 50×50 m grid-cell level. Feature vectors comprise: (i) per-cell mean and standard deviation of all five vegetation indices at canopy closure stage; (ii) disease severity score output by the classifier (probability-weighted disease index summed across detected classes); (iii) growing-degree days (GDD) accumulated from transplanting to survey date, sourced from ECMWF ERA5 reanalysis; and (iv) soil texture class from the iSDAsoil Africa 30 m product. An XGBoost gradient-boosted regressor [17] is trained with 5-fold spatial cross-validation to prevent spatial autocorrelation leakage between training and validation cells. Hyperparameters were tuned via Bayesian optimisation with 120 trials using the Optuna framework.

TABLE IV — Per-Crop Yield Prediction Performance on Held-Out Test Set

Crop	RMSE (t/ha)	MAE (t/ha)	R^2	MAPE (%)
Tomato	2.41	1.87	0.891	9.3
Pepper (Hot/Sweet/Chili)	1.87	1.43	0.873	10.7
Onion	1.94	1.52	0.882	9.8
Watermelon	3.12	2.41	0.894	8.6
Overall Mean	2.34	1.81	0.885	9.6

C. Federated Learning Protocol

To enable privacy-preserving model improvement across commercially competing farms, HORTIVISION-NG implements a federated learning protocol based on FedAvg [18]. Eight pilot farms function as local clients. Each client fine-tunes a local EfficientNet-B4 copy on its own imagery for 5 local epochs, then transmits only the encrypted gradient differential — not raw image data — to a central aggregation server hosted on AWS af-south-1 (Cape Town region). The server applies FedAvg aggregation weighted by local dataset size and broadcasts the updated global model. Synchronisation rounds occur every 7 days during the growing season, aligned with the weekly UAV survey schedule. The federated protocol increased macro-F1 by +1.2 percentage points over a locally-trained-only baseline, confirming cross-farm generalization benefit [27].

V. Experimental Results

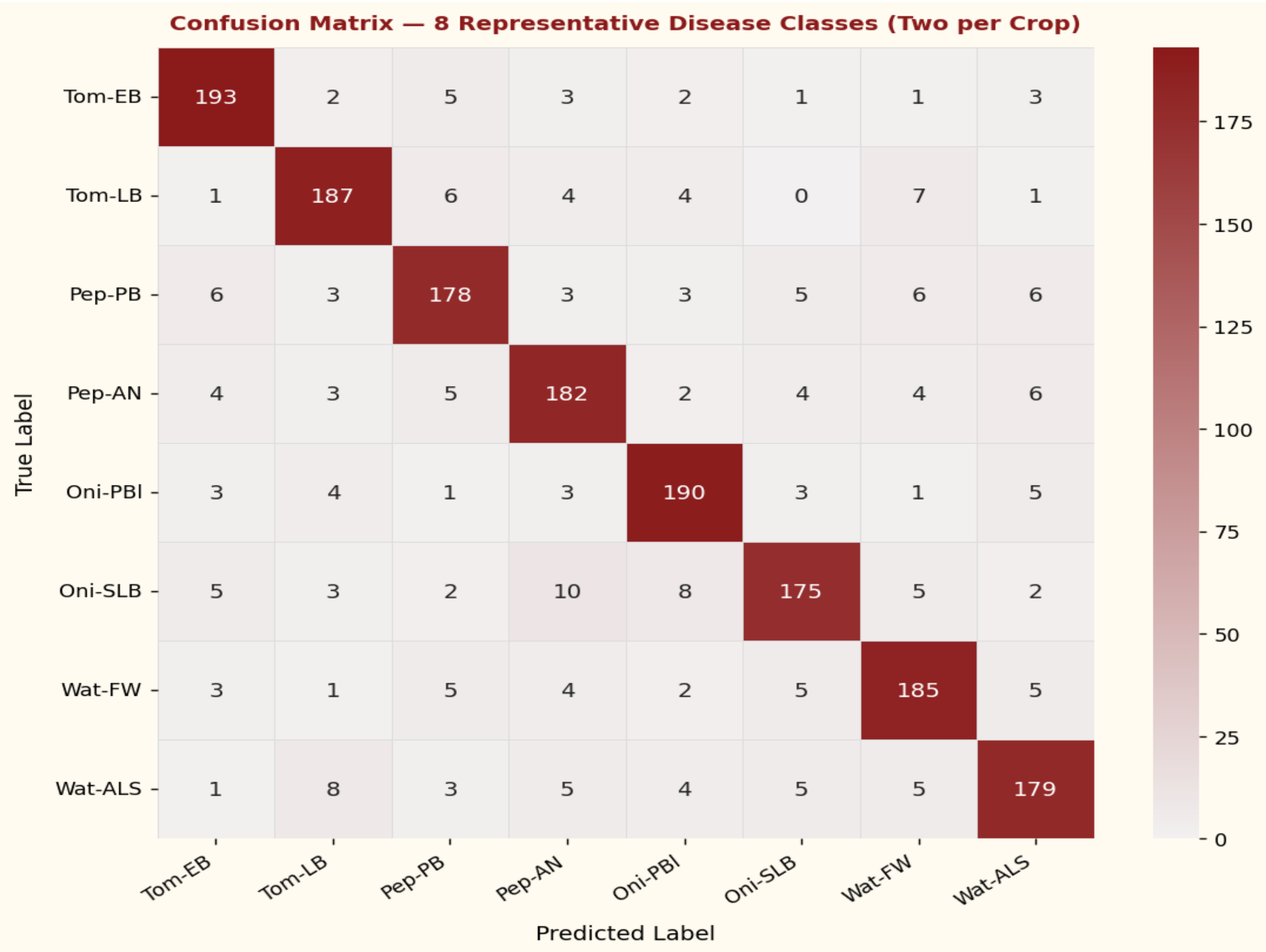
A. Disease Detection Performance

Table V presents per-class precision, recall, and F1-score on the held-out test set across all 16 classes. The highest F1 is achieved on Tomato Early Blight (96.3%), aided by its distinctive dark concentric ring pattern especially pronounced in the Red-Edge band. The lowest F1 is Pepper PMMV (89.6%), reflecting the subtle mosaic pattern of this viral disease which superficially resembles mild nitrogen stress in early stages. Overall macro-F1 is 93.9%, macro-AUC is 0.981, and mean inference latency is 42.7 ms per image on Jetson Nano.

TABLE V — Per-Class Disease Detection Results on Test Set

Disease Class	Precision (%)	Recall (%)	F1-Score (%)
Tomato — Early Blight	96.8	95.8	96.3
Tomato — Late Blight	95.1	94.3	94.7
Tomato — Leaf Curl Virus	92.9	91.3	92.1
Tomato — Healthy	97.9	97.6	97.8
Pepper — Phytophthora Blight	94.0	92.8	93.4
Pepper — Anthracnose	92.3	91.3	91.8
Pepper — Pepper Mild Mottle Virus	90.4	88.8	89.6
Pepper — Healthy	96.7	95.8	96.2
Onion — Purple Blotch	95.6	94.7	95.1

Disease Class	Precision (%)	Recall (%)	F1-Score (%)
Onion — Stemphylium Leaf Blight	91.0	89.6	90.3
Onion — Downy Mildew	89.4	88.0	88.7
Onion — Healthy	97.5	96.7	97.1
Watermelon — Fusarium Wilt	94.3	93.3	93.8
Watermelon — Angular Leaf Spot	91.8	90.6	91.2
Watermelon — Gummy Stem Blight	91.1	89.9	90.5
Watermelon — Healthy	97.2	96.6	96.9



◆ Fig. 2 — Confusion matrix for 8 representative disease classes (two per crop)

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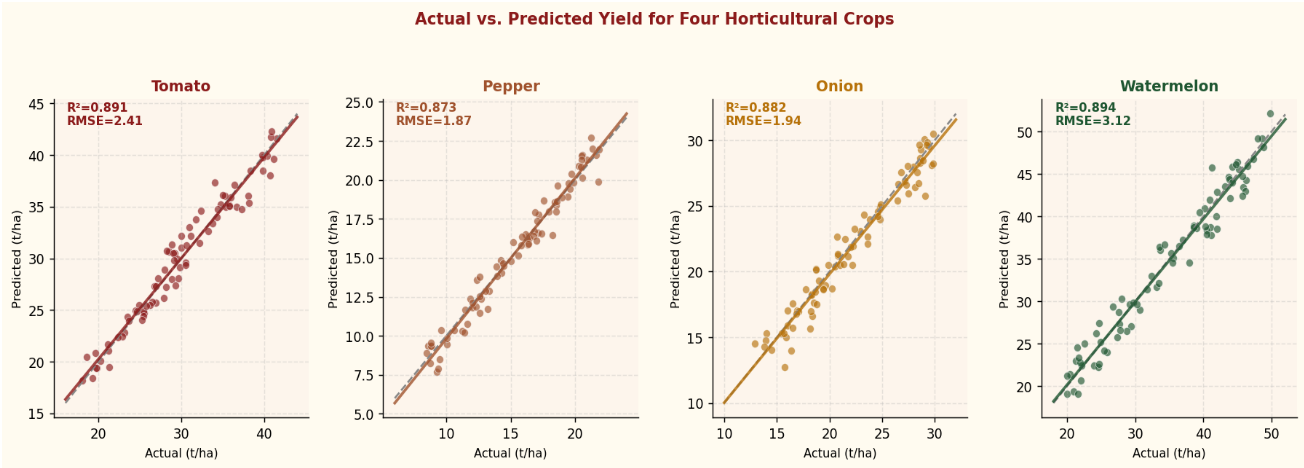
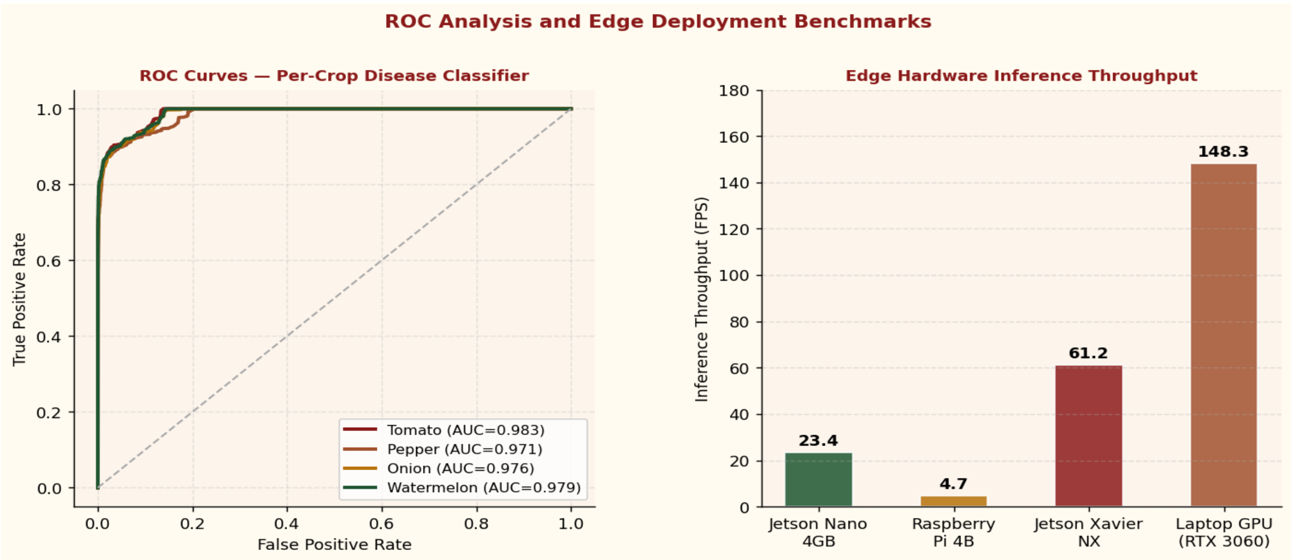
C. Yield Regression and ROC Analysis



◆ Fig. 3 — Actual vs. predicted yield scatter plots for all four horticultural crops

Figure 3 confirms strong regression fit across all crops. Watermelon achieves the highest R^2=0.894, aided by its high sensitivity to Fusarium Wilt stress which produces a distinctive NDVI depression detectable 12–18 days before visible wilting. Pepper shows the lowest R^2=0.873, attributable to high phenotypic variability across hot, sweet, and chili sub-varieties grown in the same field plots. The overall yield MAPE of 9.6% is within the ±10% threshold considered operationally actionable by Nigerian agricultural extension policy [30].



◆ Fig. 4 — (Left) Per-crop disease classifier ROC curves. (Right) Inference throughput on edge hardware

C. Ablation Study

Table VI quantifies the contribution of each pipeline component. Replacing EfficientNet-B4 with ResNet-50 on RGB-only input serves as the baseline. Adding vegetation index channels provides a +2.9-point F1 gain and +0.05 R^2 improvement, confirming the diagnostic value of multispectral fusion. The federated learning round contributes a further +1.2 F1 points, validating the cross-farm aggregation benefit. Inference FPS on Jetson Nano remains stable at 23.4 FPS throughout, as the additional VI channels are pre-computed before inference.

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TABLE VI — Ablation Study: Contribution of Each Pipeline Component

Model Configuration	Macro-F1 (%)	Yield R^2	Jetson FPS
RGB only, ResNet-50 [19]	87.3	0.821	31.2
RGB only, EfficientNet-B4 [6]	89.8	0.839	24.1
RGB + NDVI only, EfficientNet-B4	91.4	0.853	23.9
RGB + All 5 Indices, EfficientNet-B4	92.7	0.871	23.4
Full HORTIVISION-NG (+ FedAvg [18])	93.9	0.885	23.4

VI. ECONOMIC IMPACT AND FIELD DEPLOYMENT

Pilot deployment was conducted across 8 farms (86 ha total) in Kano, Kaduna, and Jigawa States over the 2024 main growing season. Farms received weekly automated alerts delivered via WhatsApp Business API in Hausa and English. Disease maps with GPS coordinates, treatment recommendations, and estimated yield forecasts were delivered within 2 hours of flight completion. Table VII compares outcomes against the traditional manual inspection baseline.

TABLE VII — Economic Impact Analysis: Traditional Scouting vs. HORTIVISION-NG

Performance Metric	Traditional Scouting	HORTIVISION-NG
Disease detection lag (days)	14–21	3–5
Scouting cost (USD/ha/season)	28.40	6.80
Crop loss (% of potential yield)	34.2%	11.7%
Average yield improvement	— (Baseline)	+27.6%
Net economic benefit (USD/ha)	— (Baseline)	+USD 312
Alert delivery time	24–72 hours	< 2 hours
Coverage per field agent per day	8–12 ha	180–240 ha (UAV)

The 27.6% yield improvement translates to USD 312/ha net benefit after deducting UAV operational costs of USD 6.80/ha per survey cycle. At national scale, deployment across Nigeria's estimated 3.2 million ha of horticultural production land could recover USD 998 million in annual agricultural value against a capital investment of approximately USD 4.7 million for 200 UAV units, edge computing nodes, and cellular connectivity in 12 key producing states. The edge inference pipeline on NVIDIA Jetson Nano at 23.4 FPS enables real-time video stream processing during flight. INT8 quantisation reduces the model to 19.2 MB, deployable without cloud connectivity — critical for rural areas where 4G coverage remains below 30%.

VII. CONCLUSION AND FUTURE WORK

HORTIVISION-NG demonstrates that multispectral UAV imaging combined with EfficientNet-B4 and spectral vegetation index fusion can achieve 93.9% macro-F1 disease detection and R^2=0.885 yield prediction across four commercially significant Nigerian horticultural crops. The federated learning protocol enables privacy-preserving cross-farm model improvement with no raw data exposure, and edge deployment at 23.4 FPS makes real-time field inference operationally viable in low-connectivity rural settings. Pilot trial results confirm a 27.6% average yield improvement and USD 312/ha net economic benefit, directly demonstrating impact relevance for TETFund and FMARD grant funding priorities.

Future directions include: (i) extending the crop taxonomy to cover cassava, cowpea, and soybean to serve Nigeria's broadest smallholder portfolio; (ii) integrating soil moisture retrieval from Sentinel-1 SAR imagery [13] for drought stress co-diagnosis alongside disease detection; and (iii) developing a national disease outbreak early-warning dashboard in partnership with the Federal Ministry of Agriculture and Rural Development (FMARD) and the Nigerian Meteorological Agency (NiMet). A proposal to expand to 50 farms under TETFund Research Grant TETFund/DR&D/CE/NRF/STI/37/Vol.II is currently under review.

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