© MAY 2026 | IRE Journals | Volume 9 Issue 11 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I11-1718149

Predictive Models for Crop Yield and Pest Detection Using Low-Cost Phone Cameras in Smallholder Agriculture

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Abstract- Smallholder farmers in Sub-Saharan Africa lack access to affordable tools for yield forecasting and early pest detection. This paper presents an end-to-end system that uses low-cost smartphone cameras combined with lightweight deep learning models to predict maize yield and detect fall armyworm infestation. We collected 18,400 field images and 1,200 plot-level yield measurements across Nigeria and Ghana over two growing seasons. A MobileNetV3-Small model for pest classification achieved 92.1% F1-score on-device, while a multimodal CNN + tabular regression model predicted yield with RMSE = 0.41 t/ha. We show that models trained on low-resolution images captured under variable field conditions generalize to unseen farms when augmented with weather and soil data. Our system runs at 18 FPS on a $80 Android phone, enabling real-time decision support without internet connectivity. Results demonstrate that low-cost mobile AI can provide actionable agronomic insights at scale for resource-constrained farmers.

Keywords: Precision Agriculture, Smallholder Farming, Crop Yield Prediction, Pest Detection, Mobile Deep Learning, Computer Vision

I. INTRODUCTION

Agriculture employs 60% of the labor force in Sub-Saharan Africa, yet yields remain 30–50% below global averages due to pests, disease, and poor input decisions. Early detection of pests like Spodoptera frugiperda and accurate yield forecasting can reduce losses and improve food security. Commercial solutions rely on drones, multispectral sensors, or cloud-based platforms that are cost-prohibitive for smallholders.

Smartphones are now ubiquitous, with 64% penetration in Nigeria and Ghana. Their cameras and on-device NPUs provide a low-cost sensing and compute platform. However, two challenges remain:

1. Models must be robust to low image quality, variable lighting, and diverse field conditions.

2. Yield prediction requires integrating visual cues with agronomic variables that are sparsely available at the farm level.

This paper addresses these gaps by developing and validating lightweight predictive models for yield and pest detection that run on low-cost Android phones without cloud dependency.

Contributions:

1. A dataset of 18,400 field images with expert annotations for fall armyworm damage and paired yield data from 1,200 plots.

2. A multimodal architecture combining on-device image features with tabular agronomic data for yield prediction.

3. Deployment and evaluation of models on $80 Android devices, including latency, accuracy, and energy benchmarks.

4. Analysis of generalization across regions, seasons, and image capture conditions.

II. RELATED WORK

Pest Detection: Prior work uses CNNs like ResNet and YOLO for insect detection on high-resolution images from controlled environments. Mobile deployment studies show MobileNetV2 and EfficientNet-Lite achieve 85–90% accuracy but often assume clean backgrounds and stable lighting. Few studies validate performance under smallholder field conditions.

Yield Prediction: Traditional methods rely on crop simulation models such as DSSAT, requiring detailed soil and management inputs. Recent work combines satellite imagery with deep learning for regional yield estimation. Farm-level prediction using smartphone imagery remains underexplored, with most studies limited to controlled plots.

Edge AI for Agriculture: Edge deployment studies focus on model compression and quantization. However, system-level evaluation on low-cost phones in real farm settings is scarce.

Our work differs by integrating on-device pest detection with yield prediction, using data collected from smallholder farms, and evaluating end-to-end system performance under realistic constraints.

III. METHODOLOGY

3.1 Data Collection

Data were collected from 240 smallholder farms in Kaduna, Nigeria and Ashanti, Ghana across the 2023 and 2024 growing seasons.

- Images: Farmers captured images of maize leaves and whole-plant scenes using \$80–\$120 Android phones. Images were taken at 3 growth stages: V6, VT, R3.

- Pest labels: Agronomists annotated 9,200 images for fall armyworm presence and damage severity on a 0–3 scale.

- Yield: At harvest, grain weight was measured for 1,200 5m × 5m plots.

- Tabular data: Planting date, fertilizer use, soil pH, and daily rainfall from local weather stations were recorded.

3.2 Models

Pest Detection: We fine-tuned MobileNetV3-Small and EfficientNet-Lite0 on the image dataset. Models were quantized to INT8 using TensorFlow Lite for on-device inference. Input resolution was 224×224.

Yield Prediction: A multimodal model fused CNN features from whole-plot images with tabular features. The image branch used a frozen MobileNetV3 backbone followed by a 128-dim projection. Tabular features passed through a 2-layer MLP. Features were concatenated and passed to a regression head predicting yield in t/ha.

3.3 Training and Evaluation

Data were split by farm to prevent leakage. We used 70/15/15 train/val/test splits stratified by region. Augmentations included random brightness, blur, and perspective transforms to simulate low-quality capture.

Metrics: F1-score, precision, recall for pest detection; RMSE, MAE, R^2 for yield prediction.

On-device benchmarks were measured on Tecno Spark 10 and Samsung A14.

IV. RESULTS

4.1 Pest Detection Performance

Table 1 shows results on the test set.

Model	Precision	Recall	F1 Score	Size (MB)	Latency (ms)
MobileNetV3-Small	0.91	0.93	0.921	4.2	56
EfficientNet-Lite0	0.93	0.92	0.925	5.8	89
ResNet18	0.94	0.91	0.924	44.7	210

MobileNetV3-Small achieved 92.1% F1 with 56 ms latency, enabling real-time feedback at 18 FPS. Accuracy dropped 4.2% on images captured at noon vs morning, indicating sensitivity to lighting.

4.2 Yield Prediction Performance

The multimodal model achieved RMSE = 0.41 t/ha and $R^2 = 0.78$, outperforming image-only [RMSE = 0.68] and tabular-only [RMSE = 0.55] baselines. Feature ablation showed that early-season images at V6 stage contributed most to accuracy. The model generalized across regions with <5% degradation.

4.3 On-Device Deployment

Both models were deployed in a Flutter app using TensorFlow Lite. On a $80 Tecno Spark 10, the app ran pest detection at 18 FPS with 320 mW average power draw. Offline inference allowed use in areas without connectivity. User testing with 45 farmers showed 87% found the feedback "easy to understand and act on".

V. DISCUSSION

Results show that low-cost phones can support accurate pest detection and yield prediction when models are tailored to field conditions. Key factors for success were:

1. Data diversity: Training on images from multiple farms and seasons improved robustness.

2. Multimodal fusion: Combining visual and agronomic data reduced RMSE by 40% vs image-only models.

3. Model efficiency: Quantized MobileNetV3-Small balanced accuracy and latency for real-time use.

Limitations include dependence on farmer compliance for image capture and limited crop scope. Future work should extend to cassava and sorghum, and integrate feedback loops where farmer actions update model predictions.

VI. CONCLUSION

We presented a system for crop yield and pest prediction using low-cost smartphone cameras and lightweight deep learning. The system achieves high accuracy, runs in real-time on affordable devices, and generalizes across smallholder farms. By removing the need for cloud connectivity and expensive sensors, this approach enables scalable, data-driven agronomy for smallholder farmers. Code and a subset of the dataset are released to support reproducibility.

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