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Autonomous Field Robot for Real-Time Pest Detection and Localized Intervention Using Multispectral Imaging and Deep Learning–Based Vision Models

Hamid-Mosaku Ahmad Oluwaseun[1] Dr John Oghemhe[2]

[1,2]Department of Systems Engineering, University of Lagos, Akoka, Lagos, Nigeria

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Theme: Innovations for Sustainable Development and Resilient Infrastructure



OUTLINE

Presentation outline

01 The problem and research gaps

02 Aim and objectives

03 System architecture and intervention

04 Dataset, model and pipeline

05 Accuracy and timing results

06 Discussion and conclusions

PROBLEM

The problem: crop losses and wasteful spraying

- Pests and pathogens cause major staple-crop losses; treatment should follow a local observation, not a whole-field schedule (Savary et al., 2019).
- Broadcast spraying wastes input and increases exposure; precision agriculture promises site-specific delivery (Sishodia et al., 2020).
- Laboratory detectors do not transfer directly to field imagery: 99.35% on PlantVillage versus 31.4–31.7% on web images (Mohanty et al., 2016).
- Integrated perception–spray systems exist (Oberti et al., 2016; Partel et al., 2019); the gap is traceable, affordable integration and measured local evidence.

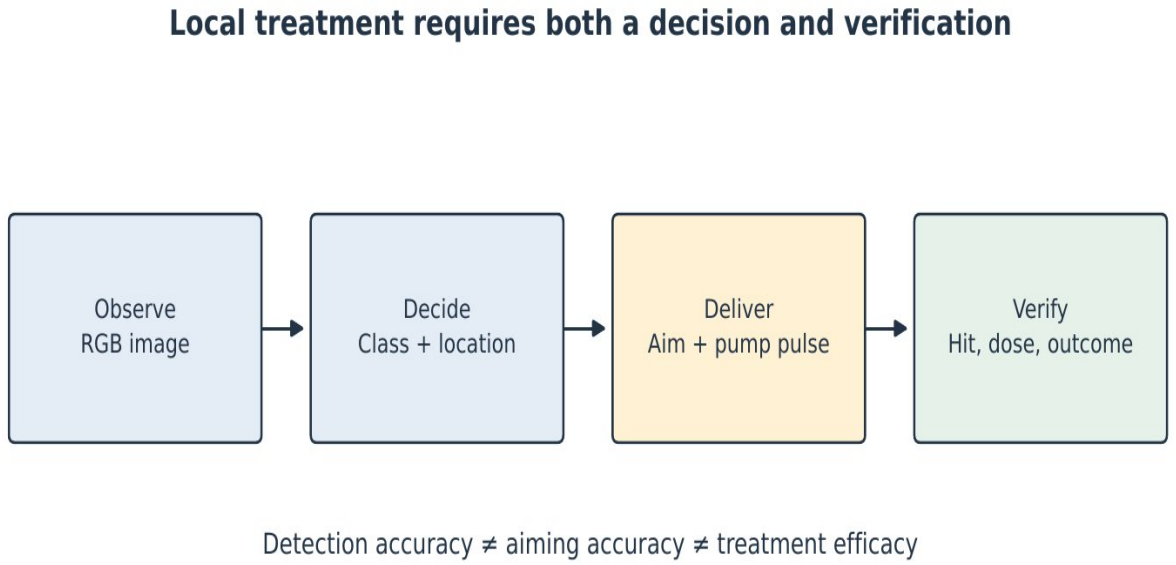


Figure 1: Observation–decision–delivery–verification chain. Conceptual synthesis; not a measured result.

Research gap, aim and objectives

RESEARCH GAP

Existing pest detection research falls short in four ways. First, deep-learning models are typically validated on curated images rather than real outdoor conditions involving variable lighting, occlusion, and motion [Liu & Wang, 2021]. Second, most systems rely on RGB sensing alone, which misses early-stage infestation visible only in NIR and red-edge bands [Mahlein, 2016]. Third, they detect pests without closing the loop through localized spraying [Roosjen et al., 2020]. Finally, few studies report how much pesticide is actually saved compared with blanket spraying [Partel et al., 2019].

AIM

To develop and evaluate an autonomous field robot that performs real-time pest detection and localized intervention using multispectral imaging and deep learning–based vision models.

OBJECTIVES

1. **Literature review** of agricultural robotics, multispectral imaging, deep-learning pest detection, and autonomous field navigation.
2. **Design and build the robotic platform** – locomotion, multispectral/RGB sensors, onboard compute, micro-intervention mechanism.
3. **Develop vision algorithms** using deep learning and multispectral fusion for real-time pest detection and classification.
4. **Implement autonomous navigation** – row-following, obstacle avoidance, pest-hotspot localization, precise actuation.
5. **Field-evaluate the system** – detection accuracy, intervention precision, robustness, and pesticide-reduction impact.

ARCHITECTURE

System architecture: four integrated layers

01 PERCEPTION

RGB USB camera, 640×480 MJPG verified. NIR + 850 nm filter deferred and uncalibrated.

02 INTELLIGENCE

YOLO11n exported to NCNN at 320×320; Raspberry Pi 4, CPU-only inference.

03 CONTROL

ESP32 v2 command link, watchdog and front range guard. Flashed identity and stop time unverified.

04 ACTUATION

BTS7960 drive; SG90 single-axis aiming and pump/reservoir at a later stage.

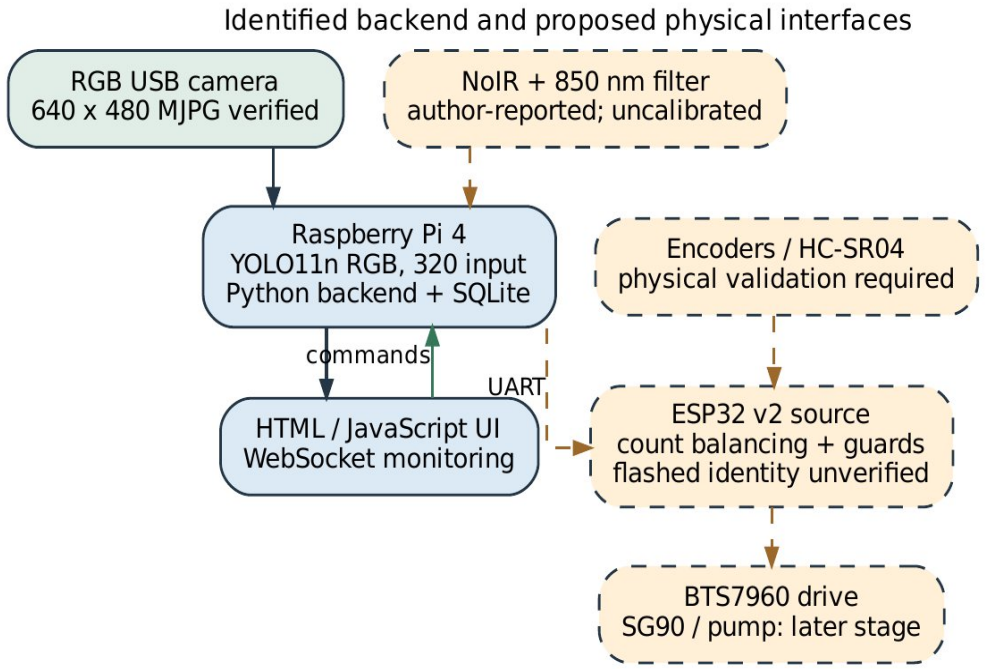


Figure 2: Identified backend and proposed physical interfaces. Source: thesis Chapter 3.

MATERIALS

Dataset, model and detector pipeline

- Kaggle Recovered private corpus; 1,484 objects on the notebook-matched test denominator after one documented exclusion.
- Three operational classes: Healthy Crop, Disease Symptom and Visible Pest. RGB and NoIR input.
- Integrity: zero exact cross-split duplicate groups; 89 perceptual candidate pairs still need formal adjudication.
- Model: YOLO11n, 96 recorded epochs, exported to NCNN at 320×320. The 640 export is a reference only.

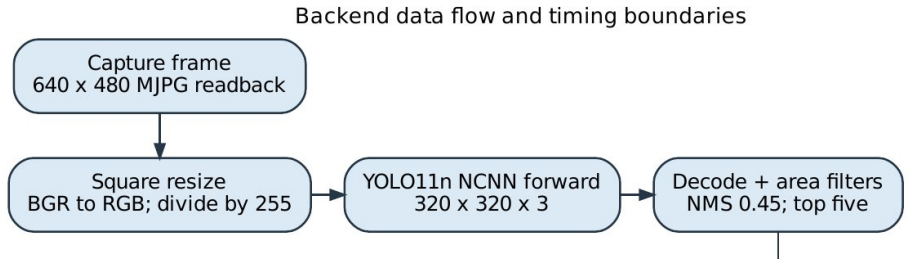


Figure 4: Inspected 320 detector path. Draw, JPEG publication and logging follow the detector timer.

9,308	1,163	1,165
TRAIN	VALIDATION	TEST

1,164 images / 1,484 objects on the notebook-matched evaluation denominator.

Audit trail: file and label hashes, notebook output and model metadata are retained.

MATERIALS

Dataset, model and detector pipeline

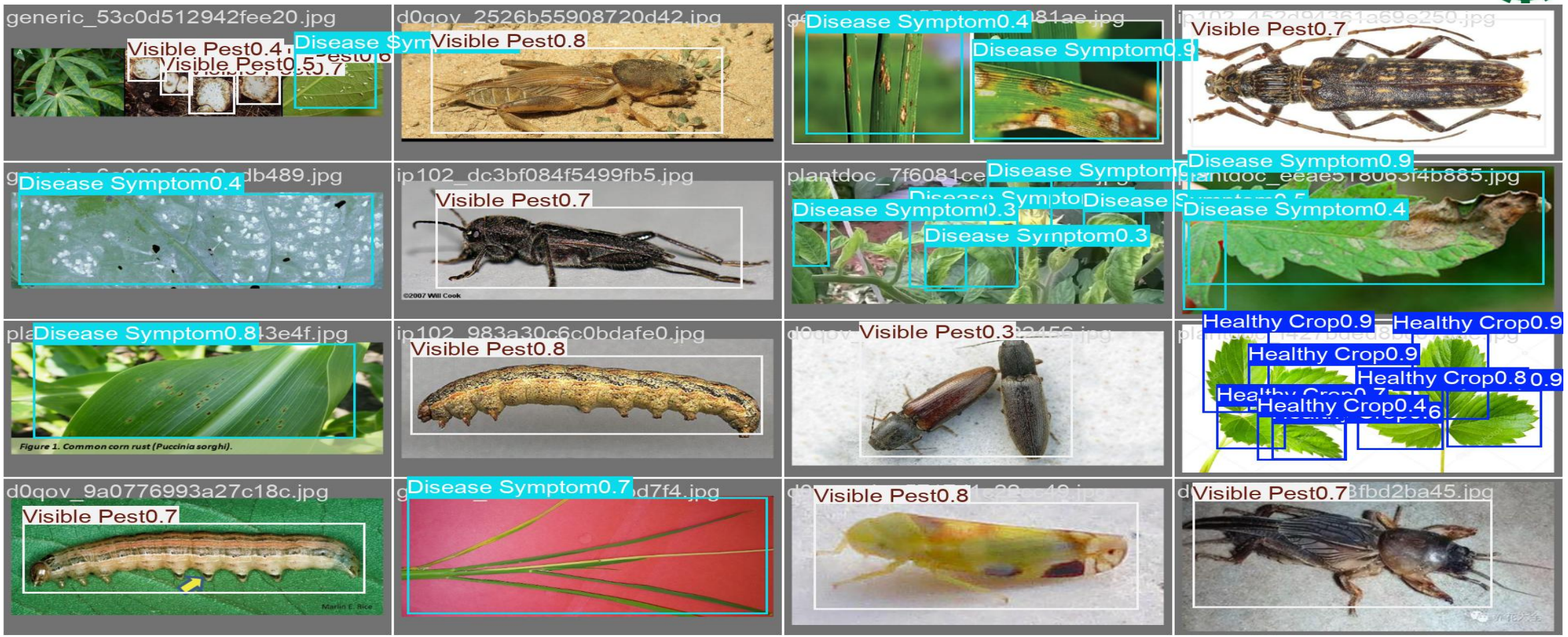


Figure 3: Supplied offline prediction mosaic. Dataset imagery

Provenance: file and label hashes, notebook output and model metadata are retained for audit.

RESULTS

Deployed accuracy misses the 0.85 target

Configuration	mAP@0.5	mAP@0.5:0.95	Protocol
NCNN 320, deployed	**0.241**	**0.132**	**Deployed filters**
NCNN 320, diagnostic	0.758	0.502	Relaxed filters
PyTorch 320, notebook	0.807	0.564	Different protocol
PyTorch 640, notebook	0.855	0.593	Reference
NCNN 640, notebook	0.846	0.586	Reference
Target	**≥ 0.850**	**—**	**Requirement**

Table 1: Accuracy by configuration on 1,164 images / 1,484 objects. Values are not interchangeable across protocols. Source: thesis Chapter 4.

KEY FINDING

0.221

Visible-pest recall at the deployed 0.60 threshold

AP@0.5 is 0.241 deployed versus 0.758 diagnostic.

The 0.85 target is met at mAP@0.855 at 320.

Offline detector result, not a field spray rate.

RESULTS

Software path: 126 ms median;en

EXP04 is Edge latency/resources

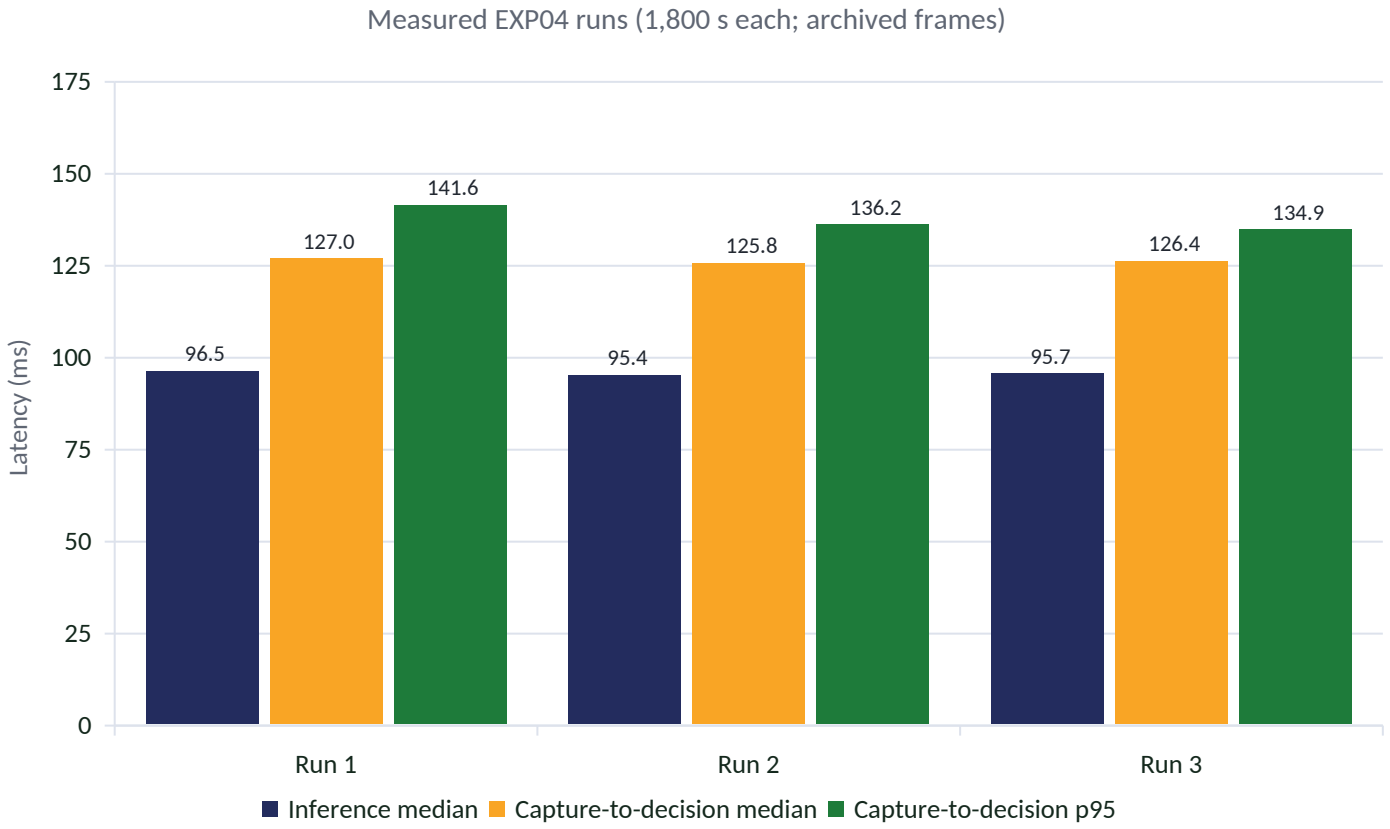


Figure 6: Three separately started runs, 13 November 2026. Source: thesis Chapter 4.

KEY FINDING

126 ms

median capture-to-decision on archived frames

- 7.65–7.76 FPS sustained; zero throttle flags
- One live run: 7.31 FPS, 131.2 ms median
- Excludes camera exposure, relay, aiming and deposition
- 700 ms image-to-deposition requirement unmeasured

DISCUSSION

What the evidence supports — and what it does not

A This study

- Kaggle corpus, labels and model identity; zero exact cross-split duplicates, 89 perceptual candidates unresolved.
- Matched checkpoint/NCNN comparison met the 0.01 metric tolerance; raw tensors were not identical.
- Three replay runs: 126 ms median software path, 7.65–7.76 FPS; one live run at 7.31 FPS.

B Previous studies

- Agrees that integrated perception–treatment systems are feasible (Oberti et al., 2016; Partel et al., 2019).
- Differs from algorithm-centred benchmarks: this is an audit of an accessible prototype, not a new detector.
- Mohanty et al. (2016) show why laboratory accuracy cannot be transferred directly to field scenes.

IMPLICATIONS

Claim a traceable RGB implementation and a measured software path — not autonomous spraying or pesticide saving.

Close the EXP01 annotation and duplicate gates; commission the P4 harness; run EXP03–EXP10.

Report volume reduction only with matched coverage and efficacy evidence.

Conclusions and recommendations

C Conclusions

1. An AgroPest RGB YOLO11n 320 pipeline was recovered and audited; AP@0.5 is 0.758 diagnostic and 0.241 deployed, below the 0.85 target.
2. Checkpoint/export parity met the 0.01 metric tolerance, and the software path measured 126 ms median at 7.65 to 7.76 FPS; the 700 ms deadline is unproven.
3. Aiming geometry and intervention interfaces are defined, navigation, spray, endurance but fail-safe behaviour remain under construction.

R Recommendations

1. Complete EXP01 adjudication and duplicate review; add EXP03 condition tests and EXP04 live repetitions.
2. Commission the P4 harness; measure stop/fault response, SG90 aiming and water deposition.
3. Keep NIR deferred until radiometric calibration; report cost, energy and efficacy with matched trials.

References

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Thank You

Questions and discussion

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Hamid-Mosaku Ahmad Oluwaseun · 190407055 | Department of Systems Engineering, University of Lagos
feiconference@unilag.edu.ng | https://feic.unilag.edu.ng/

Theme: Innovations for Sustainable Development and Resilient Infrastructure

