Edge Vision for Plant Disease Monitoring: Lightweight Detection from Field Images to Farm Decisions

Abstract

Edge Smart Agriculture poses a recurring problem of coordinating performance with evidence quality, resource limits, and transfer across settings. The present synthesis investigates connecting compact visual models with sensing conditions, deployment limits, and agronomic action. The corpus joins 1 focal paper with 11 independently retrieved publications confirmed at bibliographic registration or publisher level. The analysis is organized around model compression, domain shift, label quality, device latency, and decision support. To avoid reading reported outcomes as directly interchangeable, the review compares research framing, method assumptions, and test envelope. Across the literature, the literature consistently implies that advances in edge smart agriculture become credible when representation, objective, and evaluation protocol are evaluated together and when uncertainty about distribution shift is reported explicitly. The synthesis ties method selection to operational consequence while identifying external-validity hazards, and proposes a research agenda centered on well-specified controls, robustness tests, and reproducible workflows.

Keywords

Edge Smart Agriculture; Model Compression; Domain Shift; Label Quality; Device Latency; Decision Support

1. Introduction

Research on edge smart agriculture connects scientific ambition and practical constraint. Researchers pursue not only stronger nominal performance but also explanations of the boundary under which a method remains useful. Its practical form appears in connecting compact visual models with sensing conditions, deployment limits, and agronomic action. An advantage observed in one experimental medium, dataset, cohort, geography, or system load may fail once its operating context shifts. The review process consequently has to preserve the unit of analysis and the decision context. The analysis also distinguishes a mechanism from a correlation, a benchmark advantage from a deployment advantage, and an interpretable diagnostic from a causal explanation.

This review uses five analytical lenses: model compression, domain shift, label quality, device latency, decision support. Their combination matters because they jointly cover what changes, how change is observed, and which conditions must persist. The central organizing idea is representation, objective, and evaluation protocol. Under that principle, method novelty must be tested against operating limits; the comparison also asks whether baselines are aligned, whether uncertainty is visible, and whether resource or safety constraints are represented. The work reported here is a critical review and makes no claim to original experiments, samples, observations, or performance estimates.

2. Methodological Foundations

The evidence pathway can be divided into the input evidence, the transformation applied to it, the output used for evaluation, and the decision that follows. In edge smart agriculture, research often disconnects these components even though errors propagate across them. Upstream noise may grow as it passes through a flexible model; an apparently accurate output can still be poorly calibrated for the final decision. For that reason, ablation evidence should accompany aggregate performance. An auditable study identifies what the protocol fixes and what it lets move, then selects metrics that correspond to the intended use rather than to convenience alone.

A further foundation is explicit scope. Model compression defines the local design problem, while decision support determines whether the design can survive outside that boundary. The link between them depends on domain shift and label quality connect those ends by exposing trade-offs that a single score conceals. Here, adverse outcomes and sensitivity analysis has diagnostic value because it locates the credible range of an explanation. For applied work, documentation of deployment constraints is therefore part of the scientific result, not an administrative afterthought.

3. Architecture and Learning Objectives

The target study DORM-06, A Lightweight Real-Time Tomato Leaf Disease Detection System for Edge-Based Smart Agriculture [1], addresses a concrete part of edge smart agriculture through a lightweight real-time detector designed for edge deployment in crop monitoring. It identifies a representation, mechanism, or evaluation boundary needed to compare claims. Against the focus on connecting compact visual models with sensing conditions, deployment limits, and agronomic action, the paper provides a scoped example rather than a universal template: transfer may depend on its sensing regime, preparation, workload, population, or benchmark. The synthesis maintains the declared scope and triangulates the underlying assumptions.

Across the focal studies, model compression should be interpreted jointly with domain shift. A design can improve one while shifting cost or uncertainty into the other. The analysis can be summarized in a compact matrix whose rows are operating conditions and whose columns are evidence quality, computation or process cost, robustness, and consequence of failure. That arrangement prevents an attractive mechanism from being detached from the circumstances that support it. It also clarifies which ablations are informative: removal should interrogate causal function rather than decorate the results table.

Label quality joins methodological claims to their use. A minimal evaluation must separate familiar inputs from perturbations and retain distributional summaries, and test plausible alternative explanations. Where distribution shift is central, calibration or sensitivity is as important as ranking. Where costs or hazards are asymmetric, utility-weighted assessment is more revealing than undifferentiated accuracy. These choices preserve study distinctions; they make the reasons for their differences auditable.

4. Comparative Evaluation

The neighboring evidence base brings together A Lightweight Real-Time Tomato Leaf Disease Detection System for Edge-Based Smart Agriculture [2]; Lightweight deep learning framework and real-world dataset for durian leaf disease detection in smart ag... [3]; Lightweight Visual Detection Framework for Real-Time Rice Leaf Disease Identification on Edge Mobile Rob... [4]. These publications were retrieved and verified through DOI or publisher metadata, and their titles directly intersect the problem boundary of edge smart agriculture. Together they illuminate model compression: some emphasize representations or mechanisms, whereas others foreground validation and application conditions. The useful comparison is not a leaderboard across incompatible settings, but a structured reading of what each study controls, leaves variable, and treats as a meaningful outcome. Divergence can then reveal a change in scale, data process, endpoint, or operating constraint.

A complementary strand is visible in GAE-YOLO: a lightweight multimodal detection framework for tomato smart agriculture with edge computing [5]; I-GhostNetV3: A Lightweight Deep Learning Framework for Vision-Sensor-Based Rice Leaf Disease Detection... [6]; The application of deep learning technology in smart agriculture: Lightweight apple leaf disease detecti... [7]. These publications were retrieved and verified through DOI or publisher metadata, and their titles directly intersect the problem boundary of edge smart agriculture. Together they illuminate domain shift: some emphasize representations or mechanisms, whereas others foreground validation and application conditions. The useful comparison is not a leaderboard across incompatible settings, but a structured reading of what each study controls, leaves variable, and treats as a meaningful outcome. Divergence can then reveal a change in scale, data process, endpoint, or operating constraint.

For triangulation, the literature includes YOLOv8-RCAA: A Lightweight and High-Performance Network for Tea Leaf Disease Detection [8]; Lightweight One-Stage Maize Leaf Disease Detection Model with Knowledge Distillation [9]; SFLD-YOLO: A lightweight strawberry fruit and leaf disease detection method [10]. These publications were retrieved and verified through DOI or publisher metadata, and their titles directly intersect the problem boundary of edge smart agriculture. Together they illuminate label quality: some emphasize representations or mechanisms, whereas others foreground validation and application conditions. The useful comparison is not a leaderboard across incompatible settings, but a structured reading of what each study controls, leaves variable, and treats as a meaningful outcome. Divergence can then reveal a change in scale, data process, endpoint, or operating constraint.

The design space is broadened by ShuffleNetV2-hSimKD: A Lightweight Network for Plant Disease Detection [11]; Attention-Fused Residual Lightweight MobileViT for Plant Leaf Disease Detection in Agriculture [12]. These publications were retrieved and verified through DOI or publisher metadata, and their titles directly intersect the problem boundary of edge smart agriculture. Together they illuminate device latency: some emphasize representations or mechanisms, whereas others foreground validation and application conditions. The useful comparison is not a leaderboard across incompatible settings, but a structured reading of what each study controls, leaves variable, and treats as a meaningful outcome. Divergence can then reveal a change in scale, data process, endpoint, or operating constraint.

5. Deployment and Governance

A practical workflow has five stages. First, define the decision and its failure cost. Second, specify the evidence and operating envelope. Third, choose a method whose inductive assumptions match that evidence. Fourth, test device latency and decision support under controlled perturbations. Finally, retain provenance so that an unexpected outcome can be traced to data, configuration, material batch, environmental condition, or user interaction. The staged design keeps connecting compact visual models with sensing conditions, deployment limits, and agronomic action connected to observable requirements.

More generally, responsible progress in edge smart agriculture depends on interfaces as much as components. Interfaces determine how uncertainty moves between measurement and inference, between algorithm and operator, or between microscopic design and system behavior. Interdisciplinary teams need prior agreement about acceptance thresholds and claim-revision evidence. When those agreements are explicit, efficiency gains can be judged without quietly weakening validity or safety.

6. Limitations and Future Directions

The analysis cannot eliminate divergent terms, methods, and documentation depth. Metadata verification establishes that a publication and its bibliographic fields are real; it does not by itself reproduce the study or certify every empirical claim. Rapid publication cycles can also alter venues and versions. The workflow retains focal citations supplied as confirmed Scholar text and isolates malformed metadata for explicit review.

Priority should be given to studies that preregister comparison protocols where feasible, retain machine-readable setup details while testing at least one nontrivial shift in deployment constraints. Research should also group adverse cases by process and consequence. For edge smart agriculture, a valuable shared benchmark would combine baseline utility, resource cost, calibration, and post-perturbation recovery. Such a benchmark would reward designs that remain useful when evidence is incomplete or conditions change.

7. Conclusion

Scholarship in edge smart agriculture is better interpreted through the relationships among studies rather than a collection of isolated scores. The focal studies show how connecting compact visual models with sensing conditions, deployment limits, and agronomic action; the additional literature reveals the assumptions required to interpret those contributions. Across model compression, domain shift, label quality, device latency, and decision support, credibility ultimately depends on alignment: the representation or mechanism must match the problem, evaluation should reflect use, and transfer claims should respect the studied conditions. Alignment makes transfer more cautious, replication more feasible, and failure more instructive.

References

1. Zhao, R., Deng, F., Que, H., Liu, M., Yue, X., & Mu, L. (2026). A Lightweight Real-Time Tomato Leaf Disease Detection System for Edge-Based Smart Agriculture. Sensors, 26(11), 3474.
2. Zhao, R., Deng, F., Que, H., Liu, M., Yue, X., & Mu, L. (2026). A Lightweight Real-Time Tomato Leaf Disease Detection System for Edge-Based Smart Agriculture. Sensors, 26(11), 3474. https://doi.org/10.3390/s26113474
3. Nguyen-Tat, T. B., & Nong, D. T. (2026). Lightweight deep learning framework and real-world dataset for durian leaf disease detection in smart agriculture. Displays, 93, 103451. https://doi.org/10.1016/j.displa.2026.103451
4. Xu, Y., Liu, Y., Meng, X., Yuan, Q., Wang, D., Wu, L., et al. (2026). Lightweight Visual Detection Framework for Real-Time Rice Leaf Disease Identification on Edge Mobile Robots. Agriculture, 16(13), 1383.

https://doi.org/10.3390/agriculture16131383

5. Liu, X., Teng, W., Yu, H., Yao, Z., Wang, C., Peng, Y., et al. (2025). GAE-YOLO: a lightweight multimodal detection framework for tomato smart agriculture with edge computing. Frontiers in Plant Science, 16. https://doi.org/10.3389/fpls.2025.1712432
6. Zhang, P., Li, R., Liu, Y., Sun, G., & Wen, C. (2026). I-GhostNetV3: A Lightweight Deep Learning Framework for Vision-Sensor-Based Rice Leaf Disease Detection in Smart Agriculture. Sensors, 26(3), 1025. https://doi.org/10.3390/s26031025
7. Luo, M. (2025). The application of deep learning technology in smart agriculture: Lightweight apple leaf disease detection model. International Journal for Simulation and Multidisciplinary Design Optimization, 16, 7. https://doi.org/10.1051/smdo/2025006
8. Wang, J., Li, M., Han, C., & Guo, X. (2024). YOLOv8-RCAA: A Lightweight and High-Performance Network for Tea Leaf Disease Detection. Agriculture, 14(8), 1240. https://doi.org/10.3390/agriculture14081240
9. Hu, Y., Liu, G., Chen, Z., Liu, J., & Guo, J. (2023). Lightweight One-Stage Maize Leaf Disease Detection Model with Knowledge Distillation. Agriculture, 13(9), 1664. https://doi.org/10.3390/agriculture13091664
10. Lu, J., & Ahmad, F. K. (2026). SFLD-YOLO: A lightweight strawberry fruit and leaf disease detection method. Smart Agricultural Technology, 14, 102310. https://doi.org/10.1016/j.atech.2026.102310
11. Si, Q., Song, Y., & Han, S. I. (2026). ShuffleNetV2-hSimKD: A Lightweight Network for Plant Disease Detection. Agriculture, 16(15), 1686. https://doi.org/10.3390/agriculture16151686
12. Hussein, L. (2025). Attention-Fused Residual Lightweight MobileViT for Plant Leaf Disease Detection in Agriculture. ITM Web of Conferences, 79, 01037. https://doi.org/10.1051/itmconf/20257901037